



Analysis of Competency Structure and Employee Behavioral Characteristics in Hotel Frontline Positions

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Abstract: *Improving the competency level of frontline positions is an important way for hotels to improve service quality and operational efficiency. This study systematically analyzes the ability differences implied in employee behavioral data, focusing on the structural characteristics of job competencies. The study selected multi-source operational data from over 6,500 employees of a chain hotel, covering attendance, scheduling, performance appraisal, customer complaints, and work order processing, totaling over 19 million records. A behavioral indicator system was constructed, and cluster analysis was used to identify the characteristic differences among different performance groups. The results show that high-performing employees significantly outperformed other groups in peak-hour response speed, complaint handling efficiency, and cross-job collaboration. Based on the analysis results, job competency profiles were created and used in recruitment and probationary period evaluations, resulting in a significant increase in the probationary period pass rate for new employees. The research indicates that using behavioral data to characterize competency structure helps optimize hotel human resource decisions.*

Keywords: *Job competency; employee behavior; cluster analysis; job-person matching; hotel industry*

1. Introduction

Frontline employees play a pivotal role in shaping service quality and operational efficiency in hotel operations, as their daily actions directly influence customer experience in high-contact service encounters. Contemporary hospitality research increasingly conceptualizes job competency as a structured and multidimensional construct that integrates operational execution, interpersonal interaction, problem-solving ability, and task coordination, rather than treating performance as a single outcome indicator [1,2]. This perspective reflects the complex and time-sensitive nature of frontline work, where employees must respond to fluctuating demand, service disruptions, and customer requests under continuous operational pressure [3]. Recent large-scale studies based on hotel operational data further demonstrate that competency differences are closely

associated with workforce optimization outcomes, service consistency, and cross-cultural service engagement in digitally enabled hotel systems [4]. Alongside this conceptual shift, the structure and visibility of frontline competency are being reshaped by the digital transformation of hotel operations. The deployment of intelligent scheduling systems, real-time performance dashboards, and data-driven service management platforms has substantially increased the traceability of employee behaviors and task execution processes [5,6]. As a result, routine operational records, such as attendance logs, task completion histories, and service interaction data, now provide objective and continuous signals of how employees perform in real working conditions. Evidence from recent hospitality analytics research suggests that such behavioral data offer a more reliable basis for assessing capability differences than self-reported measures, particularly in large hotel chains with diverse employee populations [7]. A related stream of literature examines frontline behaviors that directly influence service outcomes, especially in contexts involving service recovery, coordination, and peak-period demand. Empirical findings in the hotel sector indicate that faster response speed, effective complaint handling, and cross-role collaboration are consistently associated with higher service performance and more favorable customer evaluations [8,9]. Additional studies highlight the importance of proactive problem handling and knowledge sharing, showing that these observable behaviors contribute to stronger service recovery outcomes and operational resilience [10,11]. Together, these findings suggest that routine work behaviors can serve as meaningful indicators of underlying competency structures, linking individual capability to system-level service performance. Methodological approaches to studying employee competency have also evolved in response to these developments. While survey-based frameworks remain common, they often rely on limited samples and subjective assessments, constraining their ability to capture performance variation across large-scale hotel operations [12]. In contrast, people analytics research emphasizes the integration of multi-source operational records to enhance measurement accuracy and managerial relevance [13,14]. Within hospitality settings, the availability of scheduling data, attendance records, performance evaluations, customer complaints, and service ticket logs enables longitudinal and behavior-based analysis of employee performance at scale [15]. Such data environments create opportunities to move beyond static competency models toward dynamic representations grounded in actual work behavior. Despite these advances, several limitations remain in the empirical understanding of frontline competency structures in hotels. Existing competency models are frequently validated using small or moderate samples, limiting their generalizability to large hotel chains characterized by heterogeneous workforce profiles [16]. Many studies also focus on isolated behavioral domains, such as service recovery or leadership behavior, without integrating routine operational signals that reflect everyday performance, including peak-period response speed, complaint resolution volume, and cross-department coordination [17]. Furthermore, although intelligent systems are increasingly applied to staffing and scheduling decisions, employee capability differences are rarely modeled as structured behavioral profiles that can support recruitment screening, probation evaluation, and person–job matching in operational practice [18]. This study analyzes multi-source operational data from more than 6,500 frontline employees in a hotel chain, encompassing attendance, scheduling, performance assessment, customer complaints, and service ticket handling records. A comprehensive behavioral indicator system is developed to capture key dimensions of frontline work, and clustering analysis is applied to identify distinct performance groups and their characteristic behavior patterns. These empirically derived groups are subsequently translated into competency profiles with direct relevance to human resource management. By linking large-scale behavioral data to structured competency representations, this study provides empirical evidence to support data-driven recruitment decisions, probation evaluation, and person–job matching,

thereby contributing to more effective workforce optimization and service performance improvement in digitally enabled hotel operations.

2. Materials and Methods

2.1 Sample And Study Context

The analysis used operational records from a hotel chain operating under unified management and service standards. The sample included 6,538 frontline employees working in reception, guest service support, housekeeping coordination, and shift supervision. Data were collected continuously over an 18-month period. Employees with less than six months of tenure were excluded to ensure stable work patterns. All hotels followed similar service procedures and demand structures, which reduced variation caused by location or market differences.

2.2 Study Design And Comparison Logic

A comparative design was used to identify differences in employee behavior across performance levels. Employees were grouped according to overall performance outcomes based on internal assessments and customer-related records. High-performing and reference groups were defined using percentile thresholds rather than subjective judgment. This approach allowed behavior patterns to be compared under similar scheduling intensity and workload conditions. The design follows common practices in people analytics, where group-based comparison is used to reveal hidden differences in work behavior.

2.3 Measurement And Quality Control

Employee behavior was measured using indicators constructed from attendance logs, shift schedules, task timestamps, complaint records, and cross-department work orders. The indicators reflected response speed during peak periods, complaint handling efficiency, task continuity, and cooperation across roles. Data quality checks included removal of missing records, consistency verification across data sources, and normalization to account for differences in departmental workload. Extreme observations caused by system failures or irregular events were removed to preserve typical behavior patterns.

2.4 Data Processing And Model Specification

All behavioral indicators were standardized before analysis to allow direct comparison. Employee behavior similarity was examined using clustering analysis based on Euclidean distance. The clustering objective is defined as:

$$\min \sum_{k=1}^K \sum_{i \in C_k} \|x_i - \mu_k\|^2$$

Where x_i is the behavior vector of employee i , and μ_k is the center of cluster k . To examine the association between behavior indicators and performance outcomes, a regression model was estimated:

$$P_i = \alpha + \sum_{j=1}^n \beta_j B_{ij} + \varepsilon_i$$

where P_i denotes the performance score of employee i , and B_{ij} represents standardized behavior indicators.

2.5 Validation And Robustness Analysis

Cluster stability was tested using repeated subsampling and silhouette scores. Solutions with different cluster numbers were compared to confirm consistent grouping patterns. Regression models were checked for collinearity and sensitivity to indicator selection. Additional tests were conducted by excluding employees with short tenure to verify that the results were not driven by experience length. All statistical tests were performed at a 95% confidence level.

3. Results and Discussion

3.1 Performance Grouping And Profile Separation

Clustering based on standardized behavioral indicators produced a clear separation among employee groups, with one group showing stable characteristics associated with high performance. This group displayed lower internal variation in peak-period response time and complaint-handling throughput, indicating that performance differences reflect persistent behavior patterns rather than isolated operational events. This observation is consistent with people analytics studies reporting that large-scale operational records can reveal repeatable performance profiles that are not easily identified through survey-based competency assessments [19,20]. A process-oriented reference is provided in Fig.1, which summarizes commonly used stages in HR analytics, ranging from problem definition to evaluation and feedback.

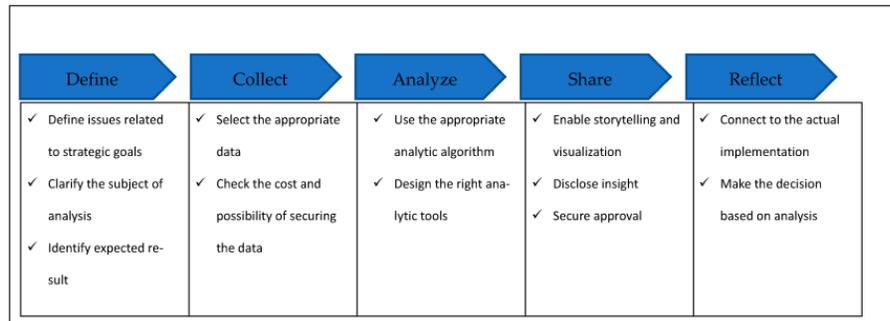


Fig.1. Workflow showing the main steps of an HR analytics process based on employee operational data.

3.2 Behavioral Characteristics Associated With High Performance

Across the full indicator set, high-performing employees showed clear advantages in response speed during peak demand periods, efficiency in complaint resolution, and frequency of cross-role coordination. These differences match service operations evidence showing that timely recovery actions and coordinated task completion reduce downstream service disruption and improve overall outcomes when pressure is high. The separation between groups was most pronounced in indicators related to end-to-end task handling, where speed, continuity, and coordination are jointly required. This pattern supports the view that frontline competency is expressed through integrated behavior sequences rather than isolated skills. Similar conclusions have been reported in hospitality operations research, where digital workflow systems increase transparency and make execution differences more visible across employees [21].

3.3 Stability Assessment And Method-Oriented Interpretation

The high-performance group remained identifiable under resampling-based stability tests and alternative cluster-number settings, indicating that the observed grouping does not depend on a single parameter choice. This is important because unstable clustering outcomes often result from noise, workload fluctuation, or recording inconsistencies, which weaken performance interpretation [22,23]. To illustrate how clustering procedures and assignment logic are commonly presented in applied research, Fig.2 shows a flowchart describing the k-means clustering process, including initialization, distance calculation, and iterative reassignment steps.

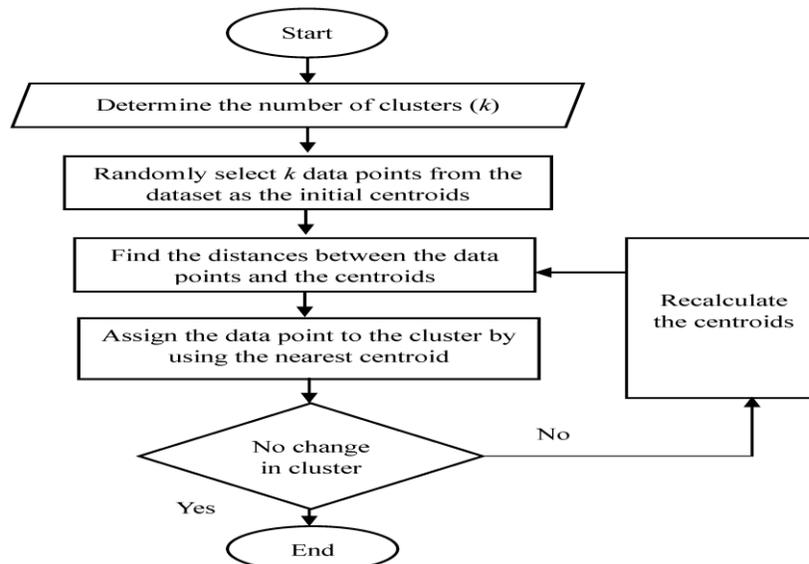


Fig.2. Flowchart showing the k-means clustering procedure used to group behavioral data.

3.4 Comparison With Prior Studies And Practical Implications

Compared with hospitality studies that focus on attitudes, engagement, or broad HR outcomes, these results point to a more operational view of frontline competency. Performance differences are most visible in time-sensitive responsiveness, complaint throughput, and coordination across roles during peak demand. This finding complements recent HR analytics research by showing that competency profiles can be built directly from routine behavioral records and applied to recruitment screening and probation evaluation, where decisions depend on observable criteria. At the same time, operational indicators reflect both employee capability and contextual conditions. Factors such as staffing density, shift composition, and task-routing rules may influence measured behavior and can differ across properties. Future work can improve inference by combining this approach with longitudinal tracking or policy changes to examine whether targeted training leads to sustained movement toward high-performance behavior profiles [24].

4. Conclusion

This study analyzes the competency structure of frontline hotel positions by linking large-scale operational behavior records to employee performance outcomes. The results show that high-performing employees differ from other groups mainly in response speed under peak demand, efficiency in complaint handling, and coordination across roles. These findings suggest that frontline competency is reflected in consistent behavior patterns rather than isolated task performance. By moving beyond survey-based evaluation, the study applies a behavior-driven approach that relies on routine operational data to identify competency profiles with clear and observable characteristics. This approach strengthens the empirical foundation of competency research in the hospitality field. From an applied perspective, the identified profiles provide practical guidance for recruitment screening, probation assessment, and person–job matching in hotel operations. Several limitations should be acknowledged. The analysis focuses on a single hotel chain, and the use of observational data means that measured behavior may be influenced by contextual factors such as staffing levels or task assignment rules. Future research may expand the scope to other service industries, adopt longitudinal designs, or examine how targeted training and management practices affect the development of frontline competency profiles over time.

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