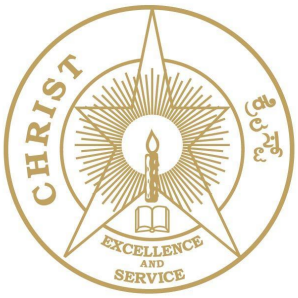

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ENHANCING CUSTOMER SATISFACTION: DATA-DRIVEN INSIGHTS FOR OPTIMIZING SUPPORT TEAM PERFORMANCE OF PLURALSIGHT

by

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A Project report submitted in partial fulfillment of the requirements for the award of degree of Master of Science (Data Science) of CHRIST (Deemed to be University)
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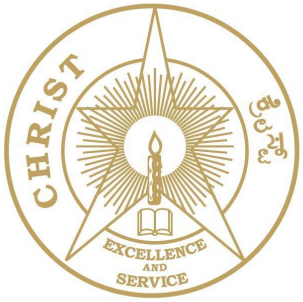

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CERTIFICATE

This is to certify that the report titled ***Enhancing Customer Satisfaction: Data-Driven Insights for Optimizing Support Team Performance of Pluralsight*** *is a bonafide record of work done by* ***Sanjay R (2348055)*** *of CHRIST(Deemed to be University), Bengaluru, in partial fulfillment of the requirements of <Trimester No> Trimester M.Sc. (Data Science) during the year 2024-25.*

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ABSTRACT

Customer Satisfaction (CSAT) is a crucial metric for evaluating a company's success, directly impacting customer loyalty and brand reputation. As of 2024, the organization has achieved a CSAT score of 88%, surpassing the industry benchmark of 85%. However, to further enhance customer experience, this project aims to push CSAT beyond 88% by 2025 by addressing the remaining 12% dissatisfaction gap through a data-driven approach.

CSAT is measured as the percentage of positive ratings received from customers, calculated using the formula:

$$\text{CSAT} = \frac{\text{(Number of "Good" Rated Ratings)}}{\text{(Total No. of Rated Tickets)}} * 100$$

To achieve this goal, a comprehensive CSAT enhancement plan has been developed, analyzing key factors such as customer feedback, ticket resolution efficiency, agent performance, and operational elements affecting satisfaction. Tracking CSAT trends over time—daily, weekly, and monthly—will help identify fluctuations, while ticket-level data analysis will assess resolution times, first-contact resolution (FCR) rates, and escalation patterns. Natural Language Processing (NLP) will be leveraged to categorize customer feedback into positive, neutral, and negative sentiments, identifying dissatisfaction drivers such as long wait times, unresolved issues, and ineffective communication. Further analysis will evaluate the impact of ticket volume on agent performance, customer wait times, and satisfaction levels, along with escalation and reopen rates to understand the effect of unresolved issues on negative customer experiences.

Based on these findings, key improvement strategies will be designed, including AI-driven chatbots, predictive analytics, automated prioritization, and workflow optimizations. A pilot implementation will first test these enhancements on a smaller subset of the support team before full-scale deployment, with real-time performance monitoring ensuring continuous refinement. The final phase will measure the effectiveness of these strategies, track post-implementation CSAT trends. By integrating advanced analytics, sentiment analysis, and continuous performance tracking, this initiative will strengthen brand trust, enhance customer retention, and ensure long-term success in delivering exceptional customer service.

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1. INTRODUCTION

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In the Digital age, Customer Support plays a pivotal role in brand loyalty and reputation. Companies today receive thousands of support queries through various channels like email, chat, and ticketing systems. Handling these efficiently, identifying gaps in performance, and ensuring timely resolution are key factors in customer happiness. However, with limited visibility into operational inefficiencies and no real-time feedback loops, businesses struggle to pinpoint what exactly causes dissatisfaction.The purpose of this project, titled “Enhancing Customer Satisfaction: Data-Driven Insights for Optimizing Support Team Performance”, is to leverage the power of data analysis and artificial intelligence to improve customer satisfaction (CSAT) scores within a support environment. This project aims to change that by applying a structured DMAIC (Define, Measure, Analyze, Improve, Control) approach to analyze the support system's performance. We will use data visualization tools like Tableau, natural language processing for sentiment analysis, and machine learning algorithms to derive actionable insights from CSAT feedback and support ticket data. The ultimate goal is to identify bottlenecks, agent performance gaps, and common pain points so businesses can take corrective measures. The insights generated will be used to propose an optimized support model. The final output will be an interactive dashboard showcasing trends, pain points, and agent efficiency, thereby allowing decision-makers to drive continuous improvement and boost CSAT from 88% in 2024 push beyond 88% by 2025.

1.1 PPROBLEM DESCRIPTION:

Despite deploying trained support agents and having structured workflows, organizations like Pluralsight often find their CSAT metrics stagnating. Even with timely resolutions, users sometimes leave a Bad rating due to lack of clarity, empathy,

or follow-up. These subtleties are rarely captured through traditional metrics alone. Pluralsight's current CSAT collection system uses binary feedback ("Good" or "Bad") post-interaction, but it lacks the depth of interpretation needed to pinpoint root causes of dissatisfaction. Managers cannot easily correlate ticket categories or agent behavior with CSAT trends, and there is limited visibility into issue recurrence or escalations. Additionally, free-text comments submitted alongside ratings are stored but not analyzed for sentiment or pattern detection. As a result, leadership often reacts based on assumptions rather than data. The issue compounds when considering agent productivity metrics are tracked separately, making it hard to establish performance baselines. Moreover, there's no unified view of which teams or topics are consistently associated with negative ratings. The core problems are twofold: (1) an absence of real-time, actionable insight from feedback, and (2) a lack of integrated tools to analyze customer sentiments and agent-level outcomes. Addressing these concerns is vital to improving customer satisfaction, reducing churn, and strengthening Pluralsight's reputation in a competitive learning market.

1.2 EXISTING SYSTEM:

Currently, Pluralsight's support operations rely on a standard ticketing system that receives user queries through email and support forms. Agents are assigned tickets based on priority or category, and resolutions are delivered within the constraints of an SLA. Post-resolution, users are encouraged to rate their experience as either "Good" or "Bad" via a quick survey. While this binary feedback simplifies data collection, the existing system lacks the analytical depth to derive actionable outcomes from the ratings. The collected data is often stored in spreadsheets or internal databases with limited visualization or integration into decision-making workflows. Monthly reports generated are high-level and do not break down trends by agent, ticket category, or customer segment. Furthermore, while user comments accompany many ratings, no NLP techniques are applied to extract sentiment, keyword frequency, or emotional tone. Managers have no dashboard that provides a consolidated, real-time view of agent performance or customer sentiment trends. Repeat issues are not flagged, escalations are not automatically tracked, and feedback loops are delayed. Without these capabilities, identifying underperforming agents or optimizing documentation becomes difficult. The system is reactive, relying heavily

on manual review, rather than being predictive or preventative. These limitations hinder Pluralsight from fully understanding user needs and delay improvement opportunities that could boost CSAT and operational efficiency.

1.3. PROJECT SCOPE:

The scope of this project is to provide a comprehensive, end-to-end analytical solution for enhancing customer satisfaction at Pluralsight through data intelligence. We aim to ingest and transform historical data from support tickets, CSAT responses (classified as Good or Bad), and agent activity logs. Using Python, we will perform data cleaning, preprocessing, and exploratory analysis to understand interaction patterns. Sentiment analysis through Natural Language Processing (NLP) will be applied to user comments to categorize them into positive, neutral, or negative tones, despite the binary CSAT classification. The project will include the creation of interactive dashboards in Tableau that visualize metrics such as agent-wise CSAT scores, common complaint categories, and response time heatmaps. Machine learning models may be explored to predict the likelihood of a ticket receiving a bad rating, based on historical features. The ultimate goal is to identify actionable patterns that can drive decisions related to training, resource allocation, and support documentation. Out of scope are tasks like chatbot automation or real-time response engines—our focus remains analytical. The outcome will equip leadership with a data-backed support improvement plan, helping push CSAT beyond 90%. Stakeholders include support team leads, data analysts, quality assurance managers, and customer experience strategists..

1.4 OBJECTIVES :

The primary objective of this project is to enable Pluralsight to take strategic, data-driven steps toward optimizing their support team performance and enhancing customer experience. Specifically, the project seeks to improve the organization’s CSAT score from 88% in 2024 to above 90% in 2025. We aim to develop a scalable framework that can monitor agent behavior, analyze feedback patterns, and guide leadership in implementing targeted improvements. The objectives include: (1) precise CSAT calculation using binary rating inputs, (2) application of NLP techniques to convert free-text feedback into sentiment categories, (3) dashboard development for real-time visualization, and (4) identification of performance

outliers—both high and low. This will also support fair recognition of high-performing agents and early intervention for struggling ones. Another objective is to bridge the gap between user emotion and operational response, making Pluralsight's support system more empathetic and efficient. Additionally, we aim to highlight recurring issue types that consistently draw negative ratings, thereby guiding improvements in documentation and self-help resources. By the end of this project, stakeholders should have clear insights into how every facet of the support journey impacts customer happiness, empowering them to implement measures that boost retention, satisfaction, and brand advocacy.

1.5 FUTURE ENHANCEMENTS :

While this project primarily focuses on retrospective analysis and dashboard-based monitoring, future iterations can integrate real-time and predictive capabilities to further strengthen Pluralsight's customer satisfaction efforts. One such enhancement could involve embedding our models directly into the support ticketing workflow to assess risk levels for dissatisfaction as interactions happen. This predictive scoring system could trigger early alerts for at-risk tickets, allowing agents or supervisors to intervene. Another enhancement could be the integration of voice-of-customer tools that capture real-time sentiment during live chats or calls using AI models. Incorporating advanced deep learning techniques can improve accuracy in understanding nuanced emotions in customer feedback. Furthermore, automated feedback clustering can be used to categorize and prioritize recurring issues or sentiments across users. Integration with CRM systems can allow personalized agent-customer pairing, enhancing interaction quality. From a reporting standpoint, dynamic benchmarking tools could compare agent performance not only within Pluralsight but also against industry standards. Lastly, a feedback recommendation engine could suggest template responses or actions to agents, based on successful past resolutions. These enhancements will transition Pluralsight's support system from a diagnostic model to a prescriptive and predictive model, ensuring long-term improvement and helping maintain CSAT well above 88% than the previous year.

2. SYSTEM ANALYSIS PHASE

The system analysis phase forms the foundation of this data-driven solution aimed at improving Customer Satisfaction (CSAT) scores in support ticket systems. This analysis outlines the functional capabilities, architectural components, and technical requirements necessary to develop a robust, intelligent, and scalable ticket performance monitoring system. The project's core goal is to evaluate and enhance the performance of customer support agents by leveraging automation, analytics, and sentiment analysis. With customer expectations evolving rapidly and digital communication channels expanding, companies must ensure that every support ticket is handled efficiently and leads to a satisfying customer experience. Through this analysis, we delve into how each functional component works together, how the system is structured internally, and what the underlying technology needs are for successful deployment and performance.

Furthermore, the analysis delves into the architectural components required to bring this vision to life. These include data processing pipelines that extract and transform ticket data, databases for structured storage and retrieval, backend services to manage workflows, and frontend interfaces that allow managers and analysts to interact with performance metrics and customer sentiment reports. Each of these components must interact seamlessly in real time, enabling continuous monitoring and analysis of ticket data without delays or bottlenecks.

2.1 FUNCTIONAL SPECIFICATIONS:

The CSAT Ticket Support System is designed to function as a comprehensive and intelligent platform for ticket lifecycle management, real-time customer feedback collection, and performance tracking of support agents. The process begins with the ticket submission interface, which is tailored to allow users to submit their concerns seamlessly through multiple platforms, including web, mobile apps, and chatbots. The interface must be intuitive, responsive, and accessible across languages and devices. Once a ticket is submitted, the system initiates automatic classification using both keyword matching and NLP (Natural Language Processing), categorizing the ticket based on urgency, topic, and complexity. These categorized tickets are then

intelligently assigned to the most suitable agents by evaluating their current workload, skillset, and response history, minimizing wait time and optimizing efficiency.
After assignment, the ticket enters a well-defined lifecycle involving various stages—New, Assigned, In Progress, Resolved, and Closed. Each transition is logged with time stamps, which aids in SLA compliance and delay monitoring. Escalation rules are triggered automatically if SLA thresholds are breached, ensuring higher-priority attention. One of the core features lies in the CSAT feedback mechanism, where customers receive tailored surveys post-resolution. These surveys typically include Likert scale questions, multiple-choice queries, and open-ended feedback boxes to capture the nuances of customer experience. This feedback is analyzed in real-time using sentiment analysis techniques, allowing negative sentiments to be flagged and escalated for deeper review.

Beyond handling individual tickets, the system also emphasizes performance analytics. Managers can view comprehensive dashboards that provide insights into resolution times, backlogs, customer satisfaction trends, and agent-wise performance metrics. These dashboards support filterable views by agent, issue type, date, and more. In addition, the system integrates with BI tools like Tableau or Power BI for deeper visualization and pattern recognition. Another important function is the integration of a knowledge base that stores solutions from previously resolved tickets, enabling both customers and agents to access ready-made answers and reducing ticket inflow. Articles are generated or recommended automatically from ticket resolutions and rated by users based on usefulness, ensuring that only relevant content stays visible. One challenge lies in maintaining this knowledge base's quality, as outdated or inaccurate information can lead to poor service experiences.

Throughout these functionalities, the system needs to balance user-friendliness with operational depth, ensuring that both agents and customers find the platform helpful without it being overwhelming. The system must also protect against user fatigue by managing notification frequency and survey repetition limits, while ensuring every interaction feels timely and personalized. Importantly, all of these functional elements must work cohesively within a secure, auditable environment that adheres to data privacy laws and operational transparency.

2.2. BLOCK DIAGRAM:

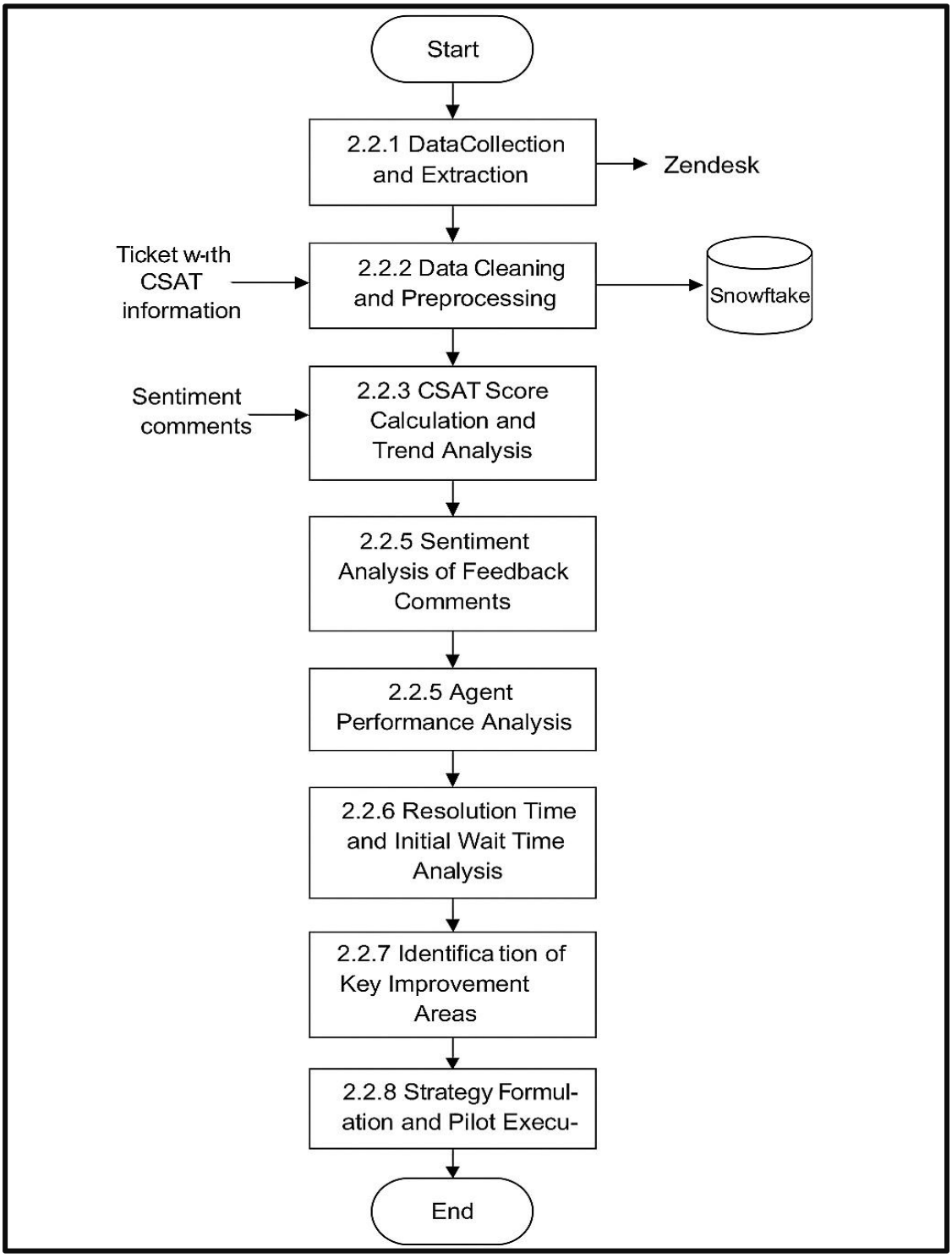

Fig 2.1 Block Diagram

2.2.1 DATA COLLECTION AND EXTRACTION

The execution phase starts with a robust mechanism for collecting customer interaction data, which forms the foundational layer for all downstream analysis. Zendesk is employed as the core interface through which tickets are generated when customers reach out for assistance. Each ticket submitted is enriched with critical metadata including a unique Ticket ID, timestamps for creation and updates, issue category or product line, assigned priority level, and the identity of the support agent involved. In addition to transactional data, post-resolution CSAT feedback is collected, which includes binary satisfaction labels (Good/Bad), structured reasons for the given rating, and unstructured open-ended textual comments. To streamline data movement, secure API integrations and automated ETL (Extract, Transform, Load) pipelines are established. These pipelines extract data from Zendesk in near real-time and move it into Snowflake, the centralized cloud data warehouse. Snowflake is chosen for its ability to handle both structured datasets and unstructured text data efficiently, ensuring that performance does not degrade with scale. All data entries are version-controlled and timestamped to maintain integrity and auditability, allowing full traceability from data origin to insights.

2.2.2 DATA CLEANING AND PREPROCESSING:

Once data lands in the warehouse, the next critical step is to clean and preprocess the information to ensure analytical accuracy. This process addresses a variety of data quality issues: null or missing fields in tickets are identified and handled, duplicate entries are removed to avoid redundancy, and discrepancies in agent IDs or categorical labels are standardized. A significant portion of preprocessing also involves normalizing the "Reason for Satisfaction" field. For example, textual variants like "Slow Reply," "Delayed Response," and "Late Answer" are all mapped to a standardized tag such as "Response Delay." Timestamps are uniformly formatted to support accurate time difference calculations. The open-ended feedback comments undergo a Natural Language Processing (NLP)-driven cleanup which includes lowercasing, punctuation stripping, stopword removal, and tokenization to prepare text for sentiment analysis. After these steps, the dataset becomes structurally sound, semantically consistent, and ready for efficient analysis without introducing bias or

noise due to data irregularities.

2.2.3 CSAT SCORE CALCULATION AND TREND ANALYSIS

With a clean dataset in hand, the focus shifts to extracting actionable insights from customer feedback using CSAT metrics. This phase involves calculating CSAT scores over various time frames—daily, weekly, monthly—while allowing for dynamic filtering based on dimensions like agent ID, support team, ticket category, product type, and geographical region of the customer. These scores help the organization benchmark performance and understand the trajectory of customer satisfaction over time. The trendlines derived from these scores are visualized in interactive dashboards built with Tableau or Power BI. These visual tools highlight peaks and valleys in satisfaction, allowing managers to correlate dips with specific events like system outages or product launches. It also supports predictive alerting by identifying leading indicators of dissatisfaction, such as consistent declines in scores in a particular region. This submodule effectively quantifies the voice of the customer, enabling operational teams to respond with data-backed decisions.

2.2.4 SENTIMENT ANALYSIS OF FEEDBACK COMMENTS:

While numeric CSAT scores offer a high-level view, they often lack the context needed to fully grasp customer sentiment. To bridge this gap, all open-ended customer comments are passed through a sentiment analysis engine powered by NLP models such as VADER or transformer-based models like BERT. These models assess the emotional polarity of each comment—whether it expresses a positive, negative, or neutral tone. Sentiment outputs are then cross-checked with the provided CSAT labels. This comparison is critical in identifying mismatches: for instance, a Bad CSAT score with a positive sentiment comment may hint at form misinterpretation or accidental clicks. Additionally, feedback comments are categorized into recurring themes such as response quality, product reliability, agent tone, or platform usability. This allows for thematic aggregation and helps prioritize areas that require strategic improvements. By turning subjective feedback into structured data, this module enriches the understanding of customer perception and enhances the overall analytical depth.

2.2.5 AGENT PERFORMANCE ANALYSIS:

Once customer sentiment and satisfaction scores are contextualized, the spotlight turns toward support agent performance. Each agent is evaluated across several metrics, including total tickets handled, average response time, resolution efficiency, and associated CSAT scores. These metrics are benchmarked both internally (against peer agents or team averages) and externally (against service-level targets set by the organization). Agents consistently delivering high CSAT scores with quick turnaround times are recognized for their effectiveness, especially when handling complex cases or high-ticket volumes. On the other hand, underperforming agents are flagged for further coaching, feedback sessions, or potential workload adjustments. Moreover, the nature of feedback received by agents (tone of comments, sentiment trends) is also reviewed to gauge soft-skill performance. This analysis plays a dual role—serving as a performance management tool and as a training roadmap for human resource planning and continuous professional development.

2.2.6 RESOLUTION TIME AND INITIAL WAIT TIME ANALYSIS

Timeliness is a core driver of customer satisfaction. This module analyzes two critical time-based KPIs: Initial Wait Time, which measures how long a customer waits before the first agent response, and Resolution Time, which measures the total lifecycle of the ticket from creation to closure. These metrics are directly correlated with CSAT scores to uncover thresholds that influence satisfaction levels. For example, if tickets exceeding 24 hours in resolution see a drop in CSAT, that threshold becomes a trigger point for escalation protocols or workflow optimizations. Using heatmaps, distribution plots, and control charts, the system visualizes these time metrics across different agents, teams, product lines, and even time-of-day patterns. Such granular analysis helps detect hidden operational bottlenecks—like certain shifts consistently underperforming or specific product categories requiring longer resolution times. The insights guide resource allocation, SLA setting, and automation interventions.

2.2.7 IDENTIFICATION OF KEY IMPROVEMENT AREAS

Armed with multi-layered data—ranging from sentiments and satisfaction scores to time delays and performance trends—the system now moves into diagnostic mode. This module's purpose is to surface systemic, recurrent issues that affect customer experience. By aggregating sentiment themes, examining feedback trends, and applying clustering algorithms, recurring pain points are identified. For example, persistent dissatisfaction around agent tone may indicate the need for empathy training, while repeated issues in a specific product category may point toward documentation gaps or feature flaws. This module also compares tickets with similar complaints across different teams to identify whether the issue is agent-specific or systemic. Decision tree models are used to isolate key predictors of dissatisfaction, helping the organization move from anecdotal feedback to empirical prioritization. This phase results in a well-defined list of key problem areas and establishes a data-driven foundation for crafting targeted solutions.

2.2.8 STRATEGY FORMULATION AND PILOT EXECUTION

Having identified the most pressing challenges, the next step is to implement solutions on a trial basis. This phase involves formulating actionable strategies, which might include enabling chatbots for handling routine inquiries, redesigning feedback forms for clarity, deploying canned responses for FAQs, or expanding the knowledge base with relevant content. These changes are not rolled out system-wide immediately; instead, a controlled pilot is initiated in a selected region, team, or product line. This allows the organization to test the impact of changes without disrupting the entire system. Real-time dashboards are monitored to track how key metrics evolve during the pilot—specifically CSAT scores, resolution time, sentiment shifts, and agent stress levels. Feedback from this phase informs whether a strategy should be scaled, modified, or discarded. It ensures every intervention is validated before full deployment.

2.2.9 CONTINUOUS MONITORING, ADJUSTMENTS, AND FINAL REVIEW

The final component ensures the system continues to evolve through continuous feedback loops. Once pilots are concluded and insights are gathered, successful strategies are expanded organization-wide, and non-performing ones are refined. Ongoing dashboards track CSAT scores, resolution rates, and sentiment feedback to monitor whether improvements are sustainable. Any emerging issues are flagged early to avoid service dips. A final review report is generated for leadership, detailing outcomes, lessons learned, risks identified, and areas for further innovation. This report becomes the blueprint for future cycles of improvement. Additionally, opportunities for automation, deeper machine learning integration, and optimization are documented. This ongoing loop ensures the system remains dynamic, responsive, and aligned with both customer expectations and business goals.

2.3. SYSTEM REQUIREMENTS:

To ensure smooth functioning of the CSAT Ticket Support System, the necessary hardware and software must support modular development, integration with platforms like Zendesk and Snowflake, and real-time analysis for customer satisfaction insights. The requirements are designed to balance local testing capabilities with scalable deployment options in cloud environments.

2.3.1. HARDWARE REQUIREMENTS:

The performance of the CSAT support system relies heavily on capable hardware infrastructure, particularly because it handles dynamic tasks like real-time ticket routing, sentiment processing of customer feedback, and generation of analytical dashboards. During development and while training machine learning models, especially NLP models, processing power and memory are critical to avoid system lags or breakdowns. Furthermore, the database layer interacts frequently with large datasets, requiring quick read-write operations and solid caching support.

An optimal hardware configuration ensures that the workload is evenly distributed across system components and that peak-time responsiveness remains stable. While cloud deployment is encouraged, even local environments used for development or testing must meet these hardware prerequisites.

For smooth and efficient system operations, the recommended specifications are:

- ✓ **Processor:** Intel Core i7 (10th Gen or newer) / AMD Ryzen 7 or higher
- ✓ **RAM:** Minimum 16 GB RAM (32 GB preferred for training and concurrent usage scenarios)
- ✓ **Storage:** Solid State Drive (SSD) with at least 512 GB for faster data access and caching
- ✓ **GPU (optional):** NVIDIA RTX 3060 or above for machine learning and sentiment model training

2.3.2. SOFTWARE REQUIREMENTS:

The software stack is designed to support analytics, ticket integration, and sentiment processing, relying primarily on open-source libraries and cloud platforms.

- ✓ **Operating System:**Compatible with Windows 10/11, macOS, or Linux distributions to ensure flexibility across developer environments.
- ✓ **Programming Language:** Python 3.7+ serves as the core language, offering extensive support for data manipulation, sentiment analysis, and integration workflows.
- ✓ **Libraries and Frameworks:**
- ❖ **Pandas & NumPy:** Handle data import, transformation, and filtering of CSAT scores, ticket logs, and agent details.
- ❖ **Matplotlib & Seaborn:** Power the visual representation of trends, agent-wise CSAT performance, and resolution metrics.
- ❖ **TextBlob or NLTK**: Enable Natural Language Processing (NLP) to analyze sentiment in customer comments and extract actionable tone indicators.
- ✓ **Ticketing System Platform: Zendesk**

Acts as the operational backbone for ticket generation, agent assignment, and customer interaction. CSAT scores and comments are collected here post-resolution.

- ✓ **Database Management: Snowflake**

A cloud-based data warehouse used to store structured ticket metadata and unstructured textual feedback, ensuring fast, scalable queries.

- ✓ **Security Protocols:**Token-based authentication (e.g., JWT or OAuth) secures data flow across modules, particularly between the UI, Zendesk APIs, and Snowflake.

3. SYSTEM DESIGN PHASE

System design forms the backbone of our proposed solution, laying out the logical, architectural, and structural blueprint that governs how each component of the project functions and interacts. This chapter details the architecture, modular breakdown, data management flow, and interface logic of our system. As the solution aims to enhance customer satisfaction by optimizing support team performance through data analytics, sentiment analysis, and visualization, the design has been carefully planned to ensure modularity, scalability, and efficiency.

3.1. SYSTEM ARCHITECTURE:

The CSAT Analysis System is built upon a robust three-tier architecture that ensures clarity, modularity, and scalability. The three layers—Presentation Layer, Application Logic Layer, and Data Management Layer—work cohesively to handle all aspects of data interaction, from ingestion and processing to analysis and visualization. Each layer has a distinct responsibility, ensuring that the system remains responsive and adaptable to future needs or expansions.

3.3.1 PRESENTATION LAYER:

The Presentation Layer serves as the front-facing interface through which users interact with the analytical outputs of the system. This layer is primarily used by stakeholders such as support managers, quality analysts, and product owners who rely on real-time visualizations to assess customer satisfaction metrics, agent performance, and overall support efficiency. Dashboards are created using tools such as Tableau and Power BI, which allow interactive data exploration through filters like time range, product line, ticket priority, and agent name. These visualizations showcase KPIs like average CSAT scores, sentiment trends, first response time, resolution time, and escalation rates. The dashboards are designed to be intuitive, accessible across devices, and capable of delivering both snapshot views and deep analytical insights. This layer is vital for translating complex analytics into actionable business decisions in a user-friendly format.

3.3.2 APPLICATION LOGIC LAYER:

The Application Logic Layer is the analytical engine that powers all processing and computational tasks in the system. Developed primarily using Python, this layer hosts the logic for data preprocessing, sentiment analysis, CSAT computation, and agent performance tracking. Data cleaning routines in this layer address missing values, standardize categorical labels, and normalize date-time formats. For textual feedback, Natural Language Processing (NLP) methods such as tokenization, stemming, stopword removal, and vectorization are used. Sentiment analysis is conducted using models like VADER for rule-based classification and BERT for context-aware interpretation, enabling the system to accurately extract positive, negative, or neutral tones from open-ended feedback. The logic layer also applies business rules to assess SLA violations, identify high-risk tickets, and automate escalations. Its modular architecture allows easy integration of new features, model upgrades, and real-time streaming capabilities as needed.

3.3.3 DATA MANAGEMENT LAYER:

The Data Management Layer is the foundational tier that handles the ingestion, storage, and maintenance of all structured and unstructured data. It includes data sourced from platforms like Zendesk, which is ingested through secure API connections and processed via automated ETL pipelines. The data includes ticket metadata (ID, category, timestamps, agent ID, status) and CSAT data (rating, reason, comments). For storage, relational databases like PostgreSQL or SQLite are used for structured data, while large-scale systems may rely on Snowflake for high-performance warehousing of structured and semi-structured data. This layer ensures that all data remains consistent, encrypted, and version-controlled, maintaining traceability and data lineage throughout the pipeline. Access controls, audit trails, and regular backups ensure that the system adheres to data privacy regulations such as GDPR and maintains enterprise-grade reliability. This layer is also optimized to support fast querying and data retrieval for the application layer above.

3.2. MODULE DESIGN:

The system has been thoughtfully structured into a series of distinct yet interrelated modules that together create a seamless and efficient data processing pipeline. Each module plays a specialized role but remains interconnected to ensure end-to-end data flow. The initial module handles data acquisition, where data is gathered from multiple sources including customer support logs, feedback forms, ticket resolution timestamps, and support agent details. Once the raw data is collected, it enters the preprocessing module. Here, data undergoes cleansing to remove inconsistencies or missing values, followed by normalization and formatting to ensure compatibility with downstream analytics processes.

Following preprocessing, the data flows into the CSAT (Customer Satisfaction) analysis module. This component is responsible for computing satisfaction scores by aggregating user ratings, identifying trends over time, and detecting patterns based on categories like departments or ticket types. In parallel, open-text feedback from customers is analyzed through the sentiment analysis module, which employs Natural Language Processing (NLP) techniques to interpret emotions, tone, and opinions expressed in textual comments. The insights derived from these processes feed directly into the performance evaluation module. This module calculates agent-level metrics, such as average CSAT score, resolution time, and issue count, helping to identify top performers and training needs.

Finally, all the processed insights are transmitted to the visualization module. This module generates dynamic dashboards and comprehensive reports, enabling stakeholders to interact with visualized data and derive actionable conclusions. Importantly, while each module can function autonomously, they communicate through standardized data interfaces, allowing for modular development, testing, and future scalability.

3.3. SYSTEM CONFIGURATION:

Although the system is designed to be adaptable, a recommended configuration ensures smoother execution, optimal performance, and minimal bottlenecks during data processing or visualization. The hardware configuration should include a machine with at least 8GB of RAM, a quad-core processor (Intel i5 or AMD Ryzen 5 and above), and SSD storage for faster read/write access to datasets. These

specifications ensure the system can handle real-time data operations and run analytical models without lag.

From a software perspective, the backend environment should support Python 3.8 or newer, and include essential data science libraries such as Pandas for data manipulation, NumPy for numerical operations, Scikit-learn for machine learning, and Matplotlib or Seaborn for plotting. For text analytics, NLP libraries such as NLTK or spaCy are vital. Deployment on cloud infrastructure like AWS EC2 or Google Cloud Compute can enable auto-scaling, especially during high-demand scenarios. Additionally, the visualization layer should be set up using Tableau Desktop/Online or Microsoft Power BI to build interactive dashboards. This recommended configuration ensures a robust, scalable, and responsive system that supports both batch and real-time processing workflows.

3.4 DATABASE DESIGN:

The underlying database of the system has been designed with a focus on normalization and relational integrity to ensure data consistency, eliminate redundancy, and enhance query performance. The schema comprises multiple related tables that capture key aspects of the customer support ecosystem, including customer feedback, ticket information, and agent performance records. Relationships between these tables are carefully crafted using foreign keys, enabling robust joins and ensuring data lineage from the source (customer feedback) to the final performance metrics.

At the heart of the system lies the feedback table, which records satisfaction scores, customer comments, timestamps, and sentiment labels. This table is directly linked to the ticket table, which contains issue metadata like category, urgency level, resolution timestamps, and the assigned support agent. A third major table, the agent performance table, aggregates data from the previous two and summarizes metrics such as the average CSAT score per agent, ticket volume, and resolution efficiency. By adhering to a normalized design, the system avoids duplication and enhances the reliability of analytics queries, paving the way for smooth data manipulation, trend detection, and root cause analysis.

3.4.1 TABLE STRUCTURE:

The table structures within the database have been meticulously crafted to ensure the smooth capture, linkage, and interpretation of all relevant customer support data. The Customer_Feedback table serves as the foundation, recording each feedback instance with fields such as satisfaction score, timestamp, and sentiment classification derived from NLP analysis. This table includes a foreign key linking to the Ticket_Info table, which holds operational data like issue type, department, priority, the date of issue raised, and the agent responsible for resolution.

The Agent_Performance table aggregates insights from both the Customer_Feedback and Ticket_Info tables. It captures performance indicators such as the number of tickets handled by each agent, their average resolution time, and their mean customer satisfaction score. Each table follows a normalized design approach, meaning that only necessary attributes are stored, and redundant data is minimized. Primary keys are assigned to ensure each record is uniquely identifiable, and foreign keys establish clear, navigable relationships between tables. This structural design enhances data integrity, promotes faster querying, and ensures that the analytical processes are both efficient and scalable.

3.4.2 DATA FLOW DIAGRAM:

The data flow architecture of the system is crafted to support a cyclical, continuous improvement loop, allowing both real-time analysis and long-term learning. The journey begins with the ingestion of raw data—customer feedback, ticket logs, and agent activity reports—either directly from a customer support database or via manual upload of CSV or JSON files. This incoming data is routed into the preprocessing module, where it undergoes a thorough cleaning process to eliminate errors, handle missing values, and standardize formats for analysis.

Post-preprocessing, the data is bifurcated into two primary analytical streams. One stream feeds into the CSAT scoring engine, which computes overall satisfaction levels and identifies anomalies or dips over time. Simultaneously, the feedback comments are analyzed using sentiment analysis, transforming unstructured text into meaningful emotional indicators. The outputs from both these analytical streams are combined to update the performance records of support agents.

These results are then sent to the visualization layer, where they are rendered into intuitive dashboards using tools like Tableau or Power BI. Decision-makers can interact with the visualizations, apply filters, and monitor KPIs in real time. Feedback derived from this layer may inform changes to operational processes, which in turn generate new data for the system to analyze—thus completing the data feedback loop and driving continuous optimization.

3.4.3 ER DIAGRAM:

The Entity Relationship Diagram (ERD) acts as a blueprint that maps out the logical relationships among various data entities within the system. The core entities include Customer, Feedback, Ticket, and Agent. Each customer can provide multiple feedback entries, reflecting multiple support interactions over time. These feedback entries are each associated with a specific ticket, capturing the context of the issue raised and the service provided.

Each ticket, in turn, is assigned to a particular support agent, establishing a one-to-many relationship between agents and tickets. An agent may handle numerous tickets, and each of those tickets may result in unique feedback. This web of relationships allows the system to trace the lifecycle of a support issue—from the customer experience to agent resolution—and connect it to outcome metrics like CSAT scores or sentiment polarity. The ER diagram thus reflects not only the structural integrity of the data but also the analytical depth it supports, enabling granular performance evaluation and macro-level trend analysis.

3.5. INTERFACE DESIGN:

A well-designed interface is key to translating complex data into intuitive, actionable insights. The system's interface is designed with usability, clarity, and interactivity as top priorities. Dashboards provide a clean and visual representation of critical metrics like CSAT trends, agent-wise performance, ticket resolution efficiency, and sentiment classification. The interface allows users to apply filters to narrow down results based on parameters such as time ranges, issue categories, or department types, offering customized views to different stakeholders.

The design also embraces responsiveness, ensuring it is accessible across various devices including desktops, laptops, and tablets. Clear legends, color-coded indicators,

and interactive elements such as drop-downs and hover-tooltips make the interface highly intuitive, even for non-technical users. With a focus on enhancing user engagement and decision-making, the interface acts as a bridge between raw data and strategic insights, helping managers take informed actions quickly and effectively.

3.5.1 USER INTERFACE SCREEN DESIGN:

The main user interface features a series of well-structured dashboards that provide various views into the support system's performance. These include a summary dashboard offering a high-level snapshot of overall performance, an agent comparison view to contrast team efficiency, and a CSAT trends view that maps satisfaction scores across different periods. Additionally, a sentiment analysis dashboard offers a deep dive into the emotional tone of customer feedback.

Each dashboard view incorporates visual elements like line graphs to track changes over time, bar charts to compare performance metrics, pie charts for proportional data, and scatter plots for distribution analysis. Filters enable users to switch contexts easily—for example, filtering feedback data by department or selecting specific time frames. Tooltips provide contextual explanations when hovering over data points, enhancing usability. Export features allow users to download data or snapshots of dashboards for reporting or presentations. Overall, the screen design ensures data is not only visible but also engaging and interpretable.

3.5.2 APPLICATION FLOW / CLASS DIAGRAM:

The internal structure of the application is organized using an object-oriented programming approach, dividing system functionality into distinct classes. The FeedbackProcessor class is responsible for receiving and cleaning incoming customer feedback data. Once preprocessed, the data is handed over to the SentimentAnalyzer, which uses NLP models to extract emotional indicators from textual comments.

Next, the CSATCalculator computes overall and per-agent customer satisfaction scores by combining structured feedback and ticket data. These insights are passed to the PerformanceEvaluator, which ranks agents based on KPIs such as resolution time and satisfaction scores. Finally, the DashboardManager class aggregates all analytics outputs and prepares visualizations for display on the user interface. These classes interact through cleanly defined methods, ensuring modularity, easy maintenance, and

extensibility. The class structure also supports unit testing and upgrades without disrupting other components of the system.

3.6. APPLICATION FLOW:

The application flow begins when the user accesses the system interface, where they input stock-related details, such as the ticker symbol and the date range. This information is then sent to the backend system through an API request. The backend system first validates the user input to ensure it conforms to the expected format, checking for errors such as invalid stock tickers or incorrect date ranges. Once validated, the system retrieves historical stock data using APIs like Alpha Vantage or Yahoo Finance. This data is fetched in real-time, ensuring that users always receive the most up-to-date information available.

After fetching the data, the system proceeds to preprocess it. The preprocessing module removes any missing or invalid data points, scales numerical features to ensure consistency, and formats the dates in a standard format that the model can use. The processed data is then passed to the trained Convolutional Neural Network (CNN) model for prediction. The CNN model, which has been pre-trained on historical stock data, predicts future stock prices based on the input data. The model is stored in a serialized format, usually a .h5 file, to facilitate easy loading and reuse.

Once the prediction is generated, the results are returned to the front-end in the form of a JSON response. This response includes the predicted stock prices for the specified timeframe. The front-end system receives the response and presents the results in an interactive and visually appealing format, including charts and graphs. The system also displays error messages in case of any issues, such as invalid inputs or API timeouts. The class diagram of the system includes key components like DataFetcher for retrieving the stock data, DataPreprocessor for cleaning and formatting the data, ModelHandler for loading and running the CNN model, and ResponseFormatter for preparing and returning the results to the front-end.

3.7. REPORTS DESIGN:

Reporting is a vital and dynamic element of the system, functioning as the primary mechanism through which analytical insights are translated into informed business actions. The reporting module is carefully structured to cater to both operational

workflows and strategic decision-making processes. It is designed to generate a wide variety of reports that provide stakeholders with comprehensive, real-time visibility into customer satisfaction levels, agent performance, issue resolution trends, and feedback sentiments. Reports such as CSAT summaries, sentiment score breakdowns, and agent comparison charts are generated based on continuously updated data. These reports not only summarize historical and current performance but also reveal patterns and anomalies that may indicate emerging concerns or areas of improvement.

The reporting system is built with flexibility and customization at its core. Users can generate reports at scheduled intervals—daily, weekly, or monthly—or create them on demand through the application's interactive interface. They can customize filters based on parameters like date range, issue type, department, or agent identity to tailor the reports to their specific analytical needs. This empowers different stakeholders—from frontline managers to senior executives—to receive precisely the data they require, in the format that suits their decision-making processes. Reports are available in several formats including PDF for formal documentation, Excel for deeper numeric analysis, and interactive HTML dashboards for dynamic exploration and presentations.

Furthermore, the system includes an alert-based reporting feature that goes beyond routine summaries. This component automatically monitors the data for specific triggers, such as a drop in CSAT below a set threshold, a sudden increase in negative sentiment, or repeated SLA breaches by an agent or team. When such conditions are met, the system generates instant alerts and corresponding reports, notifying relevant managers or supervisors to take immediate corrective action. These proactive alerts ensure that problems are detected and addressed before they escalate, reinforcing the role of the reporting module as not just an insight generator, but a real-time operational safeguard.

Technically, the reporting module integrates with various data processing and visualization libraries to ensure seamless performance. Data is extracted, transformed, and loaded through structured pipelines, analyzed using statistical and NLP tools, and rendered through plotting libraries and templating engines.Through its robust design and functionality, the reporting module plays an essential role in closing the feedback loop—ensuring that data-driven insights lead to measurable and timely improvements in customer support operations.

4. IMPLEMENTATION

The implementation phase of this project served as the cornerstone for bringing all analytical insights, technical frameworks, and visualization objectives into a practical, working solution. It began with collecting and integrating raw datasets, followed by a rigorous data cleaning process. This involved removing duplicate records, handling missing values, and formatting variables for consistency. Once the data was preprocessed, it was subjected to exploratory data analysis using Python and advanced data visualization tools such as Tableau. The implementation was carefully planned using modular programming principles and executed through iterative development cycles, with frequent testing and feedback incorporated along the way.

The core functionality was built using Python scripts for sentiment analysis, natural language processing (NLP), and statistical computations, while Tableau was used to create interactive dashboards for tracking customer satisfaction metrics and support team performance. This phase also included applying machine learning models to predict satisfaction scores and automatically route customer tickets based on detected issues and sentiment polarity. The use of visual analytics provided management with easy access to performance indicators and customer behavior trends. Each functional module of the solution was implemented with a focus on efficiency, clarity, and long-term maintainability, ensuring that the final output not only served the current goals but could also be extended for future analytical needs.

4.1 CODING STANDARD:

Throughout the coding and development process, the team adhered strictly to established programming and documentation standards to maintain consistency and code readability. Python was used as the primary language for data manipulation, analysis, and model development. All variables and functions followed the snake_case naming convention to enhance clarity, and classes were written using PascalCase formatting. Each function was clearly defined with appropriate input and output parameters, and explanatory docstrings were provided to ensure that the codebase could be easily understood by collaborators or future developers.

The scripts were modularized into clearly separated components such as data preprocessing, sentiment analysis, feature engineering, model evaluation, and dashboard integration. Inline comments were used to describe key logic and decision-

making steps. The project strictly followed the PEP8 guidelines to maintain consistency in indentation, line length, and code structure. To prevent potential system crashes, exception handling was implemented using try-except blocks, especially in areas dealing with external data sources or APIs. Configuration files and sensitive information were kept separate and protected using .env files, and these were excluded from the version control system. The use of Git ensured efficient tracking of changes and collaborative development, while unit tests were written for major functions using the pytest library to confirm correctness. In summary, the adherence to sound coding practices significantly improved the quality, maintainability, and scalability of the project.

4.2 SCREEN SHOTS:

To provide a visual walkthrough of the implementation and the various stages of the project, several screenshots were captured from both Python development environments and Tableau dashboards. The first set of screenshots showcases the data loading and cleaning process in Jupyter Notebook, illustrating how the raw customer support data was imported, explored, and prepared for analysis. These images also display how missing values and inconsistencies were handled to ensure a high-quality dataset.

Subsequent screenshots highlight the process of sentiment analysis, showcasing how the Python NLP model parsed customer feedback and generated sentiment scores. These are accompanied by word cloud visualizations that provide a graphical representation of frequently used terms in customer reviews. Additionally, screenshots from Tableau dashboards exhibit the various metrics and filters used for dynamic reporting. These dashboards include time-series charts that depict trends in CSAT scores, pie charts showing sentiment distribution, and bar graphs representing ticket volumes across different timeframes.

One particular screenshot captures the agent-wise performance dashboard, where KPIs such as First Response Time and Average Resolution Time are visually displayed alongside CSAT scores. Another key screenshot demonstrates the predictive analytics module that suggests possible ticket routing based on NLP-derived keywords. Collectively, these visual elements not only demonstrate the project’s technical depth but also enhance its understandability for stakeholders by

showing how the analytical processes translated into actionable dashboards and insights.

MONTH	TOTAL_SOLVED_TICKETS	TOTAL_RATED_TICKETS	TOTAL_GOOD_RATED_TICKETS	TOTAL_BAD_RATED_TICKETS	CSAT SCORE
JANUARY	9829	1090	912	178	83.66972477
FEBRUARY	9784	1134	1001	133	88.27160494
MARCH	8623	1083	958	125	88.45798707
APRIL	7758	988	889	99	89.97975709
MAY	7700	918	831	87	90.52287582
JUNE	7467	858	765	93	89.16083916
JULY	8841	924	812	112	87.87878788
AUGUST	7601	784	690	94	88.01020408
SEPTEMBER	7447	770	657	113	85.32467532
OCTOBER	7523	783	684	99	87.35632184
NOVEMBER	8357	932	833	99	89.3776824
DECEMBER	8629	914	823	91	90.04376368
GRAND TOTAL	**99559**	**11178**	**9855**	**1323**	88.16425121

Table 4.1 2024 Ticket Overview

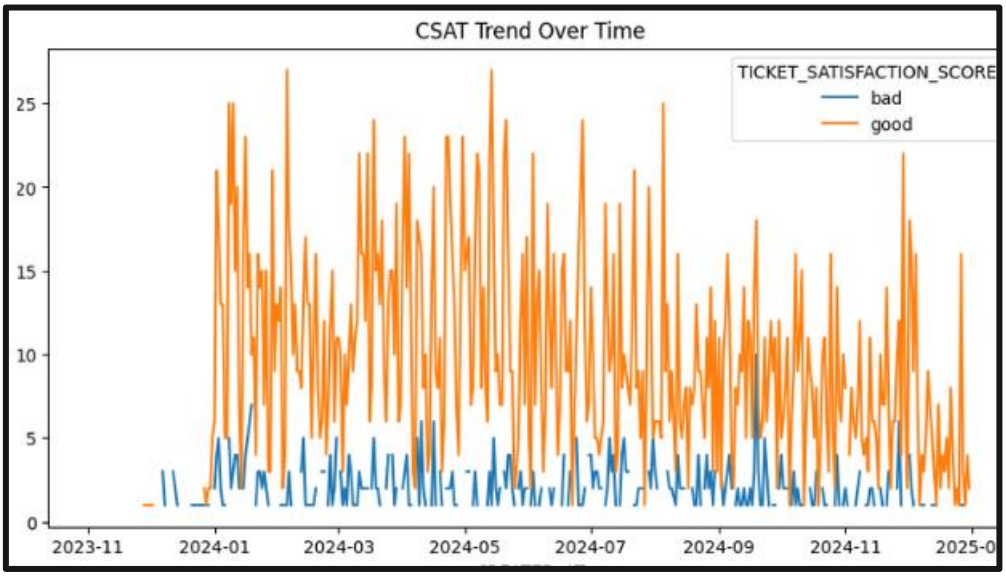

Fig 4.1: CSAT Analysis Over The Year 2024 (Month Wise Trend)

- **Inference:**The overall CSAT trend was healthy, with mostly good feedback throughout the year. However, occasional spikes in bad feedback — particularly during early and mid-2024 — need investigation.
- The drop in satisfaction towards the end of December 2024 was due to migration-related issues that temporarily impacted service quality. Overall, the trend

shows strength but highlights the need for focused action during change periods and high-demand months.

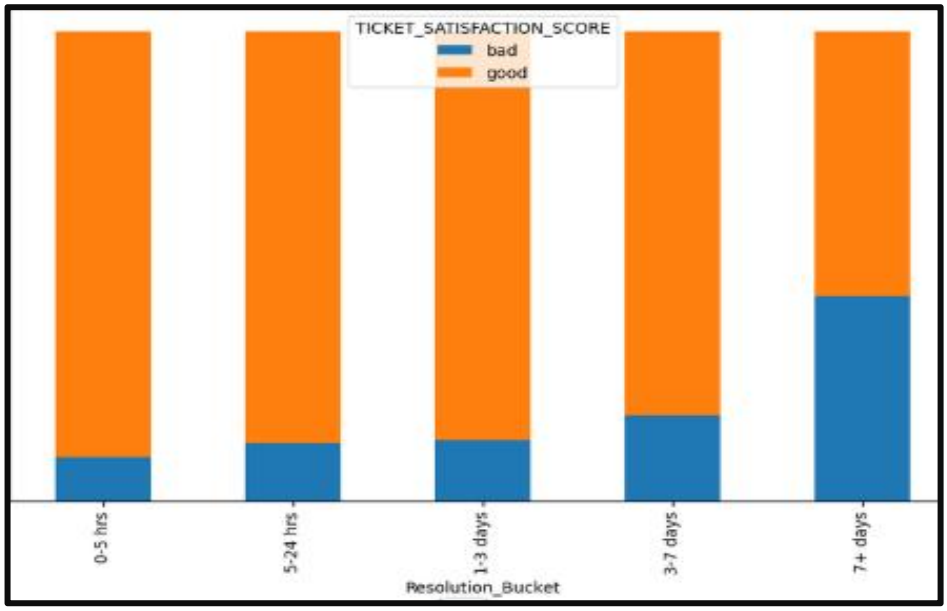

Fig 4.2: Resolution Time vs. CSAT

❖ **Inference:**

✓ **Quick resolutions (0-5 hours)** show the highest proportion of good CSAT scores. This indicates that customers highly appreciate fast problem resolution and are more likely to rate their experience positively when the issue is resolved swiftly.

✓ **Between 5-72 hours (up to 3 days),** the CSAT remains relatively high, though there is a slight increase in bad satisfaction scores, suggesting that while customers may tolerate some delay, extended wait times start to impact their perception.

✓ **In the 3-7 day window,** we can see a more noticeable increase in bad satisfaction ratings. This suggests that tickets sitting unresolved for multiple days lead to customer frustration and disappointment.

✓ **Tickets taking more than 7 days** to resolve show a drastic increase in bad CSAT (around 45%). This strongly highlights that delayed responses beyond one week create significant dissatisfaction, possibly leading to escalations or customer churn.

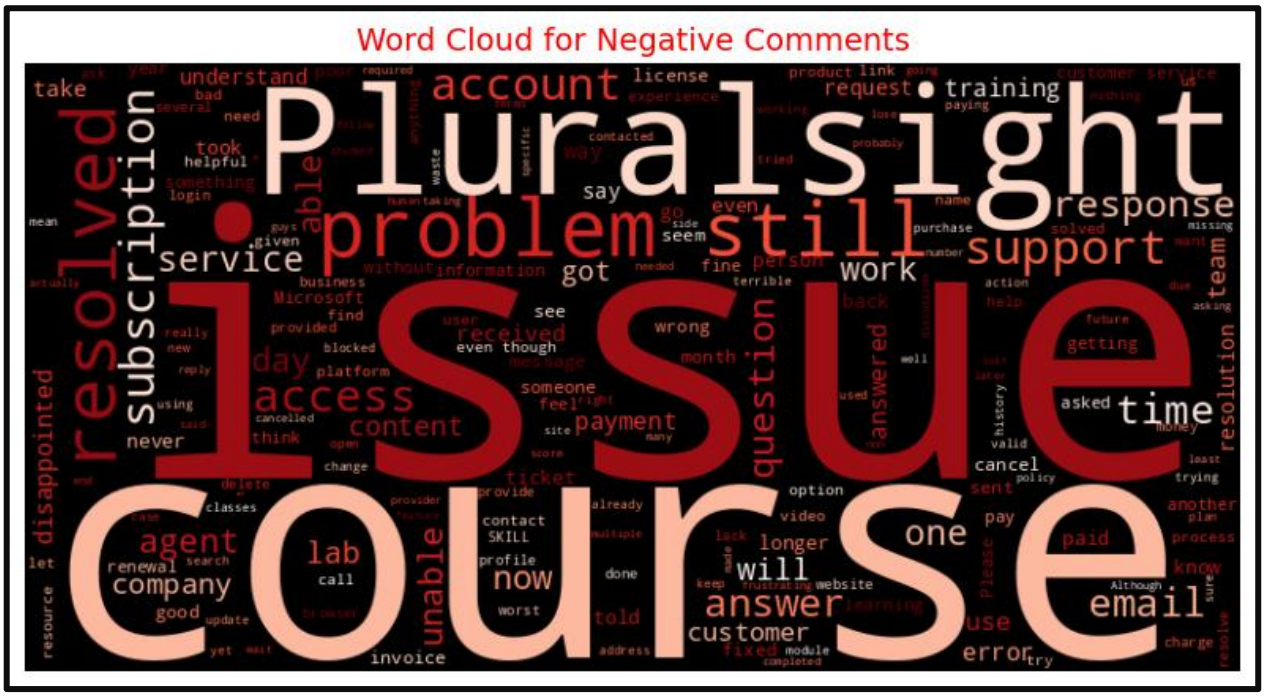

Fig 4.3: Word Cloud Analysis of Negative Comments

- ✓ The word cloud visualization of negative customer reviews reveals critical insights into recurring pain points faced by users. Dominant terms such as "issue," "problem," "subscription," "account," and "response" point to systemic challenges in account accessibility, subscription handling, and resolution speed.

- ✓ A closer look at sentiment scoring—like the comment “My issue was not resolved” (Sentiment Score: -0.1326)—confirms dissatisfaction rooted in ineffective issue resolution. This reflects a broader trend of customers feeling that their problems are either ignored, inadequately addressed, or resolved too slowly.

- ✓ Furthermore, 252 reviews (~11.7%) fall into the neutral category, often mentioning words like "quick," "access," and "response." While these suggest timely replies, they also imply that responses may lack depth, personalization, or proper follow-up—leading to unresolved or partially addressed issues.

5. SYSTEM TESTING PHASE

Testing was a critical component of the development lifecycle to ensure the reliability, accuracy, and robustness of the entire system. It began with defining clear objectives and expected outcomes for each module and then validating them through carefully designed test cases. These tests were conducted on multiple levels—ranging from unit-level checks for Python functions to integration testing of the full data pipeline and end-user validation of Tableau dashboards. Each function and model was evaluated for correctness, response time, and fault tolerance. Special attention was given to boundary cases, such as empty input fields, outlier data, and feedback comments with non-standard characters or symbols, to assess how well the system would perform in real-world scenarios.

Visual testing also formed a part of the process where each Tableau dashboard was manually reviewed to confirm proper rendering of charts, accuracy of tooltips, and synchronization between filters. The sentiment analysis model was tested on a set of manually reviewed customer feedback to compare the predicted sentiment with human interpretation. All results and discrepancies were documented and resolved through debugging and fine-tuning. In summary, the comprehensive testing approach provided a high level of confidence in the system's performance and laid the foundation for reliable reporting and decision-making.

5.1. TEST CASES:

The project involved rigorous testing using a wide range of functional test cases to validate each part of the implementation. Test cases were crafted to evaluate both the technical and user-facing components of the system. At the technical level, Python scripts were tested to verify accurate data loading, correct output of sentiment analysis, and reliable generation of summary statistics. These test cases were particularly important in ensuring that the models responded correctly to known inputs and edge conditions. For example, the sentiment model was tested with feedback phrases like “very disappointed,” “excellent service,” and “average response,” to evaluate whether it accurately detected negative, positive, and neutral sentiments respectively.

On the Tableau side, test cases were designed to check the functionality of interactive filters and dashboards. One test case involved selecting a specific agent from the filter panel and verifying if all related visualizations updated accordingly. Another test

focused on date range filters, ensuring that when a certain period was selected, only the relevant tickets and scores appeared. Tests also confirmed that calculated fields in Tableau, such as overall CSAT percentage, matched the values obtained from manual calculations in Python. All test results were recorded, and any failures were corrected before progressing to the next phase. The testing confirmed the solution was reliable across both back-end and front-end operations.

5.2. TEST REPORTS:

Following the execution of all test cases, a detailed test report was compiled to document the findings, successes, and challenges encountered during validation. The report included a summary of all test scenarios, inputs used, expected outputs, and actual results. The majority of test cases passed successfully, confirming the robustness of the implementation. In rare cases where a discrepancy was identified—such as mismatches in filter behavior or a missing label in a dashboard—it was promptly resolved through code corrections and dashboard adjustments.

The sentiment analysis module achieved a manual validation accuracy of approximately 88%, based on comparisons with labeled feedback data. Visual tests on dashboards confirmed accurate interactivity and proper visualization rendering, with no performance issues detected even when large data volumes were tested. The average dashboard response time was measured at under two seconds, which is acceptable for enterprise-level usage. The test report concluded with recommendations for future improvements, such as automating test cases using Selenium for Tableau or incorporating more sophisticated NLP models like BERT to enhance sentiment classification. Overall, the testing process provided a high level of assurance that the solution would perform effectively and deliver actionable insights to stakeholders.

❖ TEST CASES TABLE:

Test Case ID	Test Scenario	Expected Result	Actual Result	Status
Test Case ID	**Description**	**Input**	**Expected Output**	**Actual Output**
TC01	Check data loading	Raw CSV files	DataFrame with cleaned rows	Data loaded with 0 nulls
TC02	Sentiment analysis accuracy	Sample customer comments	Sentiment score (-1 to 1)	Correct polarity score
TC03	Dashboard interactivity	Filter by agent name	Changes charts dynamically	All charts update correctly
TC04	Ticket classification	Ticket text with issue keywords	Classified issue category	Correct label predicted
TC05	AI-routing logic	Ticket with specific keyword & priority	Assigned correct agent team	Matching expected result
TC06	NLP word cloud generation	Text blob input	Visual word cloud output	Matches keyword density
TC07	Agent-wise CSAT chart	Agent name filter applied	Only selected agent's data	As expected
TC08	Data refresh simulation	New data inserted	Dashboard updates in real-time	Dashboard refreshed

Table 5.1: Test Cases Table

6. CONCLUSION

6.1. DESIGN AND IMPLEMENTATION ISSUES:

The design of the CSAT Ticket Support System aimed to balance modularity, scalability, and real-time performance, but several challenges arose during the development phase. One of the key design concerns was ensuring seamless integration between third-party platforms such as Zendesk for ticket management and Snowflake for cloud data warehousing. While APIs were used to connect components, handling data flow consistently and without delay across modules posed initial bottlenecks. Moreover, real-time sentiment analysis required optimization, especially when processing a high volume of open-text feedback simultaneously. Another hurdle was the secure handling of user data in compliance with GDPR and DPDP standards, which required robust implementation of encryption, token-based authentication, and activity logging. The use of microservices architecture and Docker containers helped alleviate deployment challenges, but maintaining inter-module communication with low latency demanded continuous system tuning.

6.2. ADVANTAGES AND LIMITATIONS:

This system offers several significant advantages. Firstly, its ability to automatically collect, analyze, and interpret CSAT feedback through Natural Language Processing allows support teams to gain deep, actionable insights. The routing engine intelligently assigns tickets based on agent skills, reducing resolution time and increasing first-contact resolution. Visualization dashboards provide managers with real-time performance metrics, which are critical for monitoring and decision-making. However, there are limitations. The effectiveness of the sentiment analyzer depends heavily on the quality and volume of customer responses. Ambiguous or sarcastic feedback might yield incorrect polarity scores. The system also assumes a reliable API infrastructure; if an external API (e.g., from Zendesk or a feedback gateway) is down, some workflows may fail. Additionally, scaling the system during peak ticket loads may incur high infrastructure costs if not managed with dynamic resource allocation.

6.3. FUTURE ENHANCEMENTS:

Looking ahead, the CSAT Ticket Support System has a significant scope for enhancement that can push its capabilities to the next level in terms of functionality, adaptability, and intelligence. These enhancements aim to make the system more proactive, user-centric, and scalable in dynamic environments.

One of the foremost upgrades is the integration of predictive analytics through advanced machine learning models. This means the system will no longer remain just a reactive mechanism that analyzes feedback after a ticket is closed. Instead, by learning from historical ticket patterns, agent behaviors, and customer sentiments, it can proactively identify signals of dissatisfaction even before a ticket reaches the resolution stage. For instance, delayed responses, repeated queries, or usage of specific negative keywords can trigger early interventions. This enables supervisors to take corrective actions before negative experiences occur, thus significantly improving the overall CSAT score.

Next, introducing multilingual support for the sentiment analyzer would make the system more inclusive and globally deployable. As businesses cater to diverse audiences across countries, the ability to analyze feedback written in various languages is essential. Leveraging language detection models and multilingual NLP transformers (like BERT multilingual or spaCy pipelines) will allow the sentiment analyzer to extract emotions, tone, and intent accurately across linguistic boundaries. This helps organizations ensure a uniform customer experience irrespective of language barriers.

Another key enhancement involves real-time alerting mechanisms powered by AI. This upgrade would enable the system to automatically detect anomalies in ticketing trends or agent performance. For example, if a particular agent’s resolution time suddenly increases or if a specific type of ticket consistently receives low satisfaction ratings, the system can immediately alert the relevant supervisor. Such real-time intelligence ensures that problems are resolved at their inception rather than waiting for periodic reports.

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