e-ISSN: 3079-6377 p-ISSN: 3079-6369

Causal Analysis of the Impact of Hotel Employee Training Investment on Turnover Rate

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Abstract

High employee turnover is a common human resource management challenge faced by the hotel industry, but whether training investment can effectively reduce turnover rate still lacks rigorous causal evidence. This study uses a large hotel group as the research subject to assess the actual impact of employee training investment on turnover behavior. The research sample covers the personnel, training, and performance records of 9,842 employees for 18 consecutive months. Variables include job type, training duration, performance rating, and attendance. Propensity score matching was used to construct a comparable sample, and difference analysis was combined to identify the net effect of training intervention. Empirical results show that employees who received systematic training had a significantly lower probability of leaving during the subsequent observation period, and the longer the training duration, the more significant the decrease in turnover rate. Further analysis shows that this effect is more prominent in front-line service positions. This study verifies the role of training in employee retention from a causal perspective, providing empirical support for the allocation of hotel training resources.

Keywords

Employee training; Turnover rate; Causal analysis; Propensity score matching; Hotel management

1.Introduction

Employee turnover has long been recognized as a structural challenge in the hotel industry, where service delivery depends heavily on frontline labor and stable staffing is essential for maintaining service quality and operational efficiency. High turnover not only increases recruitment and training costs but also disrupts team coordination and weakens service consistency, particularly in customer-facing functions [1]. Recent evidence further indicates that turnover dynamics in hospitality are highly sensitive to external economic conditions and unexpected shocks, such as macroeconomic volatility, labor market tightness, and public health crises, which complicate workforce planning and amplify uncertainty in human resource management [2,3]. These characteristics underscore the importance of identifying human resource practices that can stabilize employment relationships under conditions of heightened volatility. A growing body of research suggests that data-driven human resource

e-ISSN: 3079-6377 p-ISSN: 3079-6369

strategies and structured employee engagement mechanisms can mitigate workforce instability in hospitality settings. Recent advances in large-scale personnel analytics highlight the role of training, skill development, and cross-cultural engagement in improving employee retention and organizational resilience, particularly in multinational hotel operations [4]. By integrating big data forecasting with human resource optimization, this line of research emphasizes that training investments may function not only as capability-building tools but also as strategic levers for reducing exit risk in diverse and dynamic service environments [5]. These insights point to the potential of training systems to buffer hotels against labor market shocks while supporting long-term workforce sustainability. Existing hospitality research has traditionally focused on employees' turnover intention and its psychological antecedents [6]. Empirical studies consistently document associations between job stress, emotional labor, customer-related strain, job satisfaction, perceived organizational support, and employees' stated intention to quit [7,8]. While this literature provides valuable insights into motivational and attitudinal mechanisms, most findings are derived from cross-sectional survey data and rely on self-reported intentions rather than observed exit behavior. As a result, the extent to which these correlates translate into actual turnover remains uncertain, and causal interpretation is inherently limited due to potential reporting bias and reverse causality [9]. Employee training and development are commonly regarded as practical instruments for reducing turnover because they enhance job-related skills, strengthen perceived employer support, and improve long-term career prospects [10,11]. Research in labor economics and organizational behavior generally reports a negative association between training participation and employee exit, often interpreted through human capital accumulation and social exchange mechanisms [12]. Within the hotel industry, recent studies emphasize that structured training systems and integrated human resource practices play a particularly important role in employee retention during periods of labor market disruption, including the post-pandemic recovery phase [13,14]. However, much of the existing evidence remains correlational, as training opportunities are rarely assigned randomly and employees who participate in training often differ systematically from non-participants in motivation, performance, or career orientation. These concerns have stimulated growing interest in quasi-experimental approaches that aim to strengthen causal inference using observational data. Propensity score matching is widely applied to construct comparable groups of trained and untrained employees, although its validity depends critically on comprehensive covariate selection and rigorous balance assessment [15]. Difference-in-differences designs offer an additional identification strategy by exploiting temporal variation in treatment exposure, yet

e-ISSN: 3079-6377 p-ISSN: 3079-6369

recent econometric research has demonstrated that conventional fixed-effects estimators may yield biased estimates when treatment timing is staggered or effects are heterogeneous across groups [16]. Methodological advances in this area suggest that combining matching techniques with modern difference-in-differences estimators can substantially improve the credibility of causal estimates in human resource and labor studies [17]. Against this backdrop, the present study investigates the causal effect of training investment on employee turnover using personnel-level panel data from a large hotel group. The analysis follows 9,842 employees over an 18-month period and integrates propensity score matching with a difference-in-differences framework designed to address selection bias and time-varying confounders. Beyond estimating the average treatment effect, the study examines heterogeneity across training intensity levels and job categories, providing evidence on where training yields the greatest retention benefits. By grounding the analysis in observed exit behavior rather than stated intentions, the study contributes to a more rigorous understanding of how training investments shape workforce stability. The findings offer practical guidance for hotel managers seeking to allocate training resources more effectively in environments characterized by high employee mobility and persistent external uncertainty.

2.Materials and Methods

2.1 Sample and Study Context

The study relied on personnel records from a large hotel group operating several full-service properties in major urban locations. The sample included 9,842 employees observed continuously over an 18-month period. The dataset covered frontline service roles and supporting operational positions, such as housekeeping, front desk, food and beverage, and back-of-house functions. Employees with incomplete employment histories or missing key variables were excluded to ensure consistent observation windows. The resulting panel allowed employee characteristics, training exposure, and employment outcomes to be tracked over time.

2.2 Study Design and Comparison Groups

A quasi-experimental framework was used to assess the effect of training investment on employee turnover. Employees who participated in structured training during the observation period were classified as the treated group, while employees without training formed the comparison group. Because training participation was not randomly assigned, direct outcome comparison would be biased. To reduce this bias, comparable control employees were selected based on observed characteristics measured before training. The

e-ISSN: 3079-6377 p-ISSN: 3079-6369

design assumes that, after conditioning on these characteristics, treated and untreated employees would have shown similar turnover trends in the absence of training.

2.3 Measurement and Quality Control

Employee turnover was defined as an observed employment exit occurring during the post-training period. Training exposure was captured using a participation indicator and the total number of training hours completed. Control variables included job category, tenure, attendance rate, and performance score, all measured prior to training. Data checks were performed to identify duplicate entries, implausible values, and timing inconsistencies. Records associated with non-voluntary contract termination were excluded to avoid conflating turnover with administrative exits.

2.4 Data Processing and Model Specification

Propensity scores were estimated using a logistic regression model to balance observable characteristics between trained and untrained employees. The propensity score for employee i is given by

$$P(T_i = 1 \mid X_i) = \frac{\exp(\gamma_0 + \gamma X_i)}{1 + \exp(\gamma_0 + \gamma X_i)},$$

where T_i indicates training participation and X_i represents pre-training covariates. Matched samples were constructed using nearest-neighbor matching with a caliper constraint. The effect of training on turnover was then estimated using a difference-in-differences specification:

$$Y_{it} = \alpha + \beta(T_i \times Post_t) + \delta_i + \lambda_t + \varepsilon_{it},$$

where Y_{it} denotes turnover status, $Post_t$ indicates the post-training period, δi captures individual-specific effects, and λ_t captures time effects. The coefficient β represents the average effect of training on turnover.

2.5 Robustness Checks and Evaluation Criteria

Several robustness analyses were performed to assess result stability. Alternative matching settings and caliper widths were tested to examine sensitivity to propensity score construction. Placebo tests using pre-training periods were conducted to evaluate the parallel trend assumption. Additional analyses by job category were used to explore effect heterogeneity. Statistical inference relied on standard errors clustered at the employee level to account for repeated observations.

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3.Results and Discussion

3.1 Group comparability after propensity score matching

In the original sample, employees who received training differed from non-participants in job category, tenure, attendance patterns, and baseline performance. These differences would bias a simple comparison of turnover outcomes. After propensity score matching, the treated and control groups displayed much closer alignment across observed covariates. Standardized mean differences were substantially reduced, indicating improved balance [18]. Such balance diagnostics are widely used in matched observational studies to support the credibility of post-treatment comparisons [19]. Fig.1. Covariate balance before and after propensity score matching (Love plot).

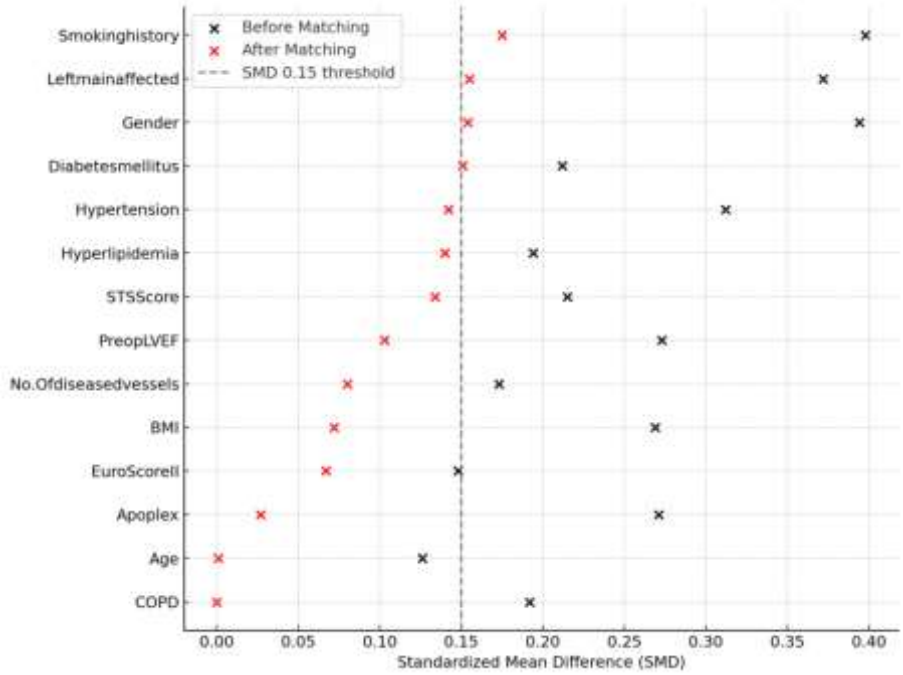

Figure 1 Balance of observed covariates for trained and untrained employees before and after propensity score matching.

3.2 Average effect of training on turnover in the matched DiD analysis

Results from the difference-in-differences analysis indicate a lower post-training turnover rate among trained employees relative to matched controls. The estimated effect remains after accounting for common time effects and stable employee characteristics. This pattern reduces concern that the observed difference reflects seasonal exit cycles or persistent individual traits. Compared with hospitality studies based on cross-sectional surveys and turnover intention, these findings rely on observed exits and longitudinal comparison, which provides stronger evidence on the retention effect of training [20,21].

e-ISSN: 3079-6377 p-ISSN: 3079-6369

3.3 Timing of impact and pre-period stability

Event-time analysis shows similar turnover trends between treated and control groups prior to training. After training exposure, the trajectories diverge and the gap persists across subsequent months. This pattern is consistent with a lasting effect rather than a short-term response immediately following training. Such dynamics are commonly used in multi-period difference-in-differences settings to assess pre-period stability and to describe how treatment effects evolve over time [22,23]. Fig.2. Event-study difference-in-differences estimates around treatment timing, showing pre-period stability and post-period effects.

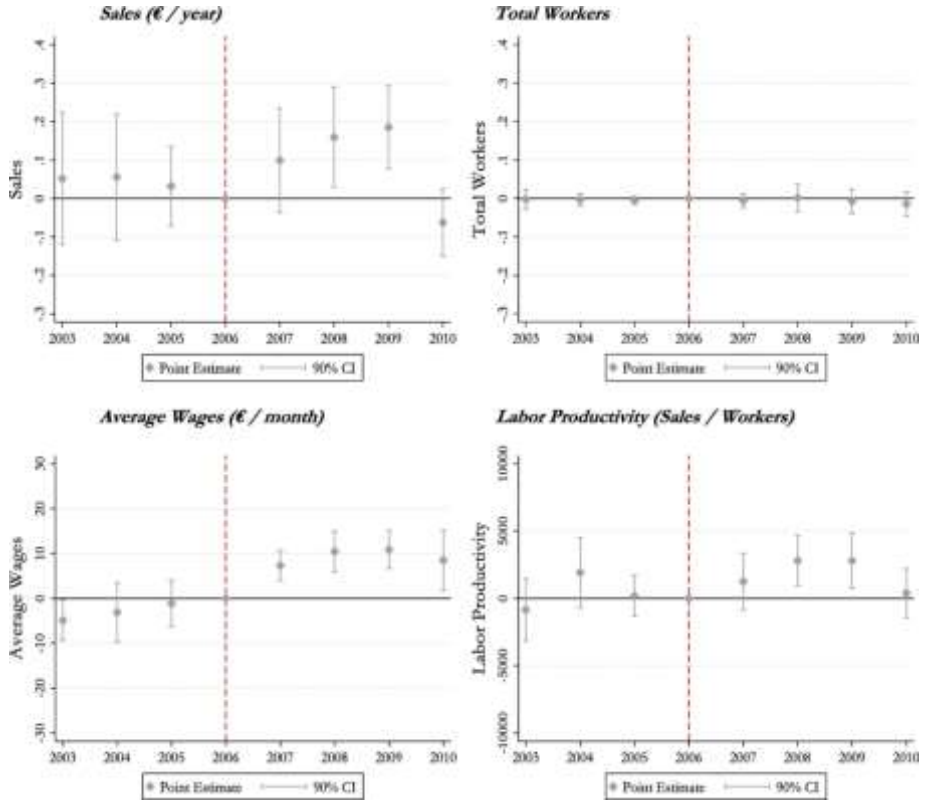

Figure 2 Event-study estimates of employee turnover before and after the training intervention.

3.4 Heterogeneity and implications for hotel training allocation

The reduction in turnover is larger for frontline service roles than for back-of-house or administrative positions. This difference is consistent with higher workload pressure and customer interaction intensity in frontline jobs. A dose pattern is also observed: longer training duration is linked to greater reductions in turnover risk. This result implies that short or limited training may be insufficient to influence retention outcomes. For hotel human resource management, the findings suggest that training resources are most effective when targeted toward high-churn frontline roles and delivered with adequate depth. Remaining limitations include potential correlation between training access and unobserved factors such

e-ISSN: 3079-6377 p-ISSN: 3079-6369

as managerial practices or team climate, which points to the value of future studies incorporating richer organizational controls or policy-driven variation [24].

4.Conclusion

The results show that training investment is associated with a lower likelihood of employee turnover in hotel operations when evaluated using a causal identification approach. By applying propensity score matching together with a difference-in-differences framework, the analysis separates the effect of structured training from observable employee differences and common time influences. Employees who received training were less likely to exit during the post-training period, and the effect was stronger among frontline service positions and for longer training duration. These findings add to the hospitality literature by focusing on observed turnover behavior rather than stated turnover intention. In practical terms, the results indicate that targeted training programs can support employee retention in hotel settings with high workforce mobility. Several limitations should be noted. The analysis relies on observational data and may still be affected by unobserved managerial or team-related factors, and the observation window does not allow assessment of long-term retention effects. Future research could address these issues by incorporating richer organizational information or using policy-based variation in training assignment.

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