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A Study on the Filling-in Cycle and Talent Mobility Characteristics of Key Positions in Public Research Institutions

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Abstract

In the process of undertaking long-term research tasks, the filling efficiency of key technical and management positions in public research institutions directly affects the project's progress. This study analyzes the impact of different position attributes on recruitment efficiency, focusing on the filling-in cycle and talent mobility characteristics. The study selected 36 months of personnel and recruitment data from a national-level research institution, covering 1,384 job openings and 12,760 candidate records. Explanatory variables included job professional requirements, project cycle stage, salary range, and team size. Survival analysis was used to characterize the filling-in time distribution, and a proportional hazards model was used to estimate influencing factors. The results show that the median filling time for positions with higher professional requirements is extended by approximately 18 days, and the filling-in risk rate significantly decreases when the project is in a critical stage. The research results provide a quantitative basis for research institutions to formulate phased talent recruitment strategies.

Keywords

Public research institutions; Job filling; Survival analysis; Talent mobility; Human resource planning

1.Introduction

Public research institutions undertake long-term scientific and technological missions in which delays in filling a limited number of key technical or managerial positions may disrupt project schedules and elevate operational risk. In such settings, recruitment lead time represents not merely an administrative outcome but a structural determinant of project execution capacity. Compared with private firms, public research organizations are commonly subject to stricter procedural oversight, standardized position classifications, and constrained compensation mechanisms, all of which may extend hiring cycles [1]. Recent international assessments report substantial variation in recruitment duration across public agencies and job categories, often ranging from several weeks to several months [2]. Evidence from science- and technology-oriented public agencies further indicates that prolonged vacancy periods constrain organizational performance and undermine project continuity [3]. Recent studies in strategic human resource leadership further demonstrate that the integration of HR

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analytics with cross-cultural coordination mechanisms enhances talent allocation efficiency and organizational resilience in globally distributed R&D environments [4]. These findings underscore the necessity of systematically examining position backfill time as a measurable indicator of recruitment efficiency in public research institutions. In labor economics and organizational research, vacancy duration has been widely adopted to capture recruitment frictions, selection intensity, and labor market tightness. Empirical analyses based on large-scale job posting data demonstrate substantial variation in time-to-fill across occupations and skill levels, reflecting both labor supply conditions and employer search strategies [5,6]. Compensation policies play a central role in this process. Within-firm wage variation is frequently associated with shorter vacancy durations, suggesting that more competitive pay structures can mitigate search frictions and accelerate hiring [7]. Studies on skill-based recruitment further indicate that stringent qualification requirements reduce applicant pools and extend hiring timelines, particularly for specialized technical positions [8]. Collectively, these findings highlight the importance of job design characteristics—such as required expertise, compensation range, and role specificity—in shaping recruitment speed. Another stream of research addresses talent mobility and workforce stability in the public sector. Administrative data analyses reveal that personnel turnover reflects both external exits and internal mobility across departments, each with distinct implications for organizational capacity [9,10]. Methodologically, employment duration and vacancy duration have been modeled as time-to-event processes, allowing more precise estimation under right-censoring and heterogeneity [11]. Research on researcher mobility shows that career stage, funding availability, and institutional reputation influence job transitions and candidate availability for research institutions [12,13]. Large-scale studies of academic labor markets also identify systematic geographic and institutional effects on talent flows, indicating that mobility patterns should be incorporated when evaluating recruitment outcomes [14]. These insights suggest that recruitment efficiency in public research institutions cannot be fully understood without considering broader labor market dynamics and organizational context. Despite these advances, important gaps remain when existing approaches are applied to public research institutions. Many empirical studies rely on publicly available job postings or aggregated indicators, which do not capture the full recruitment workflow or internal decision processes of publicly funded research organizations [15]. Project lifecycle effects are often discussed conceptually but are seldom incorporated as explicit explanatory variables. Recruitment urgency and selection standards may shift as projects move into critical implementation stages, yet this dimension has received limited quantitative examination [16,17].

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Furthermore, the expanding availability of large-scale human resources datasets introduces methodological challenges for survival analysis, including proportional hazards assumption testing, time-varying effects, and unobserved heterogeneity [18]. Addressing these issues is essential for producing reliable and policy-relevant evidence. This study responds to these limitations by analyzing detailed recruitment records from a national-level public research institution over a 36-month period, encompassing 1,384 position requests and 12,760 candidate records. Survival analysis is employed to characterize the distribution of position backfill time while accounting for right-censoring, and proportional hazards models are used to estimate the effects of job-related and organizational factors on the hazard of position closure. Core explanatory variables include professional requirement intensity, project phase, compensation range, and team size. By explicitly integrating project-stage characteristics and role attributes into a time-to-event framework, the study advances the empirical measurement of recruitment efficiency in mission-driven public organizations. The findings provide quantitative evidence on how organizational context and job design interact to shape hiring speed, offering methodological guidance for the application of survival models to large-scale HR data and practical implications for stage-sensitive workforce planning. In particular, the results support the development of evidence-based recruitment strategies that balance selection rigor and project urgency, thereby strengthening institutional capacity to sustain complex scientific and technological programs under resource and procedural constraints.

2.Materials and Methods

2.1 Sample and Study Context

This study uses administrative human resources and recruitment records from a national public research institution covering a continuous 36-month period. The dataset consists of 1,384 position requisitions linked to long-term research projects and 12,760 corresponding candidate applications. The positions include technical and managerial roles with different levels of specialization and responsibility. All recruitment activities followed unified public-sector hiring procedures and institutional regulations. Records lacking complete timestamps or key job attributes were removed to ensure accurate measurement of recruitment duration.

2.2 Recruitment Design and Comparison Structure

The study adopts a comparative design based on position characteristics and project context rather than direct experimental intervention. Position requisitions were grouped according to professional requirement level, project phase at the time of recruitment, compensation range, and team size. Positions with higher professional requirements were compared with those

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requiring general qualifications, while positions initiated during critical project phases were compared with those initiated during non-critical phases. This classification enables structured comparison under identical institutional rules and reduces confounding from procedural differences.

2.3 Measurement Procedures and Quality Control

The main outcome variable is position backfill time, defined as the number of calendar days from formal approval of a position requisition to confirmed position closure. All dates were obtained from a centralized recruitment management system to ensure consistency. Explanatory variables were extracted from standardized job descriptions, project management records, and compensation tables. Data checks were applied to identify duplicate records, inconsistent dates, and implausible durations. Observations in the upper tail of the distribution were examined individually and retained only when supported by complete and consistent records.

2.4 Data Processing and Model Specification

Recruitment duration was analyzed using survival analysis to account for right-censored cases in which positions remained unfilled at the end of the observation period. Kaplan–Meier estimators were used to describe the distribution of backfill time across comparison groups. The effects of job and project characteristics were estimated using proportional hazards models. The general form of the model is expressed as

$$h(t|X)=h_0(t)\exp(\beta_1X_1+\beta_2X_2+\cdots+\beta_kX_k),$$

where $h(t|X)$ represents the hazard of position closure at time t, $h_0(t)$s the baseline hazard, and X_k denotes job- and project-related covariates. Group differences in recruitment duration were further summarized using median backfill time, calculated as

$$\Delta T=T_{0.5}^{(A)}-T_{0.5}^{(B)},$$

where $T_{0.5}$ indicates the estimated median time-to-fill for groups A and B.

2.5 Robustness Checks and Assumption Testing

Model assumptions were examined using Schoenfeld residuals and time-based diagnostic tests to assess proportionality. Sensitivity analyses were conducted by modifying variable definitions and excluding selected covariates to evaluate result stability. Additional analyses were performed separately for technical and managerial positions to identify potential differences in recruitment patterns. Similar effect directions and magnitudes across alternative specifications were taken as evidence of robustness.

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3.Results and Discussion

3.1 Backfill-time distribution and long-tail behavior

Backfill time showed a pronounced right-skewed distribution. A large share of requisitions was closed within the early recruitment window, while a smaller group remained open for a substantially longer period. This pattern suggests that recruitment difficulty is heterogeneous rather than uniform across positions [19]. Early closures are consistent with sufficient candidate availability and efficient internal coordination. In contrast, long-tail vacancies are more likely associated with limited skill supply, repeated loss of candidates at later stages, or extended approval procedures for positions with higher strategic importance. A time-to-event perspective is therefore more informative than average duration metrics, as it captures how the probability of closure evolves over time and how difficult cases accumulate in later stages [20]. Fig.1. Kaplan–Meier curves (time-to-event display).

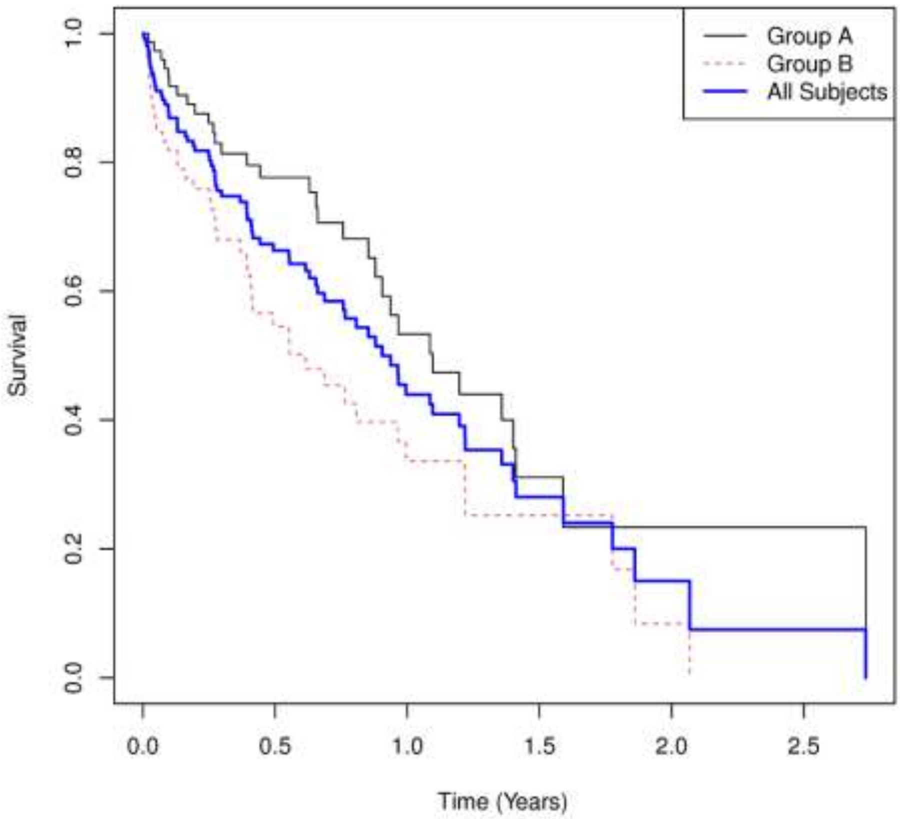

Figure 1 Kaplan–Meier curve showing the probability that positions remain unfilled over the recruitment period.

3.2 Specialization requirements and median time extension

Positions with higher specialization requirements exhibited a longer median time-to-fill, with an increase of approximately 18 days compared with roles defined by general qualifications. This result indicates that requirement intensity is a major contributor to recruitment delay, even under identical institutional hiring rules. A straightforward explanation is constrained

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matching. As skill thresholds increase, the pool of qualified candidates narrows, screening becomes more selective, and the likelihood of restarting the recruitment process after interviews rises [21]. Evidence from vacancy-duration studies in broader labor markets reports similar sensitivity of hiring speed to skill scarcity, particularly in settings where compensation or job scope cannot be easily adjusted. In public research institutions, standardized job classifications and approval procedures further limit flexibility, which can amplify delays for roles requiring rare technical expertise or project-specific knowledge.

3.3 Project-stage pressure and hazard-based interpretation

Requisitions initiated during critical project stages showed a lower closure hazard. This finding indicates that the likelihood of filling a position at any given time decreases when milestone pressure is high. Such behavior is consistent with stricter selection standards under elevated project risk. During critical phases, teams tend to emphasize reliability and role fit, while governance processes often become more cautious, leading to longer decision cycles even when candidate flow is stable. Hazard-based reporting is useful because it distinguishes positions that take longer due to inherently low closure probability from those that simply remain open because time has elapsed [22,23]. Fig.2. Forest plot showing estimated hazard ratios from a multivariable Cox proportional hazards model.

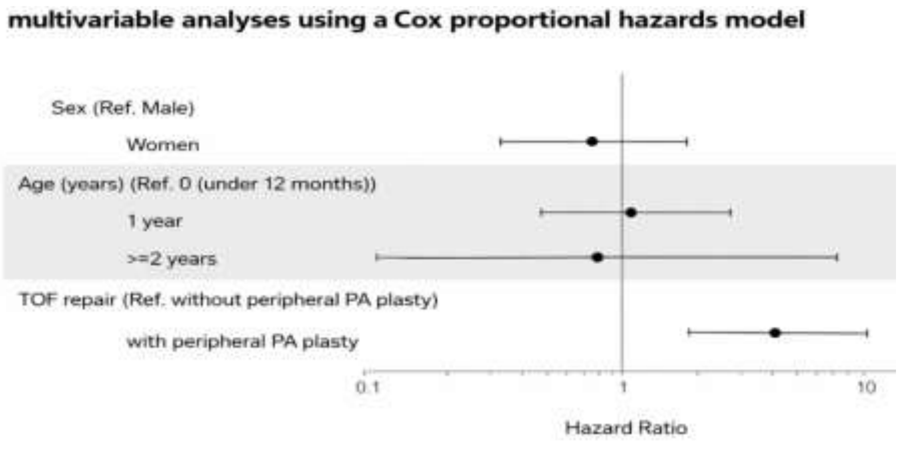

Figure 2 Forest plot of hazard ratios from the Cox proportional hazards model illustrating the effects of job and project factors on position filling rates.

3.4 Comparison with related evidence and staffing implications

Taken together, the results indicate that recruitment outcomes are jointly shaped by role design and organizational timing. Specialization intensity and project stage interact in a way that can reinforce delays. When highly specialized roles are launched close to project milestones, recruitment becomes more difficult because limited candidate supply coincides with stricter decision thresholds. This interaction helps explain why overall hiring performance may appear acceptable on average while bottlenecks persist in a small number of mission-critical positions. Similar long-tail patterns have been reported in other time-to-event studies, where easier cases resolve early and remaining cases concentrate higher constraints [24]. From a workforce planning perspective, the findings support a stage-sensitive approach. Candidate pipelines for scarce-skill roles should be developed before projects enter critical phases, while recruitment during milestone periods should focus on reducing avoidable internal delays without lowering qualification standards.

4.Conclusion

This study offers a data-driven examination of recruitment timing for key positions in a national public research institution. The analysis shows that positions with higher specialization requirements tend to remain open longer, and that vacancies initiated during critical project stages have a lower probability of being filled at any given time. These results indicate that extended backfill periods are not only the result of procedural delay but also reflect tighter selection under skill scarcity and elevated project risk. A central contribution of this work is the application of survival analysis combined with project-stage information to describe how recruitment difficulty changes over time in a public research setting. This approach provides a clearer and more realistic view of staffing dynamics than static duration measures. The findings have practical value for workforce planning, as they support early candidate pipeline development for specialized roles and targeted process streamlining during milestone periods. Several limitations remain. The data were drawn from a single institution, which may restrict broader applicability, and factors such as individual candidate decisions or informal hiring interactions were not directly observed. Further studies using multi-institution datasets and additional behavioral indicators would help strengthen and extend the evidence base for recruitment planning in public research organizations.

References

[1] Zhu, W., Yang, J., & Yao, Y. (2025). How Cross-Departmental Collaboration Structures Mitigate Cross-Border Compliance Risks: Network Causal Inference Based on ManpowerGroup's Staffing Projects.

[2] Jakubowski, M., Gajderowicz, T., & Patrinos, H. A. (2025). COVID-19, school closures, and student learning outcomes. New global evidence from PISA. npj Science of Learning, 10(1), 5.

[3] Zhu, W., Yang, J., & Yao, Y. (2025, October). How Compliance Maturity Translates to Risk Reduction: A Multi-Case Comparison of Global Operations Using fsQCA and Hierarchical

Bayesian Methods. In Proceedings of the 2025 2nd International Conference on Digital Economy and Computer Science (pp. 672-676).

[4] Li, T., Xia, J., Liu, S., & Hong, E. (2025). Strategic Human Resource Leadership in Global Biopharmaceutical Enterprises: Integrating HR Analytics and Cross-Cultural.

[5] Black, I., Hasan, S., & Koning, R. (2024). Hunting for talent: Firm-driven labor market search in the United States. Strategic Management Journal, 45(3), 429-462.

[6] Anastasia, G., Boeri, T., & Zholud, O. (2026). A wartime labor market: the case of Ukraine (No. dp2142). Centre for Economic Performance, LSE.

[7] Wang, J., & Xiao, Y. (2025). Assessing the Spillover Effects of Marketing Promotions on Credit Risk in Consumer Finance: An Empirical Study Based on AB Testing and Causal Inference.

[8] Hadžic, B., Brandner, L. T., Weber, T., & Rätsch, M. (2025). AI-driven active sourcing in recruitment: addressing contestability in automated hiring systems. Frontiers in Computer Science, 7, 1629522.

[9] Wang, J., & Xiao, Y. (2025). Research on Transfer Learning and Algorithm Fairness Calibration in Cross-Market Credit Scoring.

[10] Anderson, T. (2024). Left behind? Understanding the career consequences of collaborator exits. Academy of Management Journal, 67(2), 526-553.

[11] Gu, X., Yang, J., Tian, X., & Liu, M. (2025). Research on the Construction of a Human-Machine Collaborative Anti-Money Laundering System and Its Efficiency and Accuracy Enhancement in Suspicious Transaction Identification.

[12] Du, Y. (2025). Research on Digital Quality Traceability System for Temperature-Controlled Supply Chain of Foreign Trade Wine Driven by Blockchain and IoT. Business and Social Sciences Proceedings, 4, 57-65.

[13] Melkers, J., Woolley, R., & Kreth, Q. (2023). Research funding and scientific careers. In Handbook of Public Funding of Research (pp. 301-321). Edward Elgar Publishing.

[14] Sousa, B., Ferreira, J. J., Jayantilal, S., & Dabic, M. (2024). Global talent management–talents, mobility and global experiences–a systematic literature review. Journal of Global Mobility: The Home of Expatriate Management Research, 12(3), 444-501.

[15] Mao, Y., Ma, X., & Li, J. (2025). Research on API Security Gateway and Data Access Control Model for Multi-Tenant Full-Stack Systems.

[16] Paudel, R., Tehrani, S., & Sherm, A. (2024). Balancing act: integrating qualitative and quantitative data driven for recruitment and selection process. Jurnal Info Sains: Informatika dan Sains, 14(02), 162-177.

[17] Du, Y. (2025). Research on Deep Learning Models for Forecasting Cross-Border Trade Demand Driven by Multi-Source Time-Series Data. Journal of Science, Innovation & Social Impact, 1(2), 63-70.

[18] Sufian, M. A., Hamzi, W., Ali, M., Ali, A., & Hamzi, B. (2025). Long-term Heart Risk Prediction by

6ISSN: 3008-1769

Survival Analysis in Echocardiography: Leveraging Machine Learning, Interpretability Techniques, and Advanced Statistical Modelling.

[19] Liu, S., Feng, H., & Liu, X. (2025). A Study on the Mechanism of Generative Design Tools' Impact on Visual Language Reconstruction: An Interactive Analysis of Semantic Mapping and User Cognition. Authorea Preprints.

[20] Van Wijk, R. C., & Simonsson, U. S. (2022). Finding the right hazard function for time-to-event modeling: a tutorial and shiny application. CPT: Pharmacometrics & Systems Pharmacology, 11(8), 991-1001.

[21] Sheu, J. B., & Gao, X. Q. (2014). Alliance or no alliance—Bargaining power in competing reverse supply chains. European Journal of Operational Research, 233(2), 313-325.

[22] McCarthy, S., Karlström, A., & Blom Västberg, O. (2025). Activity duration dependent utility in a dynamic scheduling model. Transportmetrica B: Transport Dynamics, 13(1), 2436933.

[23] Gu, X., Yang, J., & Liu, M. (2025). Research on a Green Money Laundering Identification Framework and Risk Monitoring Mechanism Integrating Artificial Intelligence and Environmental Governance Data.

[24] Rahman, M. M. (2025). AI-driven predictive analytics models for enhancing group insurance portfolio performance and risk forecasting. International Journal of Scientific Interdisciplinary Research, 6(2), 39-87.