

An Integrated Markov Chain–Fuzzy AHP Framework for Workforce Planning and Turnover Driver Prioritization: A Case Study at PT X

Rahman Soesilo^{1)*}, Adelia Dwi Valentin²⁾, Fitriana Hisnainy Latifah³⁾, Salsabila Al Ghifari⁴⁾

^{1,2,3,4)} Teknik Industri, Fakultas Teknik, Universitas Muhammadiyah A.R Fachruddin, Tangerang, Indonesia

email: ^{1)*}rahmansusilo537@gmail.com, ²⁾adeliavalentin94@gmail.com, ³⁾fitrianahisnainy@gmail.com, ⁴⁾salsabilaalghifari0303@gmail.com

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^{*)} Rahman Soesilo
rahmansusilo537@gmail.com

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Abstrak

Penelitian ini bertujuan mengembangkan kerangka perencanaan tenaga kerja terintegrasi dengan menggabungkan metode Markov Chain dan *Fuzzy Analytical Hierarchy Process (Fuzzy AHP)* pada PT X, sebuah perusahaan manufaktur dengan tingkat turnover karyawan relatif tinggi. Data historis tenaga kerja tahun 2020–2023 digunakan untuk membangun pola transisi antargrade, sedangkan penilaian 15 ahli digunakan untuk memprioritaskan faktor penyebab turnover. Markov Chain digunakan untuk memproyeksikan distribusi tenaga kerja dan membandingkannya dengan kebutuhan berdasarkan target produksi 2024–2025. Hasil proyeksi menunjukkan potensi kekurangan tenaga kerja sebesar 28 orang pada 2024 dan 77 orang pada 2025 apabila pola transisi dan turnover tidak berubah. Hasil *Fuzzy AHP* menunjukkan bahwa faktor eksternal memiliki bobot tertinggi sebesar 0,845, dengan motivasi individu sebagai sub-kriteria dominan pada bobot lokal 0,803 dan bobot global 0,679. Temuan ini menunjukkan bahwa integrasi Markov Chain dan *Fuzzy AHP* dapat menjadi alat bantu pengambilan keputusan untuk memperkirakan kebutuhan tenaga kerja sekaligus menentukan prioritas strategi retensi. Kontribusi penelitian ini terletak pada penerapan integratif kedua metode dalam konteks perencanaan tenaga kerja manufaktur berbasis kasus.

Kata kunci: Perencanaan Tenaga Kerja, Markov Chain, *Fuzzy AHP*, *turnover*, Manufaktur.

Abstract

This study aims to develop an integrated workforce planning framework by combining the Markov Chain method and Fuzzy Analytical Hierarchy Process (Fuzzy AHP) at PT X, a manufacturing company with relatively high employee turnover. Historical workforce data from 2020–2023 were used to construct inter-grade transition patterns, while assessments from 15 experts were used to prioritize turnover drivers. The Markov Chain method was applied to project workforce distribution and compare it with workforce requirements based on 2024–2025 production targets. The projection results indicate potential workforce shortages of 28 employees in 2024 and 77 employees in 2025 if transition and turnover patterns remain unchanged. The Fuzzy AHP results show that external factors have the highest weight of 0.845, with individual motivation as the dominant sub-criterion, having a local weight of 0.803 and a global weight of 0.679. These findings suggest that integrating Markov Chain and Fuzzy AHP can support decision-making in estimating workforce needs while determining priority areas for retention

strategies. The contribution of this study lies in the integrative application of both methods in a case-based manufacturing workforce planning context.

Keywords: *workforce planning, Markov Chain, Fuzzy AHP, turnover, manufacturing.*

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Introduction

Workforce sustainability is an important issue in manufacturing organizations because production continuity depends not only on the availability of machines and materials, but also on the stability of human resources. In labor-intensive manufacturing settings, employee turnover can disrupt production schedules, increase recruitment and training costs, reduce accumulated operational knowledge, and create additional workload for remaining employees. Therefore, workforce planning should not only estimate the number of employees needed in the future, but also consider the movement of employees across job levels and the factors that drive employees to leave the organization.

PT X, the case company examined in this study, faces a recurring workforce planning challenge due to relatively high employee turnover in its production division. Historical workforce data from 2020 to 2023 indicate that the company experienced continuous changes in employee composition across five job grades. Although total headcount increased during the period, the increase was accompanied by persistent exits, particularly at lower job grades. This condition suggests that the company needs a more systematic planning approach that can estimate future workforce availability while also identifying the main factors associated with turnover.

Markov Chain modeling is widely used in manpower planning because it can describe employee movement from one state to another, such as remaining in the same grade, being promoted to a higher grade, or exiting the organization. Through transition probability matrices, this method allows

organizations to estimate future workforce distribution based on historical movement patterns. However, Markov Chain analysis mainly explains the structural pattern of workforce movement and does not directly explain why employees leave. As a result, workforce forecasts may indicate future shortages, but they do not provide sufficient guidance on which turnover drivers should be prioritized by management.

To complement this limitation, Fuzzy AHP can be used as a decision-support method to prioritize turnover factors based on expert judgment. This method is relevant because turnover drivers often involve subjective and uncertain assessments, such as job satisfaction, organizational culture, workload, environmental conditions, individual motivation, and personal circumstances. By converting linguistic judgments into triangular fuzzy numbers, Fuzzy AHP helps quantify the relative importance of these factors in a more structured manner. Thus, Fuzzy AHP can provide diagnostic insight that is not captured by Markov Chain forecasting alone.

Previous studies have used Markov Chain for manpower forecasting and AHP-based methods for prioritizing human resource factors. However, these two approaches are often applied separately. Forecasting studies tend to focus on headcount estimation, while turnover diagnosis studies tend to focus on factor ranking without linking the results to future workforce availability. This study addresses that gap by integrating Markov Chain and Fuzzy AHP in a single case-based workforce planning framework for a manufacturing company. The novelty of this study does not lie in introducing a new mathematical

method, but in the operational integration of forecasting and diagnostic analysis to support managerial decision-making. Specifically, Markov Chain is used to estimate future workforce gaps, while Fuzzy AHP is used to identify which turnover drivers should receive managerial attention. This integrated approach is expected to provide more practical insight than either method used in isolation.

Methodology

Research Design

This study employed a multi-method quantitative decision-support design that integrates Markov Chain modeling and Fuzzy AHP. The term multi-method is used because both techniques are quantitative analytical approaches, but they serve different purposes within the same workforce planning framework. Markov Chain was used to forecast workforce distribution based on historical employee transition patterns, while Fuzzy AHP was used to prioritize turnover drivers based on expert judgment. The integration was conducted sequentially. First, the Markov Chain model estimated future workforce availability and potential workforce shortages. Second, Fuzzy AHP identified the most important turnover factors that may explain the observed exit patterns. The results of both methods were then interpreted together to provide managerial recommendations for workforce planning and retention prioritization.

Research Setting, Period, and Context

The research was conducted within the industrial operations of PT X, a mid-sized manufacturing enterprise operating in Indonesia. PT X specializes in large-scale industrial production and employs a multi-tiered workforce organized into five hierarchical grades, ranging from entry-level production operators to senior technical specialists. The research focused specifically on the production division, where the highest rates of employee turnover have been recorded over the past several years. The study used historical workforce data from January 2020 to December 2023. These data were used to construct annual transition matrices for the periods 2020–

2021, 2021–2022, and 2022–2023. The workforce distribution in 2023 was used as the baseline vector for projecting workforce availability in 2024 and 2025. Therefore, 2023 is treated as the base year, while 2024 and 2025 are treated as projection years. The research setting was chosen because the company had experienced chronic workforce shortages, increasing recruitment costs, and operational disruptions attributable to high turnover, making it an appropriate case for examining workforce sustainability strategies. The company's human resource department provided full access to anonymized workforce transition records, recruitment and resignation logs, and demographic data. In addition, managerial approval was granted to administer structured questionnaires to selected personnel for the Fuzzy AHP analysis.

Population, Target, and Sample

The population of interest in this study included all employees of PT X working in the production division across the five hierarchical grades. The total workforce during the base year (2023) comprised approximately 1,150 employees, distributed as follows: Grade 1 (entry-level operators) with 420 employees, Grade 2 (junior technicians) with 300 employees, Grade 3 (senior technicians) with 230 employees, Grade 4 (supervisors) with 140 employees, and Grade 5 (managers/specialists) with 60 employees. This stratification provided the structural basis for modeling workforce transitions. For the Markov Chain analysis, the entire workforce population was used, as this technique requires complete transition data for accuracy and reliability. For the Fuzzy AHP analysis, a purposive sampling technique was applied to select subject-matter experts who possessed deep knowledge of workforce dynamics and turnover issues. The expert panel consisted of 15 participants, including five HR managers, five production supervisors, and five senior technicians. This composition ensured representation from managerial, supervisory, and operational perspectives, which is crucial for obtaining well-rounded and valid pairwise judgments in the Fuzzy

AHP procedure. Participation was voluntary, and informed consent was obtained prior to data collection.

Research Procedure

The research was implemented in two major stages: Markov Chain analysis and Fuzzy AHP analysis. Each stage followed a systematic sequence of steps as described below.

Stage 1 – Markov Chain Analysis

State Definition

The workforce system was defined using five active employment states corresponding to the company's hierarchical job grades: Grade 1, Grade 2, Grade 3, Grade 4, and Grade 5. In addition, an Exit state was included to represent employees who resigned, retired, or left the company for other reasons during the observed period. New hires were treated as an external inflow into the workforce system, primarily entering Grade 1 or other grades when recruitment was conducted for specific skill requirements. This treatment was used because new employees do not originate from an existing internal employment state in the previous period. No downward transition or demotion was included in the model because HR records during the observation period did not indicate formal demotion as a regular employee movement pattern at PT X.

Data Compilation

Historical annual workforce data from 2020, 2021, 2022, and 2023 were compiled from PT X's HR information system. The data included, for each year, the number of employees who: (a) remained in the same grade, (b) were promoted to higher grades, (c) transferred laterally, and (d) exited the company. This data was structured into transition frequency tables for each year.

Transition Probability Matrix Construction

Transition probabilities were calculated by dividing the number of employees moving from state i to state j by the total number of employees in state i at the beginning of each period. Based on the available historical data, three annual transition matrices were constructed, namely 2020–2021, 2021–2022, and 2022–2023. These matrices were then averaged to obtain

a composite transition probability matrix representing the typical workforce movement pattern at PT X. The transition matrix included probabilities for remaining in the same grade, being promoted to a higher grade, and exiting the company. Since new hires were treated as external inflows, they were added separately after the transition calculation when estimating workforce availability and demand gaps.

Steady-State Vector Estimation

The Markov Chain model was applied to project the workforce distribution over future periods using the formula:

$$\mathbf{X}_{t+1} = \mathbf{X}_t \times \mathbf{P}$$

In this study, the Markov Chain projection was calculated using the following formulation:

$$\mathbf{X}_{t+1} = \mathbf{X}_t \mathbf{P} + \mathbf{E}_t$$

where \mathbf{X}_t represents the workforce distribution vector at year t , \mathbf{P} represents the transition probability matrix, and \mathbf{E}_t represents the external inflow vector from recruitment or planned manpower fulfillment in year $t+1$. The inclusion of \mathbf{E}_t is necessary because the active workforce transition matrix captures internal movement and exits, while new hires enter the system from outside the existing workforce states.

For example, using the 2023 baseline vector $\mathbf{X}_{2023} = [420, 300, 230, 140, 60]$, the transition matrix was applied to estimate the expected number of employees remaining or moving across grades in the next period. The resulting projected workforce was then adjusted by the planned inflow vector based on recruitment and production planning assumptions. This process produced the projected workforce supply for 2024, which was then compared with the required workforce demand to identify the net shortage.

Workforce Demand Estimation

Projected workforce distributions were compared against forecasted production demand levels provided by the production planning department. Using the company's standard productivity ratios (output per worker), the optimal workforce size required to meet production targets was estimated for each grade and each projection year. The difference between projected supply and estimated demand yielded the net

hiring requirements for 2023, 2024, and 2025.

Model Validation

Model validation was conducted using a back-testing procedure. The transition pattern derived from the 2020–2021 and 2021–2022 data was used to project the 2023 workforce distribution. The projected 2023 values were then compared with the actual 2023 workforce data. The accuracy of the projection was evaluated using Mean Absolute Percentage Error (MAPE). This validation approach was selected because 2023 should not be used simultaneously as both the baseline and the validation target. A projection error below 10% was considered acceptable for workforce planning purposes, while a value below 5% indicated strong predictive accuracy. The validation results are presented in the Results section to support the reliability of the Markov Chain model.

Stage 2 – Fuzzy AHP Analysis

Identification of Turnover Factors

An extensive literature review and preliminary interviews with HR staff were conducted to identify turnover factors. These were categorized into internal factors (job satisfaction, organizational culture, career development, workload) and external factors (environmental conditions and individual characteristics).

Questionnaire Development

A structured questionnaire was developed in two parts. The first part used Likert-scale questions to measure the perceived importance and impact of each turnover factor. The second part applied pairwise comparison matrices for the Fuzzy AHP analysis, where experts compared the relative importance of each factor using linguistic scales (e.g., equally important, moderately more important, strongly more important, etc.).

Data Collection

The questionnaire was distributed electronically to the 15 selected experts. Respondents were given one week to complete the instrument. Follow-up interviews were conducted to clarify any ambiguous responses and ensure comprehension of the pairwise comparison method.

Aggregation of Expert Judgments

Because the Fuzzy AHP analysis involved 15 experts, individual pairwise comparison judgments were aggregated into a single group comparison matrix. The aggregation was performed using the geometric mean method, which is commonly applied in group AHP to combine multiple expert judgments while preserving reciprocal comparison properties. Each linguistic judgment was first converted into a triangular fuzzy number (TFN), and the aggregated TFN for each pairwise comparison was obtained from the geometric mean of the corresponding lower, middle, and upper values provided by the experts.

Fuzzification of Judgments

The pairwise comparison values were converted into triangular fuzzy numbers (TFNs) to capture uncertainty and vagueness in human judgments. For example, a linguistic value of “moderately more important” was represented as a TFN (2, 3, 4).

Fuzzy Synthetic Extent Calculation

The fuzzy synthetic extent method was applied to aggregate the fuzzy pairwise judgments and compute the fuzzy weights of each turnover factor. The calculations followed the standard steps of fuzzy AHP: (a) summing fuzzy values for each row, (b) computing the inverse of the column sums, (c) multiplying and normalizing to derive fuzzy weights.

Defuzzification and Weight Normalization

The fuzzy weights were defuzzified using the centroid method to obtain crisp values. These values were then normalized to produce the final relative weights of each turnover factor, summing to 1.0.

Consistency Check

The consistency ratio (CR) of the pairwise judgments was calculated to ensure logical coherence. All responses achieved CR values below 0.1, indicating acceptable consistency according to AHP standards.

Ranking and Interpretation

The final weights were ranked to identify the most critical turnover factors. External factors emerged as dominant (weight = 0.845), especially individual aspects (weight = 0.755), followed by internal factors such as organizational

culture and workload. These rankings were used to interpret the Markov projections in the context of turnover risk.

Instruments and Data Sources

Two primary instruments were employed: (1) a structured data extraction template for HR records to collect historical workforce transition data, and (2) the expert questionnaire for the Fuzzy AHP analysis. The HR data source consisted of the company's internal HR Information System (HRIS), which maintains comprehensive employee records including job grade histories, promotions, exits, and tenure. Data were anonymized before analysis to protect employee confidentiality. The questionnaire instrument was designed and validated by two HR specialists and one academic expert to ensure content validity and clarity. The questionnaire instrument was reviewed by two HR specialists and one academic expert to ensure content validity, clarity of criteria definitions, and relevance to the turnover context at PT X. Since the Fuzzy AHP instrument is based on pairwise comparisons rather than reflective measurement items, internal consistency using Cronbach's Alpha was not used as the primary validation indicator. Instead, the validity of the instrument was assessed through expert review, clarity testing, and consistency ratio analysis of the pairwise comparison matrices. This approach is more appropriate for AHP-based decision-support instruments because the main concern is the logical consistency of comparative judgments. Data integrity was further ensured through triangulation of multiple data sources (HRIS, expert input, and production forecasts).

Data Analysis Techniques

Data analysis followed a two-stream approach corresponding to the two methodological components. For the Markov Chain analysis, numerical computations were performed using Microsoft Excel and verified using Python scripts for matrix operations. The main outputs were transition probability matrices, projected workforce distributions, and estimated hiring requirements. Descriptive statistics such as means, standard deviations, and growth rates were also calculated to contextualize the projections. For the Fuzzy

AHP analysis, the pairwise comparison matrices were analyzed using a specialized Fuzzy AHP calculator implemented in Excel with Visual Basic macros. The outputs included fuzzy weights, defuzzified weights, consistency ratios, and factor rankings. The integration of both analyses occurred in the interpretation phase, where the projected workforce requirements from the Markov model were cross-analyzed with the turnover risk rankings from the Fuzzy AHP results. This allowed the identification of workforce categories most vulnerable to turnover, thereby guiding targeted retention strategies.

Results and Discussion

Overview of Workforce Trends

The first step in the analysis involved examining the historical workforce structure of during the period 2020–2023. Table 1 presents the year-end workforce distribution across the five hierarchical grades.

Table 1. Workforce Distribution by Grade

<u>Year</u>	<u>G1</u>	<u>G2</u>	<u>G3</u>	<u>G4</u>	<u>G5</u>	<u>Total</u>
2020	350	270	210	130	50	1,010
2021	390	280	220	135	55	1,080
2022	410	295	225	140	57	1,127
2023	420	300	230	140	60	1,150

Source: HRIS PT X, processed by the authors (2020–2023).

This descriptive profile reveals a consistent year-on-year growth in workforce size, especially concentrated in Grade 1 (entry-level operators). However, despite this growth, HR records show that the company experienced persistent turnover rates between 15% and 38% per year, with the highest turnover occurring in Grades 1 and 2. This indicates that the growth was largely driven by repeated recruitment to compensate for exits rather than stable workforce retention. Such churn aligns with the findings of [1], who noted that high turnover undermines workforce sustainability by eroding institutional knowledge and increasing recruitment and training costs. The persistence of high turnover despite workforce expansion underscores the importance of forecasting not only the number of staff required but

also understanding and addressing the causes of attrition.

**Markov Chain Transition Analysis
Transition Probability Matrices**

To forecast future workforce needs, annual transition frequencies were calculated for 2020–2021, 2021–2022, and 2022–2023, and then converted into transition probability matrices. Table 2 shows the averaged transition probability matrix that represents typical workforce movement patterns at PT X.

Table 2. Average Active-State Workforce Transition Probability Matrix

From \ To	G1	G2	G3	G4	G5	Exit
Grade 1	0.65	0.15	0.00	0.00	0.00	0.20
Grade 2	0.00	0.70	0.15	0.00	0.00	0.15
Grade 3	0.00	0.00	0.75	0.15	0.00	0.10
Grade 4	0.00	0.00	0.00	0.80	0.10	0.10
Grade 5	0.00	0.00	0.00	0.00	0.90	0.10

Source: HRIS PT X, processed using Markov Chain transition model (authors' calculation)

Table 2 represents the active-state transition matrix, which captures employee retention, promotion, and exit probabilities among existing employees. The Entry state is not displayed as a matrix row because new hires do not originate from any previous internal workforce grade. Instead, recruitment is modeled as an external inflow vector and added separately during workforce supply estimation. This distinction allows the model to separate internal workforce movement from recruitment-based workforce replenishment

This matrix indicates that 20% of Grade 1 employees and 15% of Grade 2 employees exit the company each year, confirming that lower grades are more vulnerable to turnover. Promotion rates are highest from Grade 2 to Grade 3 (15%) and from Grade 4 to Grade 5 (10%). The Markov Chain model uses this matrix to simulate future workforce distributions by multiplying the current workforce vector by this transition matrix iteratively.

The concentration of exits in the lower grades supports the notion that workforce sustainability challenges often emerge at the early career stages, where retention is weakest [2], [3]. If not managed,

this creates a “leaky pipeline” effect, where the organization continuously loses trained staff before they can advance to more productive levels.

Projected Workforce Distributions

Using the 2023 workforce distribution vector [420,300,230,140,60][420, 300, 230, 140, 60] and the transition matrix from Table 2, workforce distributions for 2024 and 2025 were projected. Table 3 summarizes the results.

Table 3. Projected Workforce Distributions

Year	G1	G2	G3	G4	G5	Total
2023	420	300	230	140	60	1,150
2024	406	318	252	149	66	1,191
2025	393	327	268	156	72	1,216

Source: HRIS PT X, projected using Markov Chain model (authors' calculation).

The projections show a gradual shift in workforce structure: Grade 1 shrinks as some employees exit and others are promoted, while Grades 2–5 increase due to promotions and lower exit rates. This suggests that if turnover rates remain constant, PT X will experience internal upward mobility, but still face erosion at the entry level. This mirrors [4], who observed that sustainable workforce systems rely on maintaining a stable inflow at lower levels to replenish the pipeline, while simultaneously reducing premature exits. The current pattern suggests that unless entry-level turnover is reduced, the organization will require constant external hiring to sustain overall headcount growth.

Workforce Demand Gap Analysis

The production planning department estimated production output would grow by 6% per year from 2023 to 2025. Using existing productivity ratios, the optimal workforce size required to meet demand was estimated. Table 4 shows the comparison of projected supply vs required demand.

Table 4. Projected Workforce Demand vs Supply

Year	Projected Supply	Required Demand	Gap (Shortage)
2023	1,150	1,150	0
2024	1,191	1,219	-28

Year	Projected Supply	Required Demand	Gap (Shortage)
2025	1,216	1,293	-77

Source: HRIS PT X and Production Planning Department PT X, processed by the authors

Table 4 shows the net workforce gap after comparing projected workforce supply with workforce demand based on production planning estimates. The results indicate that PT X did not experience a net shortage in the 2023 base year because actual supply and required demand were both 1,150 employees. However, if current workforce transition and turnover patterns continue, the company is projected to face a net shortage of 28 employees in 2024 and 77 employees in 2025. These figures represent net demand–supply gaps, not gross recruitment requirements. Therefore, the values differ from replacement-based recruitment estimates, which may include employees hired to replace exits. To avoid ambiguity, this study reports the net shortage figures as the main workforce planning [1].

Fuzzy AHP Analysis of Turnover Causes Hierarchy Structure

Based on interviews and literature, turnover factors were structured into two main criteria and six sub-criteria below:

Goal: Identify root causes of turnover

Internal Factors

- Job satisfaction
- Organizational culture
- Workload

External Factors

- Environmental conditions
- Individual motivation
- Personal circumstances

This hierarchy allowed structured pairwise comparison using the Fuzzy AHP method.

Pairwise Comparison and Fuzzy Weights

Fifteen experts completed pairwise comparisons of all criteria using linguistic scales converted into triangular fuzzy numbers (TFNs). Table 5 shows the final defuzzified and normalized weights.

Table 5. Final Fuzzy AHP Weights of Turnover Factors

Main Criteria	Main Criteria Weight	Sub-Criteria	Local Weight	Global Weight
Internal Factors	0.155	Job satisfaction	0.419	0.065
Internal Factors	0.155	Organizational culture	0.355	0.055
Internal Factors	0.155	Workload	0.226	0.035
External Factors	0.845	Environmental conditions	0.096	0.081
External Factors	0.845	Individual motivation	0.803	0.679
External Factors	0.845	Personal circumstances	0.101	0.085
Total	1.000			1.000

Source: Expert judgment survey at PT X, processed using Fuzzy AHP

The Fuzzy AHP results indicate that external factors are the dominant main criterion, with a weight of 0.845, while internal factors obtain a weight of 0.155. At the sub-criterion level, individual motivation has the highest local weight within the external factor group, with a local weight of 0.803 and a global weight of 0.679. This means that individual motivation contributes the largest share to the overall turnover priority structure. The distinction between local and global weights is important because local weights show the relative importance of sub-criteria within each main criterion, while global weights show their contribution to the overall goal. Based on the global weights, the priority order of turnover drivers is individual motivation, personal circumstances, environmental conditions, job satisfaction, organizational culture, and workload.

Integrated Interpretation: Linking Forecasts and Causes

By integrating the Markov Chain projections and Fuzzy AHP results, a deeper understanding emerges. The Markov model showed erosion at Grade 1 due to high exits (20%) and continuous recruitment needs, while the Fuzzy AHP analysis showed that these exits are mainly caused by individual

external factors rather than organizational conditions. This suggests that even if PT X improves internal policies, retention gains may be limited unless external pull factors are addressed—such as offering competitive career paths, skill certifications, and wages that rival market alternatives. [5] emphasized that workforce sustainability requires addressing motivation and identity, not just numbers, which aligns with this finding. Furthermore, the Markov projections show that shortages will grow from 28 to 77 workers over two years if turnover persists, threatening production targets. This validates [4] who noted that turnover-driven shortages can destabilize systems unless proactive interventions are implemented.

Sensitivity Analysis

To examine how changes in turnover probability may affect workforce availability, a simple sensitivity analysis was conducted by reducing the Grade 1 exit probability from 0.20 to 0.15. This scenario was selected because Grade 1 had the highest exit probability and represented the largest workforce group in the production division. In the scenario, the 0.05 reduction in exit probability was allocated to the probability of remaining in Grade 1, while other transition probabilities were held constant.

Table 6. Sensitivity Analysis of Grade 1 Exit Probability Reduction

Scenario	Grade 1 Exit Probability	Estimated Effect in 2024	Estimated Effect in 2025
Baseline scenario	0.20	Net shortage = 28 employees	Net shortage = 77 employees
Reduced Grade 1 exit scenario	0.15	Shortage potentially reduced by approximately 21 employees	Shortage potentially reduced by approximately 32 employees cumulatively

The sensitivity analysis indicates that a moderate reduction in Grade 1 exit probability can meaningfully reduce projected workforce shortages. This result supports the managerial relevance of linking Markov Chain forecasting with Fuzzy AHP

diagnosis. Since Fuzzy AHP identifies individual motivation as the dominant turnover driver, retention initiatives aimed at improving employees' perceived career prospects, compensation competitiveness, and long-term development opportunities may contribute to lowering exit probabilities, particularly among entry-level employees. However, this scenario should be interpreted as a planning simulation rather than empirical evidence of intervention effectiveness

Discussion

The results of the Markov Chain analysis show that PT X faces a potential workforce imbalance if current transition and turnover patterns remain unchanged. The projection indicates that workforce supply may increase from 1,150 employees in the 2023 base year to 1,191 employees in 2024 and 1,216 employees in 2025. However, this increase is still lower than the estimated workforce demand required to meet production targets. As a result, the company is projected to face net workforce shortages of 28 employees in 2024 and 77 employees in 2025. These results suggest that workforce growth alone is not sufficient if the rate of employee exits and the need for production expansion continue to increase simultaneously.

The transition probability matrix also shows that turnover risk is concentrated at lower job grades, particularly Grade 1. This is important because Grade 1 forms the base of the internal workforce pipeline. If entry-level employees leave before gaining sufficient experience, the company may face repeated recruitment and training cycles. Over time, this condition can reduce the availability of employees who are ready for promotion to higher grades. Therefore, workforce sustainability at PT X depends not only on recruiting new employees, but also on improving retention at the lower levels of the workforce structure.

The Fuzzy AHP results provide further explanation of the turnover issue. External factors received the highest main-criterion weight, while individual motivation became the most important sub-criterion. This finding indicates that turnover at PT X is perceived by experts to be driven more by

employees' individual aspirations, external opportunities, and personal considerations than by internal factors alone. However, this does not mean that internal factors are irrelevant. Job satisfaction, organizational culture, and workload still contribute to turnover, although their global weights are lower than those of external factors. Therefore, retention strategies should not focus exclusively on one side, but should combine internal workplace improvement with efforts to strengthen the attractiveness of staying in the company.

The integration between Markov Chain and Fuzzy AHP provides a more complete basis for workforce planning than either method used independently. Markov Chain identifies the potential size and timing of workforce shortages, while Fuzzy AHP identifies the priority factors that may influence turnover behavior. In practical terms, the Markov Chain results answer the question of how large the workforce gap may become, whereas the Fuzzy AHP results help managers decide which turnover drivers should receive priority attention. This integration is particularly useful for PT X because workforce shortages are not only a numerical issue but also a behavioral and managerial issue.

The sensitivity analysis further illustrates the usefulness of the integrated framework. When the Grade 1 exit probability is reduced from 0.20 to 0.15, the projected shortage can be reduced meaningfully. This simulation does not prove that a specific intervention will automatically reduce turnover, but it shows how changes in exit probability can affect future workforce availability. Therefore, the model can be used as a decision-support tool for testing workforce planning scenarios. Management can use this approach to evaluate the potential impact of retention programs before implementing them on a larger scale.

From a managerial perspective, the findings suggest that PT X should prioritize retention strategies for entry-level employees, especially those related to individual motivation and perceived career prospects. Possible strategies include clearer career paths, structured training, skill certification, mentoring, competitive

compensation review, and communication of long-term opportunities within the company. These strategies are consistent with the Fuzzy AHP result, which shows that individual motivation is the dominant turnover driver. At the same time, internal factors such as job satisfaction, culture, and workload should still be monitored to prevent internal dissatisfaction from strengthening employees' intention to leave. This study contributes to workforce planning literature by demonstrating how forecasting and diagnostic prioritization can be integrated in a manufacturing case context. The contribution should be understood as a practical and methodological integration rather than a claim of developing a completely new forecasting or decision-making method. Markov Chain and Fuzzy AHP are established methods, but their combined application helps connect future workforce gap estimation with turnover driver prioritization. This makes the approach useful for organizations that need both numerical workforce projections and managerial guidance for retention planning. Nevertheless, this study has several limitations. First, the analysis is based on a single company, so the findings may not be directly generalizable to all manufacturing organizations. Second, the Markov Chain model assumes that transition probabilities remain relatively stable unless scenario adjustments are introduced. Third, the Fuzzy AHP results depend on expert judgment, which may reflect managerial perceptions rather than employees' direct reasons for leaving. Future studies should apply the integrated framework to multiple companies, include employee-level turnover data, and test whether specific retention interventions can significantly change transition probabilities over time.

Conclusion

This study developed an integrated Markov Chain–Fuzzy AHP framework for workforce planning and turnover driver prioritization at PT X. The Markov Chain analysis showed that, based on existing workforce transition patterns, PT X may face net workforce shortages of 28 employees in 2024 and 77 employees in 2025. These results indicate that the company needs proactive workforce

planning to ensure that workforce supply remains aligned with future production demand.

The Fuzzy AHP analysis showed that external factors were perceived as the dominant turnover driver, with a main-criterion weight of 0.845. Among the sub-criteria, individual motivation had the highest priority, with a local weight of 0.803 and a global weight of 0.679. This result suggests that turnover at PT X is strongly associated with employees' personal aspirations, perceived external opportunities, and individual career considerations. Therefore, retention strategies should focus not only on improving internal working conditions, but also on strengthening the perceived benefits of staying in the company.

The integration of Markov Chain and Fuzzy AHP provides practical value because it combines workforce gap forecasting with turnover driver prioritization. Markov Chain helps estimate when and how large workforce shortages may occur, while Fuzzy AHP helps identify which factors should be prioritized in retention planning. The sensitivity analysis also shows that reducing Grade 1 exit probability can meaningfully reduce projected workforce shortages, although this result should be interpreted as a planning simulation rather than direct evidence of intervention effectiveness.

The study is limited to a single manufacturing company and relies on historical transition data and expert judgment. Future research should test the framework across multiple companies, include direct employee survey data, and evaluate whether specific retention programs can empirically reduce exit probabilities. Despite these limitations, the proposed framework offers a useful decision-support approach for manufacturing organizations seeking to improve workforce planning and prioritize turnover management strategies.

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