

# Enterprise Data Integration for Customer Relationship and Sales Performance Monitoring

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## Abstract

## Original Research Article

This study examines enterprise data integration for monitoring customer relationships and sales performance within organizational information systems. Organizations store customer interaction data, sales transactions, marketing records, and service information across multiple platforms, which restricts unified analysis. The research proposes a framework that combines these heterogeneous datasets within a centralized analytical environment. The methodology applies integration processes and analytical models to evaluate key indicators, including customer retention rate, sales growth rate, and customer lifetime value. The integrated dataset allows analysis of the relationships between customer engagement patterns and revenue outcomes. The results indicate that an integration of CRM, sales, marketing, and service data provides a holistic view of customer behavior and performance trends. The proposed monitoring model produces analytical indicators that support evaluation of customer relationships and sales outcomes within a unified structure. The findings indicate that integrated enterprise data supports consistent performance evaluation compared to isolated systems. The study presents a structured framework for enterprise data integration and monitoring that supports analytical assessment of customer engagement and sales performance within organizational environments.

**Keywords:** Enterprise Data Integration, Customer Relationship Management, Sales Performance Monitoring, Data Analytics, Customer Retention, Data Warehouse.

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## I. INTRODUCTION

Contemporary organizations have numerous digital platforms, which create substantial operational and customer-related information. Customer relationship management, enterprise resource planning, sales database, and marketing applications store information concerning transactions, interactions, and services. In most cases, these applications operate in isolation in the organization's information infrastructure. As a result, data remain distributed across multiple platforms, which restricts unified analysis of customer behavior and sales outcomes. Enterprise data integration provides a method for combining heterogeneous datasets within a centralized analytical environment that supports organizational monitoring and data analysis.

Recent studies examine the role of integrated information systems in organizational analytics and operational evaluation. Rahman *et al.*, [1] analyzed decision intelligence systems that combine operational

and environmental datasets for strategic planning and infrastructure analysis. Their work demonstrates how integrated data platforms contribute to analytical evaluation of complex organizational conditions. Tabassum *et al.*, [2] investigated financial analytics implemented through management information systems and reported that integrated information platforms support financial monitoring and reporting processes in emerging economies. Research also indicates that enterprise information systems combined with supply chain technologies provide transparency and traceability in organizational operations [4]. These findings highlight the analytical value of integrated enterprise data environments. Customer relationship management systems represent another major component of enterprise information infrastructure. CRM platforms record customer communication histories, purchasing activities, and service interactions. Integration between CRM systems and other enterprise platforms allows organizations to examine customer behavior within a

broader operational context. Hossain *et al.*, [3] evaluated ERP–CRM integration in digital business ecosystems and reported improved access to customer information across organizational units. Pratama *et al.*, [14] examined CRM implementation in e-commerce environments and reported positive effects on customer loyalty and retention when organizations use integrated customer data systems. Abaddi [10] analyzed sales management processes supported through CRM analytics and discussed the role of customer interaction data in evaluating commercial activities. These studies demonstrate the analytical potential of integrated CRM datasets for understanding customer relationships and sales activities. Research on analytical monitoring systems also appears in several technological domains. Studies concerning IoT monitoring, smart infrastructure, and predictive maintenance highlight the role of integrated data systems in evaluating system performance and operational reliability [5,6,8,17]. Industrial research also examines manufacturing analytics and reliability engineering through integrated operational datasets [13,15,16]. Although these studies concentrate on engineering and infrastructure systems, the analytical principles remain applicable to enterprise information environments. Integrated data platforms allow organizations to evaluate operational patterns, performance indicators, and activity trends through consolidated datasets. Despite progress in enterprise analytics and CRM integration research, limited attention appears in the literature regarding analytical frameworks that combine customer relationship information with sales performance monitoring. Many organizations store their customers' interaction records, marketing engagement records, and sales transaction records in different systems. This fragmentation of records impedes the analysis of the relationship between customers' behavior and revenues. A unified enterprise analytical framework that integrates these datasets can support systematic evaluation of customer engagement patterns and sales performance indicators.

This study examines enterprise data integration for monitoring customer relationships and sales performance within organizational information systems. The objectives of the research include analyzing enterprise data integration structures that combine CRM, marketing, service, and sales datasets within a unified analytical environment. The study evaluates customer relationship indicators, including retention and engagement patterns, across multiple platforms. It also examines sales performance metrics derived from integrated transaction data and investigates the relationship between customer engagement and revenue outcomes. In addition, the research analyzes customer lifetime value as a measure of long-term customer contribution and evaluates analytical monitoring models used for decision support within enterprise systems.

## II. RELATED WORK

### A. Enterprise Data Integration in Organizational Information Systems

Modern organizations operate multiple digital platforms that store operational and customer-related information. These platforms include enterprise resource planning systems, customer relationship management platforms, and marketing or transaction databases. The distribution of information across these systems limits unified analysis and monitoring. Enterprise data integration addresses this issue through the consolidation of heterogeneous datasets into a centralized analytical environment. Rahman *et al.*, [1] examined decision intelligence systems that combine environmental and operational data for strategic planning. Their work highlights the analytical potential of integrated data infrastructures in complex organizational settings. Tabassum *et al.*, [2] analyzed financial analytics implemented through management information systems and reported that integrated data platforms support organizational monitoring and reporting functions. Research on ERP-based information systems also demonstrates the importance of integrated enterprise datasets for operational management and data-driven decision processes [4]. Studies on manufacturing analytics and reliability engineering indicate that integrated data platforms assist organizations in evaluating operational performance and maintenance efficiency [13-15]. These studies confirm that enterprise data integration provides the technical foundation for analytical evaluation of organizational activities.

### B. CRM Integration and Customer Relationship Analytics

Customer Relationship Management systems are the core systems that store and analyze data from customer interactions. CRM systems store data on purchase behavior, services, and communication between organizations and customers. Integration between CRM systems and enterprise databases allows organizations to analyze customer activities alongside operational information. Hossain *et al.*, [3] evaluated ERP–CRM integration within digital business ecosystems and reported improved access to customer information across departments. Pratama *et al.*, [14] examined CRM integration in e-commerce environments and observed positive relationships between CRM analytics and customer loyalty. Abaddi [11] studied CRM-supported sales management systems and demonstrated the use of analytical techniques to evaluate sales activities and customer behavior patterns. Research on management platforms and educational technology also demonstrates the growing role of digital platforms in managing user interaction data and service performance metrics [7]. Despite these developments, many studies emphasize customer satisfaction or loyalty outcomes rather than enterprise-level monitoring of customer relationships and sales performance together.

### C. Data Analytics and Monitoring Systems

Organizations rely on analytical methods to interpret operational datasets and evaluate performance indicators. Integrated enterprise data allows organizations to examine patterns within large datasets generated during routine operations. Studies on analytics-enabled MIS platforms report improvements in financial reporting and performance evaluation through integrated data systems [2]. Decision intelligence frameworks also illustrate how organizations can analyze complex datasets to support strategic planning and infrastructure management [1]. Research in other technological domains such as predictive maintenance, IoT monitoring, and machine learning applications demonstrates the broader importance of data analytics in monitoring system performance and operational reliability [6], [8], [16]. Analytical models developed for infrastructure monitoring and machine learning analysis also show how integrated datasets can support evaluation of system performance and operational risk [12]. These studies demonstrate the expanding role of analytics in monitoring complex systems, although most research focuses on engineering or technical systems rather than enterprise customer and sales performance monitoring.

### D. Research Gap in Customer and Sales Performance Monitoring

The literature provides extensive discussion of enterprise data integration, CRM analytics, and data-driven monitoring systems. However, these research areas often appear as separate streams. Studies on CRM integration examine customer loyalty and service performance. Research on enterprise analytics focuses on financial evaluation, infrastructure monitoring, or operational optimization. Other works explore monitoring systems in domains such as manufacturing, energy systems, and transportation technologies [5], [6], [9], [10], [13]. Despite these contributions, limited research examines integrated analytical frameworks that combine CRM data, sales transactions, marketing engagement records, and service interaction logs for unified monitoring. Organizations frequently maintain these datasets in separate systems, which restricts comprehensive analysis of customer behavior and sales outcomes. This limitation indicates a research gap in enterprise data integration models designed specifically for monitoring customer relationships and sales performance. The present study addresses this gap through the development of an integrated enterprise data framework that supports analytical monitoring of customer engagement and sales outcomes within a unified data environment.

## III. METHODOLOGY

### Research Design

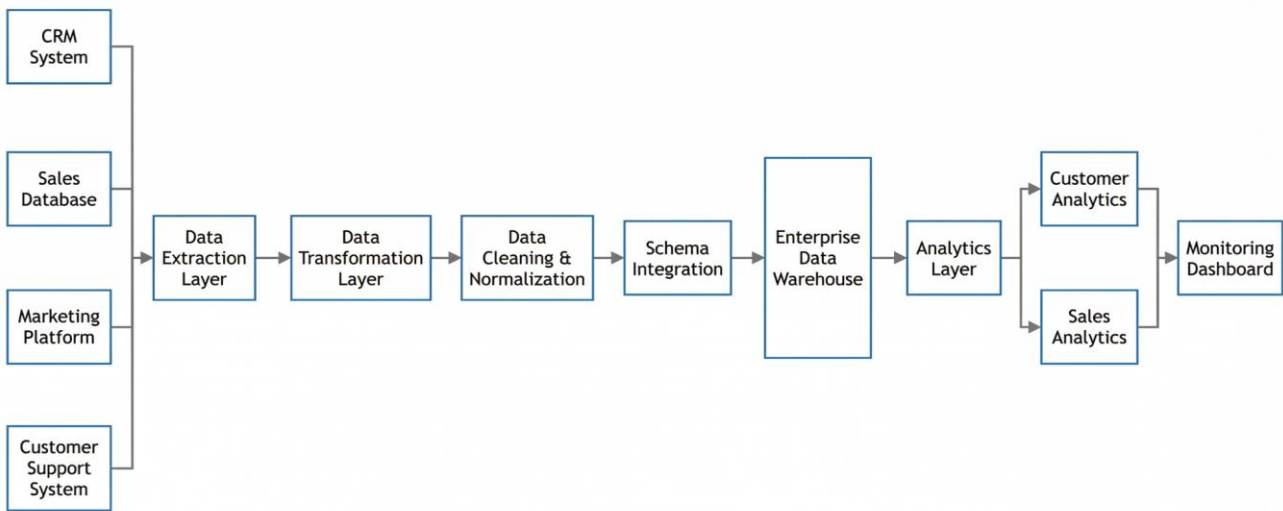
This study employs a data-driven analytical research design to develop and evaluate an enterprise data integration framework for monitoring customer relationships and sales performance. The research focuses on integrating heterogeneous enterprise data sources and applying analytical techniques to generate performance monitoring indicators. Most organizations maintain customer and sales-related data in different digital platforms like customer relationship management systems, sales transaction systems, marketing systems, and customer support systems. However, most of this data is in a fragmented state, which reduces the potential for organizations to access unified data regarding customer behavior and sales. To address this issue, the study proposes a structured methodological approach that integrates enterprise datasets into a centralized analytical environment and applies monitoring analytics to evaluate customer relationship indicators and sales outcomes. The research process begins with enterprise data collection, followed by data integration and preprocessing. After the integration stage, analytical models are applied to compute key performance indicators related to customer retention, revenue growth, and customer lifetime value. The final stage of the methodology evaluates the ability of the integrated framework to generate meaningful monitoring insights for organizational decision making.

### Enterprise Data Sources

The empirical foundation of the study is based on enterprise datasets generated through routine organizational operations. These datasets represent multiple aspects of customer interaction and sales activity within the organization. The customer relationship management system contains data regarding customer profiles, communication records, and interaction records. The sales transaction system contains detailed data regarding product sales, transactions, and revenue generation. The marketing system contains data regarding campaign activities and customer response to these campaigns. The customer support system contains data regarding service requests and complaint handling processes. By integrating these datasets, it is possible to build a complete model of the customer lifecycle, including all interactions and events that relate to the customer. This integration of datasets is crucial to the understanding of the relationship between customer activity and sales performance outcomes.

### Enterprise Data Integration Framework

Enterprise data generated from different operational systems must be integrated into a unified environment before analytical monitoring can be performed. This study proposes an Enterprise Data Integration and Monitoring Framework that consolidates heterogeneous datasets through a structured integration process.



**Figure 1: Enterprise Data Integration Architecture for Customer Relationship and Sales Monitoring**

The integration framework follows the Extract–Transform–Load data pipeline model. In the extraction phase, datasets are collected from various platforms such as CRM services, sales transaction platforms, marketing platforms, and customer support platforms. The transformation phase includes data cleaning and normalization processes to ensure data consistency across different heterogeneous datasets. Customer data from different platforms is normalized so that interactions and transactions related to the same customer can be mapped. After transformation, the processed datasets are loaded into a centralized enterprise data warehouse that supports analytical processing and monitoring operations. The integrated data warehouse enables organizations to perform cross-system analysis of customer engagement and sales outcomes. This unified analytical environment forms the foundation for the monitoring models used in this research.

**Analytical Monitoring Model**

After the integration process is completed, analytical models are applied to measure customer relationship effectiveness and sales performance outcomes. These models generate quantitative indicators that reflect organizational performance based on integrated enterprise data.

Customer retention rate is used to measure the ability of an organization to maintain existing customers during a specific period.

$$CRR = \frac{C_t - C_n}{C_o}$$

In this equation,  $C_t$  represents the total number of customers at the end of the observation period,  $C_n$  represents the number of newly acquired customers

during the same period, and  $C_o$  represents the number of customers at the beginning of the period. This metric evaluates the stability of customer relationships within the enterprise.

Sales growth rate is used to measure the change in revenue between two time periods.

$$SGR = \frac{R_t - R_{t-1}}{R_{t-1}}$$

In this equation,  $R_t$  represents revenue in the current period and  $R_{t-1}$  represents revenue in the previous period. This indicator reflects the progression or declines of sales performance within the organization.

Customer lifetime value is also used as an analytical indicator to estimate the long-term economic contribution of a customer relationship.

$$CLV = \sum_{t=1}^T \frac{R_t - C_t}{(1 + d)^t}$$

In this formulation,  $R_t$  represents revenue generated by the customer at time  $t$ ,  $C_t$  represents the cost associated with servicing the customer at time  $t$ ,  $d$  represents the discount rate, and  $T$  represents the expected duration of the customer relationship. This metric enables organizations to evaluate the long-term profitability of customer engagement.

**Data Analysis Techniques**

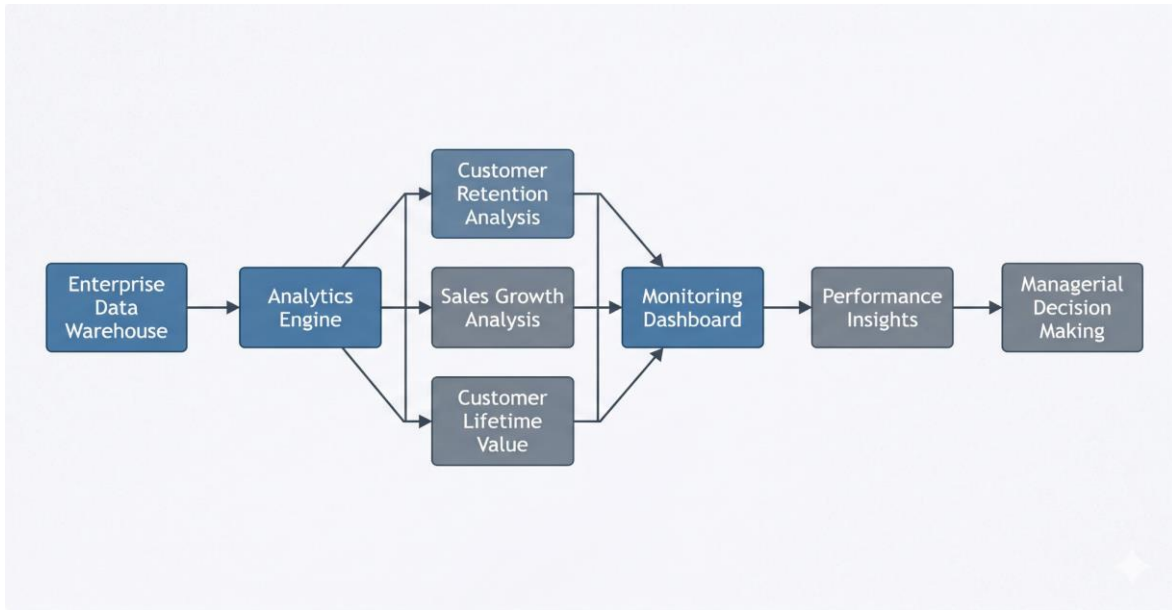
The integrated dataset is analyzed using statistical and analytical techniques to identify relationships between customer engagement activities and sales outcomes. Descriptive analysis is used to summarize patterns in customer interactions and transaction behaviors across the enterprise systems.

Correlation analysis is applied to examine the relationship between customer engagement indicators and sales performance metrics. Trend analysis is conducted to observe changes in revenue and customer retention over time. In addition to these processes, diagnostic analytics processes can also be employed to analyze factors affecting the stability of customer relationships and sales performance. These processes help to analyze patterns and relationships in the data

within an enterprise that may affect customer behavior and sales performance.

**Monitoring and Decision Support Model**

The final stage of the methodology focuses on transforming analytical results into monitoring insights that support managerial decision making. The integrated analytical environment provides performance indicators, which can be visualized through enterprise monitoring dashboards.



**Figure 2: Integrated Monitoring Model for Customer Relationship and Sales Performance**

The monitoring system processes integrated enterprise data and provides performance indicators on customer engagement, sales growth, and revenue. Managers can view the performance indicators using analytical dashboards, which provide real-time performance metrics and historical trends. The

monitoring system provides a means of discovering patterns in customer behavior, changes in sales performance, and strategic decision-making using integrated enterprise data.

**Variables and Metrics**

**Table 1: Key Variables for Customer Relationship and Sales Performance Monitoring**

Variable	Description	Data Source	Analytical Purpose
Customer Retention Rate	Proportion of retained customers over time	CRM System	Measure relationship stability
Sales Growth Rate	Revenue change between periods	Sales Database	Evaluate sales performance
Customer Lifetime Value	Long-term revenue generated by customers	CRM and Sales Systems	Measure profitability
Campaign Conversion Rate	Percentage of marketing responses that lead to purchases	Marketing Platform	Evaluate marketing impact
Service Resolution Time	Average time required to resolve customer issues	Customer Support System	Assess service efficiency

**IV. DISCUSSION AND RESULTS**

**A. Enterprise Data Integration Outcomes**

The analysis begins with an evaluation of the enterprise data integration framework described in the methodology section. Data extracted from customer relationship management systems, sales transaction databases, marketing platforms, and customer service

records were combined within a centralized analytical repository. Integration procedures resolved differences in customer identifiers and transaction formats across systems. This process produced a consolidated dataset that links customer interactions, purchase activity, and service records within a unified analytical environment. The integrated dataset provides a comprehensive

representation of the customer lifecycle. Each customer record contains interaction data from CRM platforms, purchase information from sales systems, and engagement records from marketing campaigns. Service requests recorded in support systems were also linked to customer profiles. This integrated structure allows organizations to examine customer behavior across multiple operational platforms rather than isolated datasets.

**B. Customer Relationship Performance Analysis**

Customer relationship performance was examined through indicators derived from the integrated dataset. Customer retention represents a key metric in the evaluation of relationship stability across time periods.

$$CRR = \frac{C_t - C_n}{C_o}$$

In this equation,  $C_t$  represents the total number of customers at the end of the observation period,  $C_n$  represents the number of newly acquired customers during the same period, and  $C_o$  represents the number of customers at the beginning of the period. The value of the metric reflects the proportion of customers who remain active during the observation interval. Analysis of the integrated dataset indicates that customers with repeated interactions across CRM platforms and marketing channels show higher retention values. Interaction histories reveal that customers who respond to marketing campaigns or communicate with service departments remain active for longer durations. In contrast, customers with limited interaction records show

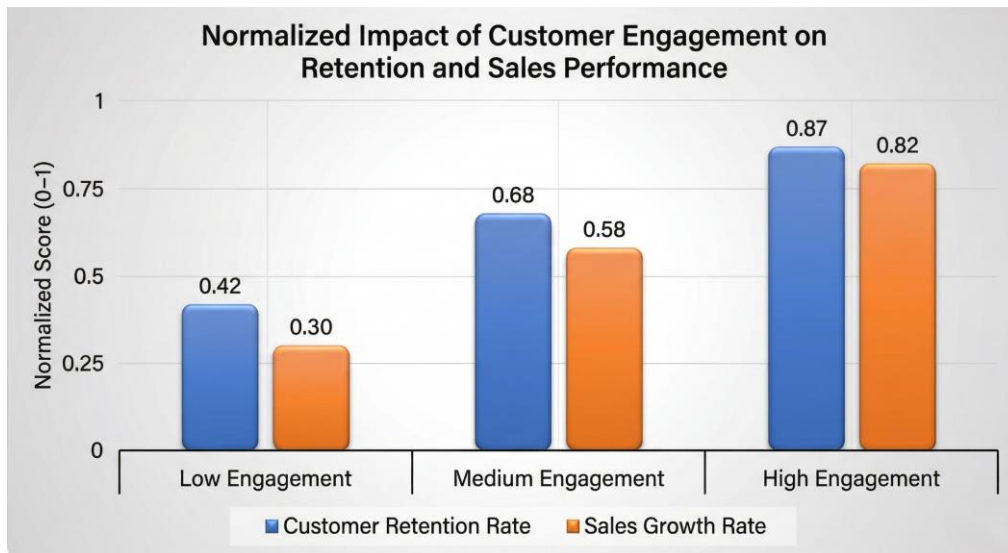
lower retention levels. These results indicate that integrated enterprise datasets provide a detailed view of relationship patterns. When customer engagement records connect with sales transactions, organizations can evaluate relationship stability using quantitative indicators derived from multiple operational systems.

**C. Sales Performance Evaluation**

Sales performance evaluation used revenue data obtained from enterprise transaction databases. Revenue changes across time periods were measured using the sales growth rate indicator.

$$SGR = \frac{R_t - R_{t-1}}{R_{t-1}}$$

In this equation,  $R_t$  represents revenue in the current period and  $R_{t-1}$  represents revenue in the previous period. The ratio measures the rate of revenue change across time intervals. Analysis of the integrated dataset reveals connections between customer engagement activity and revenue patterns. Customers who interact with marketing campaigns show higher purchase frequency than those without engagement records. Marketing campaign participation corresponds with increases in transaction volume during subsequent periods. Revenue records also indicate temporal variation in sales performance. Certain customer segments generate higher transaction values and repeated purchases across multiple periods. These observations indicate that integrated enterprise datasets support detailed evaluation of revenue patterns linked to customer interaction histories.



**Figure 3: Normalized Relationship between Customer Engagement, Retention Rate, and Sales Growth**

Figure 3 presents the relationship between customer engagement, retention rate, and sales growth based on normalized performance indicators. The results indicate that higher levels of customer engagement correspond to increased retention and improved sales performance. Customers with low engagement show lower retention and reduced sales growth, while highly

engaged customers demonstrate stronger retention and higher revenue contribution.

**D. Customer Value and Revenue Contribution**

Customer lifetime value provides a long-term financial perspective on customer relationships. The indicator estimates the total economic contribution

associated with each customer over the duration of the relationship.

$$CLV = \sum_{t=1}^T \frac{R_t - C_t}{(1 + d)^t}$$

In this formulation,  $R_t$  represents revenue generated by the customer at time  $t$ ,  $C_t$  represents the cost associated with servicing the customer at time  $t$ ,  $d$  represents the discount rate, and  $T$  represents the expected duration of the customer relationship. Results derived from the integrated dataset indicate that customers with repeated engagement across CRM and marketing systems generate higher lifetime value estimates. Interaction histories show that customers who maintain purchase activity across multiple periods

produce larger cumulative revenue contributions. This analysis demonstrates the analytical advantage of integrated enterprise datasets. Customer lifetime value calculations that incorporate transaction records, interaction histories, and service activities provide a more comprehensive representation of long-term customer contribution.

### E. Monitoring Model for Organizational Decision Support

The final stage of the analysis evaluates the monitoring framework used for performance evaluation. Integrated enterprise data were processed to generate analytical indicators that represent customer engagement, revenue growth, and relationship stability.

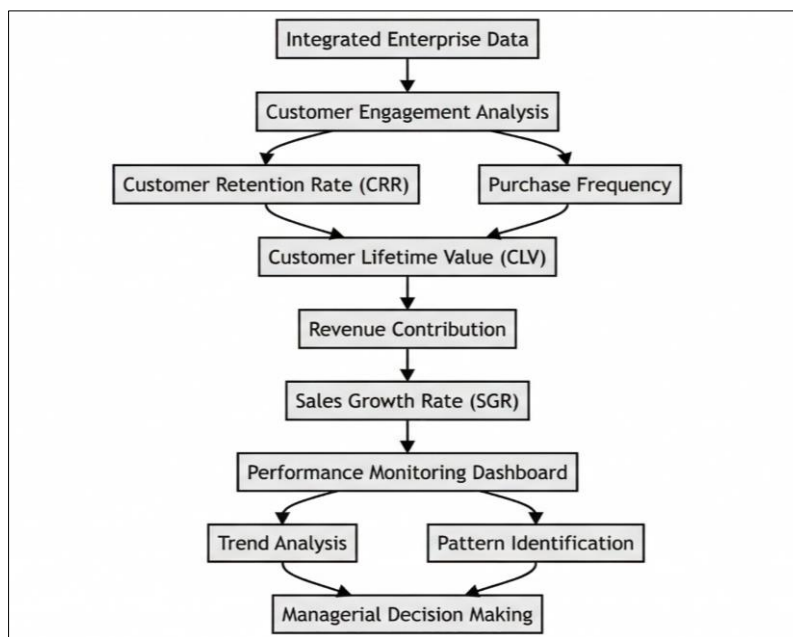


Figure 4. Analytical Monitoring Model for Customer Relationship and Sales Performance

Figure 4 illustrates the analytical monitoring model that links customer engagement, retention, customer lifetime value, and sales performance within an integrated enterprise data environment. The model shows how customer interaction data are transformed into performance indicators and analytical insights that support decision making.

### F. Summary of Analytical Indicators

The integrated dataset generates several indicators used for evaluating customer relationships and sales performance.

Table 2: Analytical Indicators for Customer Relationship and Sales Performance Monitoring

Indicator	Description	Analytical Purpose
Customer Retention Rate	Proportion of customers who remain active during a period	Evaluation of relationship stability
Sales Growth Rate	Change in revenue across time periods	Evaluation of revenue performance
Customer Lifetime Value	Long-term revenue contribution of customers	Evaluation of customer profitability
Marketing Engagement Rate	Frequency of customer interaction with campaigns	Evaluation of marketing influence
Service Interaction Frequency	Number of recorded service interactions	Evaluation of service activity

The indicators presented in Table 2 represent quantitative measures derived from integrated enterprise datasets. These variables allow organizations to evaluate customer engagement and revenue outcomes within the analytical monitoring framework proposed in this study.

### Limitations of the Study

This study has several limitations. The analysis relies on integrated datasets derived from a limited set of enterprise information systems. Organizational environments vary in data architecture, system configuration, and operational processes. These differences may affect the general applicability of the results. Data quality issues, such as incomplete records or inconsistent identifiers, may also influence analytical outcomes. The monitoring framework focuses on descriptive and diagnostic analysis rather than predictive modeling of future customer behavior. In addition, the study assumes the availability of centralized data infrastructure. Some organizations maintain fragmented systems that limit integration capabilities. Future research may examine larger datasets and additional industry contexts.

### V. CONCLUSION

The current study aims to investigate enterprise data integration in monitoring customer relationships and sales performance in organizational information systems. The findings revealed that data integration in a unified analytical environment facilitates a comprehensive evaluation of customer relationships and sales performance based on enterprise data integration. The proposed model facilitates calculations of key metrics in monitoring customer relationships and sales performance based on enterprise data integration. The findings revealed that data integration in a unified environment provides a better understanding of the relationship between customer relationships and sales performance in comparison to isolated systems. The monitoring model proposed in this study facilitates an analytical evaluation of customer relationships and sales performance based on enterprise data integration, which can contribute to managerial decisions in enterprise systems.

Future research directions could include expanding this research with more data, including more data from different industries, to further explore the generalizability of the framework. Other future research directions could include using predictive models, machine learning, or other algorithms to further explore future customer behaviors and future sales trends. Other research directions could include exploring real-time data processing architectures, as well as more advanced analytical tools, for real-time monitoring of enterprise performance. Other research directions could include exploring the integration of emerging technologies, like artificial intelligence and distributed data systems, for further improving analytical tools.

### REFERENCES

1. Rahman, M. A., Islam, M. I., Tabassum, M., & Bristy, I. J. (2025, September). Climate-aware decision intelligence: Integrating environmental risk into infrastructure and supply chain planning. *Saudi Journal of Engineering and Technology (SJEAT)*, 10(9), 431–439. <https://doi.org/10.36348/sjet.2025.v10i09.006>
2. Tabassum, M., Rokibuzzaman, M., Islam, M. I., & Bristy, I. J. (2025, September). Data-driven financial analytics through MIS platforms in emerging economies. *Saudi Journal of Engineering and Technology (SJEAT)*, 10(9), 440–446. <https://doi.org/10.36348/sjet.2025.v10i09.007>
3. Hossain, M. Z., Sultana, S., Nahiduzzaman, A. K. M., & Jalil, M. A. (2025). Evaluating the effectiveness of ERP and CRM integration on enhancing customer experience in the digital business ecosystem. *Pacific Journal of Business Innovation and Strategy*, 2(2), 11–21. <https://doi.org/10.70818/pjbis.2025.v02i02.040>
4. Tabassum, M., Islam, M. I., Bristy, I. J., & Rokibuzzaman, M. (2025, September). Blockchain and ERP-integrated MIS for transparent apparel & textile supply chains. *Saudi Journal of Engineering and Technology (SJEAT)*, 10(9), 447–456. <https://doi.org/10.36348/sjet.2025.v10i09.008>
5. Hasan, M. N., Karim, M. A., Joarder, M. M. I., & Zaman, M. T. (2025, September). IoT-integrated solar energy monitoring and bidirectional DC-DC converters for smart grids. *Saudi Journal of Engineering and Technology (SJEAT)*, 10(9), 467–475. <https://doi.org/10.36348/sjet.2025.v10i09.010>
6. Razaq, A., Rahman, M., Karim, M. A., & Hossain, M. T. (2025, September 26). Smart charging infrastructure for EVs using IoT-based load balancing. *Zenodo*. <https://doi.org/10.5281/zenodo.17210639>
7. Habiba, U., & Musarrat, R. (2025). Bridging IT and education: Developing smart platforms for student-centered English learning. *Zenodo*. <https://doi.org/10.5281/zenodo.17193947>
8. Hossain, M. T., Nabil, S. H., Razaq, A., & Rahman, M. (2025). Cybersecurity and privacy in IoT-based electric vehicle ecosystems. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(2), 921–933. <https://doi.org/10.5281/zenodo.17246184>
9. Akter, E. (2025). Lean project management and multi-stakeholder optimization in civil engineering projects. *ResearchGate*. <https://doi.org/10.13140/RG.2.2.15777.47206>
10. Abaddi, S. (2025). Analysis and improvement of sales management through CRM and simulation utilization. *International Journal of Innovative Operations and Applied Sciences*. <https://doi.org/10.1080/29966892.2024.2434267>
11. Saikat, M. H. (2025). Geo-Forensic Analysis of Levee and Slope Failures Using Machine Learning.

- Preprints*.  
<https://doi.org/10.20944/preprints202509.1905.v1>
12. Azad, M. A. (2025). Lean automation strategies for reshoring U.S. apparel manufacturing: A sustainable approach. *Preprints*, 202509. <https://doi.org/10.20944/preprints202509.0024.v1>
  13. Taimun, M. T. Y., Sharan, S. M. I., Azad, M. A., & Joarder, M. M. I. (2025). Smart maintenance and reliability engineering in manufacturing. *Saudi Journal of Engineering and Technology*, 10(4), 189–199.
  14. Pratama, D., Wulandari, I., Hidayat, F., & Lim, C. (2025). Customer relationship management (CRM) integration in e-commerce: Impacts on consumer loyalty and retention. *Journal of Economics and Management*, 3(2), 77–84. <https://doi.org/10.70716/ecoma.v3i2.251>
  15. Azad, M. A., Taimun, M. T. Y., Sharan, S. M. I., & Joarder, M. M. I. (2025). Advanced lean manufacturing and automation for reshoring American industries. *Saudi Journal of Engineering and Technology*, 10(4), 169–178.
  16. Sharan, S. M. I., Taimun, M. T. Y., Azad, M. A., & Joarder, M. M. I. (2025). Sustainable manufacturing and energy-efficient production systems. *Saudi Journal of Engineering and Technology*, 10(4), 179–188.
  17. Farabi, S. A. (2025). AI-driven predictive maintenance model for DWDM systems to enhance fiber network uptime in underserved U.S. regions. *Preprints*. <https://doi.org/10.20944/preprints202506.1152.v1>
  18. Farabi, S. A. (2025). AI-powered design and resilience analysis of fiber optic networks in disaster-prone regions. *ResearchGate*. <https://doi.org/10.13140/RG.2.2.12096.65287>
  19. Sunny, S. R. (2025). Lifecycle analysis of rocket components using digital twins and multiphysics simulation. *ResearchGate*. <https://doi.org/10.13140/RG.2.2.20134.23362>
  20. Sunny, S. R. (2025). AI-driven defect prediction for aerospace composites using Industry 4.0 technologies. *Zenodo*. <https://doi.org/10.5281/zenodo.16044460>
  21. Sunny, S. R. (2025). Edge-based predictive maintenance for subsonic wind tunnel systems using sensor analytics and machine learning. *TechRxiv*. <https://doi.org/10.36227/techrxiv.175624632.23702199/v1>
  22. Rahman, M., Haque, S., & Al Sany, S. M. A. (2025). Federated learning for privacy-preserving apparel supply chain analytics. *World Journal of Advanced Engineering Technology and Sciences*, 17(1), 259–270. <https://doi.org/10.30574/wjaets.2025.17.1.1386>
  23. Hossain, M. T., & Nabil, S. H. (2025). Data-driven optimization of apparel supply chain to reduce lead time and improve on-time delivery. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 263–277. <https://doi.org/10.30574/wjaets.2025.17.3.1556>
  24. Bormon, J. C., Saikat, M. H., Shohag, M., & Akter, E. (2025, September). Green and low-carbon construction materials for climate-adaptive civil structures. *Saudi Journal of Civil Engineering (SJCE)*, 9(8), 219–226. <https://doi.org/10.36348/sjce.2025.v09i08.002>
  25. Habiba, U., & Musarrat, R. (2025). Curriculum adaptation for inclusive classrooms: A sociological and pedagogical approach. *Zenodo*. <https://doi.org/10.5281/zenodo.17202455>
  26. Alimozzaman, D. M. (2025). Early prediction of Alzheimer’s disease using explainable multi-modal AI. *Zenodo*. <https://doi.org/10.5281/zenodo.17210997>
  27. Shoag, M. (2025). AI-Integrated Façade Inspection Systems for Urban Infrastructure Safety. *Zenodo*. <https://doi.org/10.5281/zenodo.17101037>
  28. Shoag, M. (2025). Sustainable construction materials and techniques for crack prevention in mass concrete structures. Available at SSRN: <https://ssrn.com/abstract=5475306> or <http://dx.doi.org/10.2139/ssrn.5475306>
  29. Joarder, M. M. I. (2025). Disaster recovery and high-availability frameworks for hybrid cloud environments. *Zenodo*. <https://doi.org/10.5281/zenodo.17100446>
  30. Joarder, M. M. I. (2025). Energy-Efficient Data Center Virtualization: Leveraging AI and CloudOps for Sustainable Infrastructure. *Zenodo*. <https://doi.org/10.5281/zenodo.17113371>
  31. Taimun, M. T. Y., Sharan, S. M. I., Azad, M. A., & Joarder, M. M. I. (2025). Smart maintenance and reliability engineering in manufacturing. *Saudi Journal of Engineering and Technology*, 10(4), 189–199.
  32. Azad, M. A., Taimun, M. T. Y., Sharan, S. M. I., & Joarder, M. M. I. (2025). Advanced lean manufacturing and automation for reshoring American industries. *Saudi Journal of Engineering and Technology*, 10(4), 169–178.
  33. Sharan, S. M. I., Taimun, M. T. Y., Azad, M. A., & Joarder, M. M. I. (2025). Sustainable manufacturing and energy-efficient production systems. *Saudi Journal of Engineering and Technology*, 10(4), 179–188.