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Multidimensional Assessment of Call Center Customer Service Representative Performance Using Association Analysis and Anomaly Detection Methods

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A B S T R A C T

Call centers are a critical component of customer service and sales-focused activities, and in outbound calling operations, the performance and behaviors of customer service representatives constitute a key factor in securing competitive advantage for firms. However, traditional evaluation approaches typically concentrate on unidimensional metrics and fail to capture the multifaceted activities and anomaly tendencies of representatives throughout the workday. Against this backdrop, the present study seeks to remedy this shortcoming in current call center operations by examining representative performance within a multidimensional analytical framework, thereby offering a novel perspective both theoretically and practically. To this end, datasets from a telecommunications-sector call center were consolidated across three separate datamarts, and analyses were conducted at both daily and monthly levels. The methods of clustering, TOPSIS, anomaly detection, and association rule mining were applied in an integrated fashion, enabling the identification of behavioral profiles and nonstandard behaviors among representatives in different segments. The results furnish operations managers with the capability for real-time intervention in the short term, while yielding targeted insights for employee training and development in the long term. This study advances a multidimensional performance management model that transcends unidimensional metrics by incorporating behavioral data, thereby contributing to both organizational behavior theory and the data science literature. The proposed approach not only supports concrete steps toward workforce optimization, enhanced customer satisfaction, and improved overall service quality within the call center ecosystem but also provides a robust methodological foundation for future research.

1. INTRODUCTION

Call centers play an indispensable and critical role in contemporary business by serving as a core component of customer service and sales processes [1,2]. Because integrated marketing communications prioritize relationship building, call centers have emerged as a vital channel for customer interactions [3,4]. As such, they function today as interactive platforms that enable firms to strengthen customer relationships.

The services provided by call centers are typically categorized into two primary types based on which party initiates the contact: inbound calls and outbound calls. Inbound calls refer to those initiated by customers to communicate their needs, whereas outbound calls are those initiated by the firm—often leveraging its database—to provide services or information to existing or prospective customers [5]. Effective evaluation of customer service representatives' performance in outbound operations not only enhances operational efficiency but also confers a significant competitive advantage [6,7]. Customer service representatives—also known as call center agents—serve as the liaison between external customers and the organization's internal operations; consequently, their individual performance and behavior profoundly influence both service quality and customer perceptions, thereby impacting overall productivity [8-11]. Moreover, efficient management of call centers is essential for optimally configuring workforce capacity and service performance, given that approximately 70 % of a call center's budget is allocated to labor costs [12].

Numerous methods have been developed to evaluate the performance of call-center personnel. While the literature contains various studies on call-center agent performance analysis, most analytics applications concentrate on unidimensional performance indicators—such as call duration, first-call resolution rate, customer satisfaction, and sales conversion rates [13-18]. In contrast, multidimensional approaches that simultaneously examine agents' intraday activities (e.g., break duration, inter-call waiting time, instantaneous productivity), behavioral patterns, and potential anomaly tendencies are notably scarce. This gap underscores the need for new methods and frameworks that permit a deeper and more comprehensive investigation of call-center performance [19,20].

Within this study, and in order to fill identified gaps in the literature, data from call-center outbound operations were analyzed through a holistic approach. Activity log records, sales figures, and call details for each representative were merged into an integrated dataset, upon which advanced analytic techniques were applied. Specifically, clustering analysis, anomaly detection, natural language processing (NLP), and association-rule mining were employed in concert to define distinct performance segments and uncover behavioral patterns. The results highlighted a number of non-standard events, the effects of which on organizational efficiency proved striking. By integrating multiple data-mining methods, this approach transcends traditional paradigms and delivers an end-to-end performance evaluation model tailored to the call-center context. In particular, the adaptation of association analysis—commonly used in retail and e-commerce—to call-center data constitutes one of this study's most innovative contributions.

This research seeks to make the analysis of call-center agents' performance and behaviour more effective. The application of anomaly detection and pattern-analysis techniques enables operations managers to identify potential problem areas proactively and intervene swiftly, thereby enhancing service quality. Furthermore, clustering analysis segments agents by performance level, permitting more targeted training and development actions. The proposed integrated framework underpins data-driven decision making in call-center management, contributing to workforce optimization and overall operational efficiency. The methods and findings presented here offer a solid foundation for future studies, including the deployment of similar analytical approaches in other industries and the exploration of novel modelling techniques.

2. CONCEPTUAL FRAMEWORK

By design, call centers serve as strategically positioned communication hubs that address the dynamic needs of diverse customer segments; they play a pivotal role in customer relationship management and in sustaining sales targets and/or service quality. These labor-intensive, data-rich environments facilitate interactions that are critical to a firm's competitive positioning [21-24]. According to the literature, the operational costs of call center activities continue to rise daily, with approximately 70 % of these costs attributable to labor and capacity-planning expenses [12]. The Economist estimates that there are roughly 17 million call center employees worldwide [25]. This prevalence transforms call centers from mere cost centers into strategic assets for customer satisfaction and brand loyalty [1]. Consequently, effective management of these complex operations—encompassing comprehensive planning, analysis, and oversight—is essential for accurate capacity planning, workforce analysis, and the measurement of both customer satisfaction and agent performance.

Capacity planning in call centers involves determining the required number of agents to meet anticipated call volumes [26]. Because capacity planning is directly linked to incoming call demand, operational workloads increase as service offerings and customer requests grow. Therefore, capacity planning emerges as a critical parameter for personnel and service scheduling, enabling improvements in both operational efficiency and customer satisfaction [26,27].

Customer-service representatives' performance and its management have long constituted a focal point in the literature. However, most studies address this complex environment through a narrow set of metrics, reducing call-center agent evaluations to unidimensional indicators such as call duration, first-call resolution rate, or sales conversion success [15,28,29]. Such an approach overlooks the dynamic nature of employee behaviors and contextual variability: it fails to capture agents' state transitions throughout the day, break patterns, queue-waiting intervals, and other behavioral data that relate closely to operational efficiency. In reality, call-center performance assessment ought to encompass both outcome-based and process-oriented measures [30,31].

Given the inherent structural complexity of call centers, effective performance evaluation is critical not only for these operations but also for any enterprise seeking strategic advantage [32]. The literature has proposed a variety of quantitative metrics for assessing call-center performance—abandonment rate, blocked-call percentage, average queue wait time, service level, average handle time, after-call work time, first-call resolution rate, agent occupancy, and customer satisfaction [33-37]. While these traditional indicators prove useful for monitoring operational efficiency, their unidimensional and purely quantitative nature renders them insufficient for capturing service-quality nuances and contextual factors that influence agent performance [1,26].

According to the organizational behavior literature, performance appraisal should incorporate not only objective metrics but also contextual data [38,39]. In high-interaction settings such as call centers, employee contributions must be evaluated holistically across both task performance and contextual performance dimensions, since these two facets jointly enable recognition of all behaviors that drive organizational success and ensure fair, comprehensive assessments [20,40,41]. Nevertheless, traditional performance-evaluation methods in call centers continue to dominate practice, often relegating the importance of contextual performance to the background [27,42]. This distinction is critical in outbound calling operations, where an agent's effectiveness is shaped not only by sales outcomes but also by their contributions to operational flow. Consequently, analysis of behavioral data demands an interdisciplinary approach grounded in organizational psychology, human-resource management, and service-quality research. A conceptual framework is therefore needed that integrates technical-operational metrics with dimensions of human behavior and service quality to facilitate sound performance analysis in call centers [1].

A review of the extant literature reveals significant efforts to integrate data-analytics methods into call-center operations [43-45]. Clustering analysis has been widely used to group agents exhibiting similar behavioral patterns, enabling the development of tailored management and development strategies for each segment [46,47]. However, the application of anomaly-detection algorithms remains limited, despite their strategic value in early identification of irregular behaviors, prevention of performance issues, and modeling of exceptional successes in operational systems. Algorithms such as Isolation Forest (IF) offer particular advantages in data-intensive environments like call centers, owing to their ability to detect outliers with high precision in multidimensional datasets [48-51]. In recent years, multidimensional data-analytics approaches have come to the fore in call-center performance evaluation, as machine-learning and data-mining techniques are increasingly employed to move beyond classical metrics in big-data contexts [52].

One of the more recently adopted techniques is the combination of anomaly detection and natural language processing (NLP). By applying anomaly-detection methods to large volumes of call records, atypical operations can be automatically identified and early warnings delivered to managers [53]. NLP enables the analysis of call transcripts as text, allowing each interaction's sentiment and thematic content to be extracted. Indeed, the literature confirms the value of these data: sentiment-analysis models built with advanced NLP and machine-learning techniques can classify customer emotions as positive, negative, or neutral and thus serve as a measure of customer satisfaction [54,55].

Association analysis is employed to discover frequently co-occurring patterns within call-center data. For example, identifying that certain complaint types frequently coincide with long call durations or repeat-call probabilities can reveal opportunities to improve service processes [1]. Through these multidimensional analytic approaches, call centers can uncover patterns and relationships that traditional reporting methods obscure, thereby generating valuable insights to enhance both operational efficiency and service quality [1].

Although various studies have investigated call-center agent performance, research that holistically examines representatives' activities across different statuses, anomaly tendencies, and performance disparities remains scarce. Nonetheless, in-depth analysis of agents' intraday behaviors—such as break durations, inter-call waiting times, and efficiency levels—has provided valuable operational insights. In the present study, activity-log records, sales data, and call details for call-center agents were consolidated into an integrated dataset and subjected to analysis. Machine-learning techniques—specifically clustering analysis, anomaly tagging, scoring, and pattern-mining methods—were employed to delineate performance categories and identify anomalies. Moreover, to enhance data-driven decision-making in call-center operations, association analysis—a method commonly applied in other sectors—was combined with these approaches to create an end-to-end analytical solution.

3. METHODOLOGY

This research was conducted by examining the outbound calling operations at the call center of a global telecommunications firm in Turkey. The performance and behavioral patterns of the customer service representatives engaged in these outbound operations were investigated using multidimensional data-analytics approaches.

3.1 Procedure

The company, aiming to boost its current sales, generates a list of potential customers and uploads it into the call-center system for dialing by customer service representatives, to whom individual leads are then assigned. After each call, representatives conclude the interaction by applying a disposition code. Upon call termination, metrics such as call outcome, talk time, agent performance, and sales success are recorded in the database under the "Call Detail Data" repository to enable efficient management and analysis of call-center operations.

Figure 1 illustrates the overall architecture of the call-center system. This diagram presents the key components involved in outbound operations, including the call list generation, disposition recording, and data flow between the operational database and analytic platforms. The architecture ensures the seamless integration of call outcomes, agent activities, and transactional metrics, enabling comprehensive performance monitoring.

Fig. 1. Call-Center Architecture.

Call-detail data encompasses the dialled-call records for customers included in the call lists. Conversations conducted by agents may conclude under various disposition categories based on the customer's response and the agent's persuasion effectiveness. For instance, a successful interaction is recorded as "Customer accepted: Product X," whereas unsuccessful outcomes are coded as "Customer declined" or "Customer does not wish to be contacted." These disposition codes originate either from agent-entered data or automatically assigned by the switch application and thus reflect the agent's declaration. However, because they rely on the agent's input, they do not directly confirm whether the customer actually completed the purchase. The definitive source for verifying transaction completion is the realized-sales dataset, which indicates whether the customer's financial and operational processes were finalized.

All work-status events for outbound-operation agents are logged in the "Activity Log" table. This table details each agent's status over specific time intervals and the duration spent in each status. A total of 23 distinct statuses have been defined in the system, each reflecting key aspects of agent work dynamics and process activities. These statuses enable granular monitoring of intraday agent activities and support evaluations of process efficiency. Moreover, they serve as a critical data source for workforce planning, performance management, and operational improvement initiatives. The prominent statuses include:

- **Call:** The duration during which an agent is actively engaged in conversation with a customer.
- **After-Call Work:** The process of updating customer records or performing follow-up tasks once the call has concluded.
- **Waiting for Call:** The status in which an agent awaits assignment of the next call by the system.
- **Break:** The status used for short rest periods taken by agents during the workday.
- **Meeting:** The time allocated for team meetings, training sessions, or other corporate events.
- **Lunch:** The designated period for the agent's meal break.

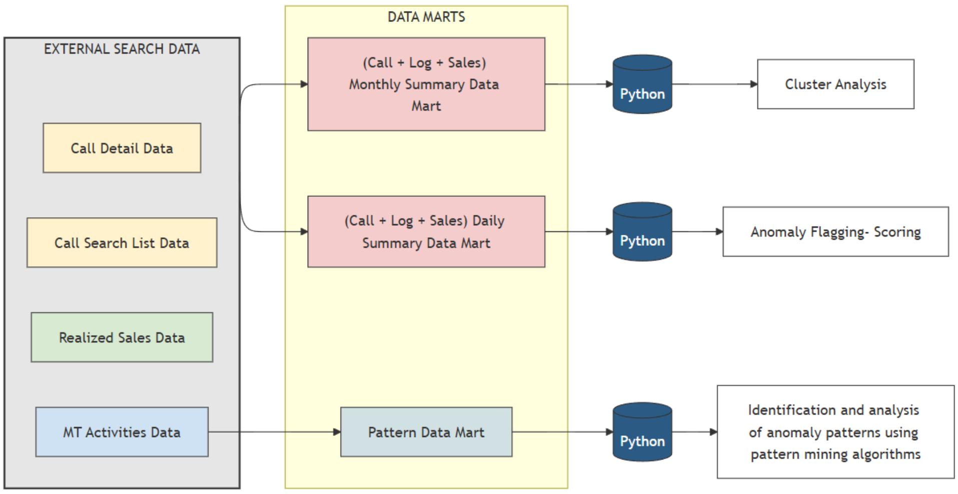

Fig. 2. Agent Anomaly-Detection Architecture.

Three primary summary datamarts were implemented to streamline the analytic workflow and integrate disparate data sources. Each datamart—automatically refreshed on a daily and monthly cadence—constitutes a foundation for advanced analytics and contains multidimensional variables such as agent call volumes, wait times, sales-conversion rates, consecutive break incidences, and other quantitative indicators. The monthly datamart is designed to reveal overarching trends and segment structures within the call center, whereas the daily datamart emphasizes metrics that support rapid, operational decision making.

Figure 2 demonstrates the anomaly-detection architecture developed to monitor agent behaviors. It visualizes the flow from raw activity logs to processed anomaly insights, including variable extraction, data preprocessing, and application of the Isolation Forest algorithm. This structured architecture allows for early detection of irregular patterns and facilitates actionable operational interventions. The datamarts include the following variables:

- **Average Inter-Call Time:** The mean interval between call terminations and the initiation of the next call for each agent, measured in seconds.
- **Off-Production Ratio:** The percentage of an agent's total logged work time spent in non-production activities (e.g., breaks, meetings).
- **Breaks-per-Call Ratio (count):** The number of break-status events divided by the total number of calls handled by the agent.
- **Sales Conversion Rate:** The proportion of calls that result in a sale, calculated as (number of calls with a sale / total number of calls) × 100 %.
- **Average Production Time (seconds):** The mean duration of production-related activities (talk time and persuasion) for calls that resulted in sales, measured in seconds.

F1-Score (Disposition Accuracy): An F1-score derived from a machine-learning confusion matrix that assesses the accuracy of the agent's declared sale dispositions against actual completed sales; values closer to 1 indicate a higher correspondence between disposition entries and realized transactions.

3.2 Implementation

Figure 3 presents the project architecture combining performance scoring and anomaly detection processes.

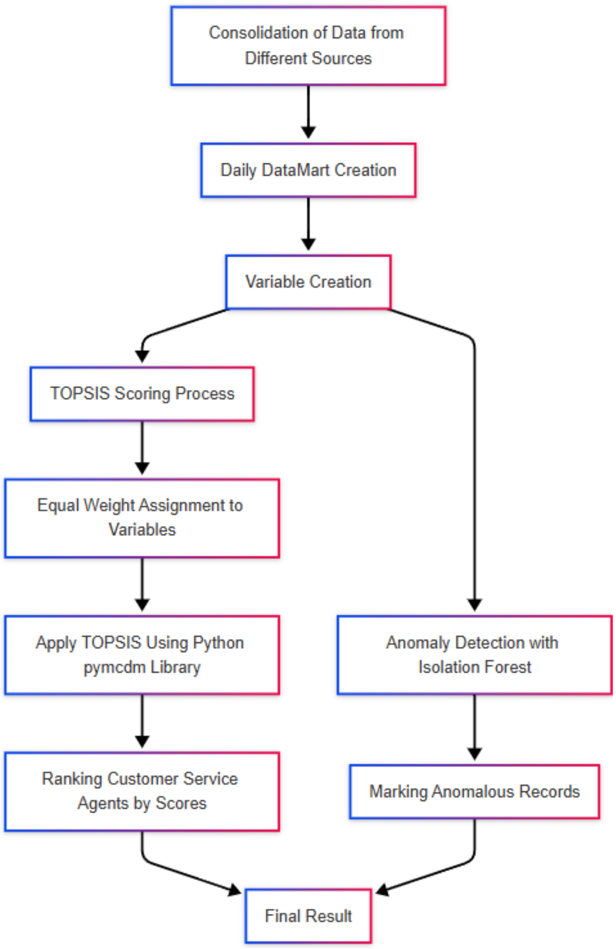

Fig. 3. Agent Anomaly-Detection Project: Scoring and Anomaly Architecture.

In the first phase, the monthly datamart was employed to perform clustering analysis and derive representative segments of customer service agents. The optimal number of clusters was determined using Silhouette scores, the Elbow method, and dendrogram inspection. Subsequently, the K-Means algorithm was applied to partition agents into distinct clusters. On the basis of the resulting cluster structures, team leaders were enabled to provide targeted feedback and to establish a peer-coaching system that leverages high- and low-performing agents to support one another.

In the second phase, the daily datamart was used to score agents according to the Technique for Order Preference by Similarity to Ideal Solution

(TOPSIS). Selected performance variables served as criteria in this multi-criteria decision-making framework, producing a composite score for each agent that reflects their relative standing on key operational metrics.

The third phase applied the Isolation Forest (IF) algorithm to the daily datamart to detect whether any agents' records deviated positively or negatively from normative behavior. The principal advantage of IF lies in its construction of random feature-and-split-based decision trees, which rapidly isolate anomalies along shorter path lengths [48,56]. Additional attributes—linear time complexity, low memory footprint, efficacy in high-dimensional spaces, unsupervised operation, interpretability, adaptability to various data types, and absence of distributional assumptions—further justified its selection. Through this approach, extreme dwell times in "Waiting for Call," repetitive use of "Break" status, and pronounced inconsistencies between declared and realized sales were swiftly identified as anomalous behaviors.

3.3 Analysis

During the preparation of pattern data, behavioral sequences in call-center status transitions were examined on a "transaction" basis, with the aim of detecting unexpected or infrequent patterns. To this end, the Activity Log was restructured into "status sequences occurring between two consecutive calls," and the Apriori algorithm was applied to mine both common and anomalous status combinations. Analysis of support and confidence metrics facilitated the identification of sequences that deviate from normal operational flows.

Figure 4 outlines the pattern-processing architecture used for behavioral analysis. It details the transformation of status sequences into structured transaction data and highlights the pipeline that applies the Apriori algorithm and anomaly detection methods to uncover unusual workflow behaviors.

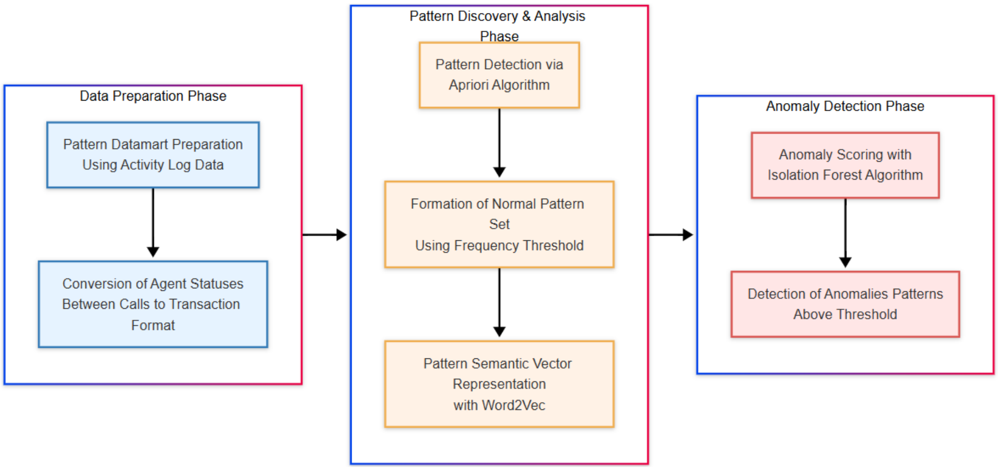

Fig. 4. Agent Anomaly-Detection Pattern-Processing Architecture.

After restructuring the data in this manner, the Apriori algorithm was applied to analyze the co-occurring status sequences. Apriori was chosen because it employs the downward-closure property—"if an itemset is frequent, all of its subsets must also be frequent"—to efficiently extract association rules from large datasets [57]. In this study, the inverse of this principle was leveraged to detect anomalies: rather than focusing on frequently occurring status combinations, the analysis targeted infrequent yet repetitive patterns of status transitions. Specifically, patterns exhibiting low support but high confidence were identified as candidates for anomalous behaviour.

Transactions in which the canonical sequence of "campaign call," "follow-up," and "available" statuses occurred were excluded from anomaly detection, as these reflect standard operational flow. The remaining transactions were then subjected to anomaly tagging.

Figure 5 provides an example of a normal activity-log sequence, demonstrating a standard operational flow. Figure 6 illustrates how transaction IDs are generated from raw activity logs. Each distinct sequence between two call events is assigned a transaction identifier, allowing for precise tracking and pattern analysis across large datasets.

Status	Date Time	End Time	Hour	Duration	Min.
Campaign Call	09:01:38	09:01:45	9	7	0.1
Follow Up	09:01:45	09:01:46	9	1	0.0
Available	09:01:46	09:02:39	9	53	0.9

Fig. 5. Customer-Service Representative Activity-Log Record Example – Normal Pattern.

STATUSGROUP	STATUSKEY	STATUSDATETIME	ENDDATETIME	STATEDURATION	TRANSACTION_ID
available	campaign call	2 Jan 2024 09:00	2 Jan 2024 09:01	37	90036253_20240102_4
followup	follow up	2 Jan 2024 09:01	2 Jan 2024 09:01	10	90036253_20240102_4
break	break	2 Jan 2024 09:01	2 Jan 2024 09:01	4	90036253_20240102_4
available	available	2 Jan 2024 09:01	2 Jan 2024 09:02	73	90036253_20240102_4
available	campaign call	2 Jan 2024 09:02	2 Jan 2024 09:04	131	90036253_20240102_8
followup	follow up	2 Jan 2024 09:04	2 Jan 2024 09:04	1	90036253_20240102_8
available	available	2 Jan 2024 09:04	2 Jan 2024 09:05	26	90036253_20240102_8
available	campaign call	2 Jan 2024 09:05	2 Jan 2024 09:06	60	90036253_20240102_11

TRANSACTION_KEY	TRANSACTION_ID	STATUS_PATTERN	STATE_DURATION
4	90036253_20240102_4	campaign call, follow up, mola, available	124
8	90036253_20240102_8	campaign call, follow up, available	158
11	90036253_20240102_11	campaign call, follow up, available	87

Fig. 6. Customer-Service Representative Activity-Logs – Transaction-ID Generation.

To facilitate semantic analysis of the extracted patterns, the detected sequences were converted into vector representations using the Word2Vec algorithm. This transformation created a low-dimensional vector space that preserves the semantic relationships among patterns. In the final stage, the vectorized patterns were processed by the Isolation Forest algorithm to compute anomaly scores. Leveraging its principle of isolating data points, Isolation Forest—renowned for its efficacy in outlier detection—was employed to distinguish pattern vectors that deviated from normal behavior. Patterns with anomaly scores exceeding a predefined threshold were flagged as potential abnormal behaviors.

4. FINDINGS

The analyses conducted in this study yielded insights that enrich call-center operations management with both daily and monthly perspectives. In the daily analyses, the integration of TOPSIS scoring and anomaly-detection approaches enabled team leaders to identify agents who either excelled or deviated from expected performance levels on any given day. In the monthly analyses, clustering results were used to segment agents by similarity, and each segment's distinctive performance characteristics were examined in detail.

Within the daily datamart, TOPSIS first consolidated multiple performance indicators into a single composite metric, facilitating comparison of agents' overall efficiency. High-scoring agents typically demonstrated a positive balance across indicators such as sales-conversion rate, average production time, and inter-call wait time. Conversely, low-scoring agents exhibited behaviors that pose operational risks—such as extended breaks or inconsistent disposition declarations. Application of the Isolation Forest algorithm to the same dataset flagged records that, while not immediately conspicuous, generated abnormal fluctuations in the performance curve, thereby enabling managers to take proactive, data-driven corrective actions.

Clustering analysis conducted on the monthly datamart revealed six distinct segments that differed meaningfully in their performance profiles. For instance, agents grouped in the segment designated as Cluster 1—despite exhibiting above-average tenure—were found to underperform across key metrics relative to expectations. Conversely, segments characterized by high sales-conversion rates and consistent disposition accuracy displayed more stable performance trajectories, thereby serving as benchmarks for best practices. Figure 7 displays the clustering results via an interactive dashboard. Immediately following the identification of anomaly patterns, the impacts of these patterns were also assessed. The results are presented in Figure 8.

As illustrated in Figure 8, for each customer-service representative, the count, proportion, duration, and non-production ratios of anomaly events were quantified. These metrics demonstrate that the developed model derives actionable insights from raw operational data and delivers them to decision makers via an interactive dashboard. This integrated analytics solution facilitates the objective evaluation of performance metrics and behavioral patterns across the call-center ecosystem.

Furthermore, by providing real-time outputs, this analytical framework enables operational managers to proactively detect deviations from standard processes. Consequently, team leaders can implement targeted, agent-level interventions to enhance both operational effectiveness and efficiency.

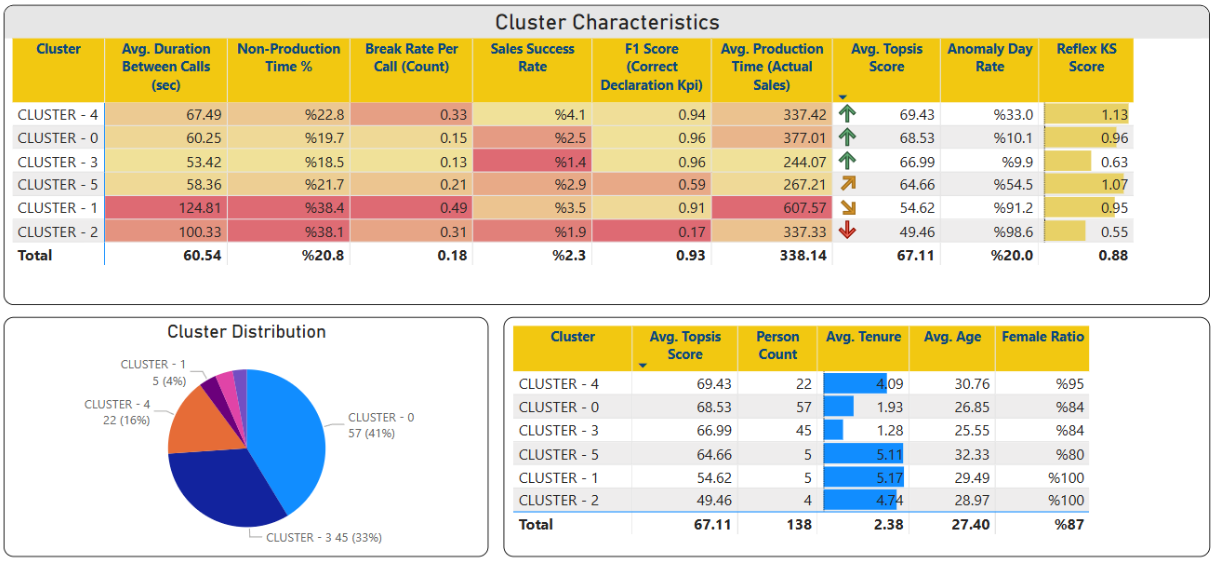

Fig. 7. Dashboard View of Clustering Results.

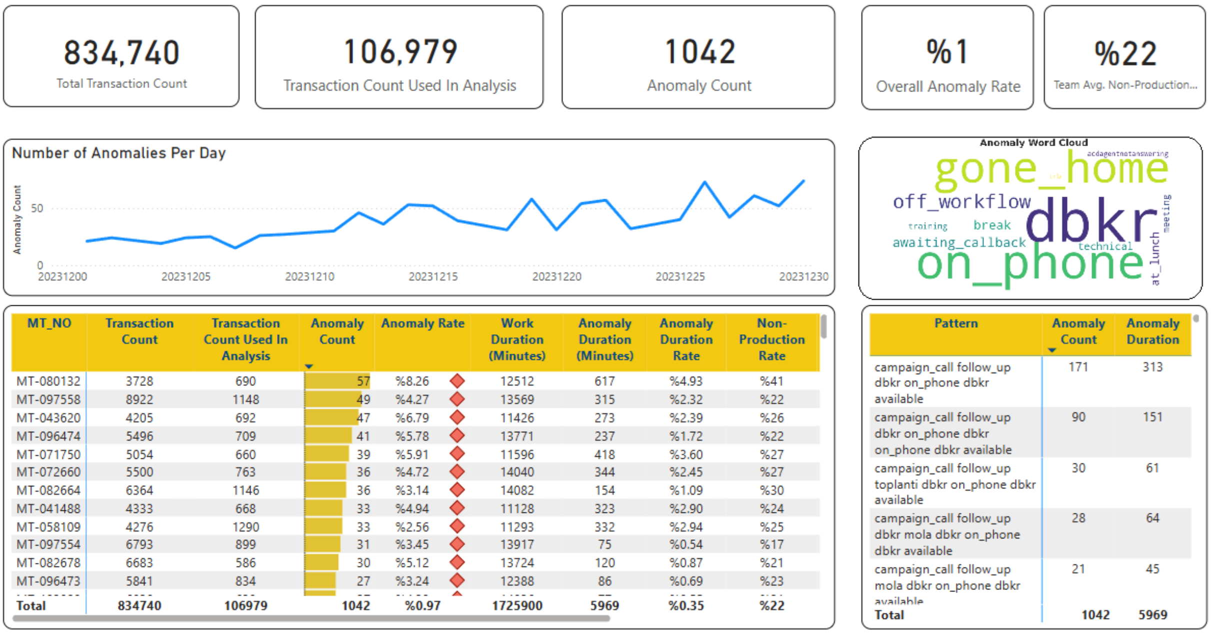

Fig. 8. Dashboard View of Pattern Outputs.

5. DISCUSSION AND CONCLUSION

This study aimed to develop a comprehensive performance-evaluation model for call-center outbound operations that transcends traditional assessment methods by applying a multidimensional data-analytics approach to customer-service representatives' performance and behavioral patterns. The framework integrated clustering, multi-criteria decision-making and scoring, anomaly detection, and association-rule mining by leveraging diverse data sources. The findings demonstrate that insights generated on both daily and monthly bases can be rapidly communicated to operations management, thereby facilitating data-driven, targeted decision making.

For daily operational performance assessment, a robust methodology was devised using a range of critical performance indicators (KPIs) extracted from the data warehouse. Daily TOPSIS scoring consolidated these metrics into a single quantitative measure, enabling tracking of short-term performance trends and focusing attention on agents with low or unpredictable scores. Concurrently, Isolation Forest–based anomaly detection applied to the same up-to-date dataset swiftly flagged unusual behaviors and performance records, thereby empowering team leaders to enact immediate corrective and preventive actions. Monthly clustering analysis segmented agents by similarity, making each segment's unique development needs and strengths clearly visible. Through these analyses, segments exhibiting high sales conversion but prolonged wait times or elevated disposition-error rates were identified, while for low-performing clusters, potential root causes—such as experience level, motivational deficits, or process inefficiencies—could be examined in greater depth.

The insights obtained extend beyond unidimensional metrics by capturing individual agents' behavioral nuances and dynamics, thereby reinforcing a data-driven decision-making culture in call-center management. Specifically, team leaders will be able to monitor real-time daily rankings and anomalies while also reviewing agents' monthly segment memberships to develop comprehensive, long-term development plans.

The results indicate that high-performing agents manage inter-call transition times and break usage more consistently, yielding steadier outcomes in both sales conversion and customer satisfaction. In contrast, agents with low performance scores and elevated anomaly indices tended to enter break status more frequently or exhibited significant discrepancies between declared and actual sales. Association analysis further revealed that these low-performing agents followed distinctive behavioral sequences that increased their off-production time, enabling operations managers to devise targeted interventions for performance optimization.

The findings demonstrate that the combined application of diverse data-mining techniques yields far greater value than their isolated use. In particular, association analysis of agents' status-transition patterns played a crucial role in detecting behavior models that deviate from standard workflows, furnishing management with granular operational data. Consequently, it became possible to identify agents whose work sessions were fragmented into brief breaks despite remaining predominantly in the "call" status, or who unexpectedly alternated consecutively between "meeting" and "lunch" statuses. When integrated with Isolation Forest, this approach enabled the precise flagging of rare or atypical patterns as anomalies, thereby substantially reducing false-positive rates. This study thus makes three key contributions: (1) it tests a novel methodology not previously explored in the literature; (2) it enriches organizational-behavior and performance-management scholarship by embedding a multidimensional perspective into data-science–driven decision processes; and (3) it offers a framework capable of supporting proactive management interventions.

The outputs and methods developed herein are applicable not only to call centers but to any sector characterized by intensive customer interaction and sales orientation. The integrative framework—by unifying heterogeneous data sources within a single analytics platform—demonstrates significant advantages in operationalizing complex, multidimensional analyses in a practical, scalable manner.

Nevertheless, this study has several limitations. The consistency of records drawn from disparate data sources, the accuracy of self-reported dispositions, and the uniform application of standardized process definitions across the organization may all influence the quality and generalizability of the findings. Furthermore, validating the model across different cultural and institutional contexts represents an important avenue for future research. Despite these constraints, the analytic approach developed herein has been shown to strengthen performance management in outbound calling operations.

In conclusion, this study aims to enhance the effectiveness of performance and behavior analysis for call-center agents. By integrating multidimensional data-mining methods into a unified framework, it offers a more flexible, comprehensive, and high-value solution compared with traditional evaluation techniques. This contribution is significant both for academic scholarship and for industry practice, as it promotes the wider adoption of data-driven management. Looking ahead, deploying advanced analytic technologies—such as deep-learning models or real-time data-processing architectures—could enable the integration of insights into live operational decision mechanisms. Such developments would make it possible to achieve critical objectives: improving customer satisfaction, optimizing workforce utilization, and increasing the efficiency of sales operations.

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