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Article

Enhancing Procurement Efficiency through Vendor Relationship Management (VRM) in the FMCG Sector: An Illustrative Research Framework Integrating Natural Language Processing (NLP) and Sentiment Analysis

Gunjan Bhayana[1*], Vanik Gosain[2]

[1*]Department of Management Studies, The Technological Institute of Textile & Sciences, Bhiwani
Email id- gunjanbhayana18@gmail.com
[2]Researcher
Email id- vanik.gosain789@gmail.com
[1*]Corresponding Author: Dr Gunjan Bhayana

Abstract: The Fast-Moving Consumer Goods (FMCG) industry operates in a highly competitive environment characterized by short product life cycles, volatile demand, and complex supplier ecosystems. Traditional Vendor Relationship Management (VRM) approaches primarily rely on structured performance metrics such as cost, quality, and delivery performance, often overlooking valuable unstructured information embedded in emails, supplier feedback, meeting transcripts, complaint records, and social media discussions. This conceptual paper proposes an integrated research framework that combines Vendor Relationship Management with Natural Language Processing (NLP) and sentiment analysis to enhance procurement efficiency. The framework suggests that automated analysis of textual interactions can generate actionable insights into supplier trust, collaboration quality, risk signals, and relationship health, thereby improving procurement outcomes. The proposed model contributes to digital procurement literature by positioning AI-enabled text analytics as a strategic capability for procurement decision-making in the FMCG sector.

Keywords: Vendor Relationship Management, Procurement Efficiency, FMCG, Natural Language Processing, Sentiment Analysis, Artificial Intelligence, Supplier Performance

1. Introduction

Procurement functions in FMCG organizations have evolved from transactional purchasing toward strategic supplier collaboration. As supply chains become increasingly digital, procurement managers require continuous monitoring of vendor performance beyond conventional quantitative indicators. Large volumes of textual data generated through supplier communications remain underutilized despite containing valuable insights into vendor reliability and emerging risks. Natural Language Processing (NLP) and sentiment analysis provide mechanisms to transform unstructured textual information into measurable intelligence. Integrating these technologies with Vendor Relationship Management may improve supplier evaluation, dispute resolution, early risk detection, and procurement decision quality.

The Fast-Moving Consumer Goods (FMCG) sector is one of the most dynamic and competitive industries in the global economy. Characterized by high sales volumes, short product life cycles, rapidly changing consumer preferences, and extensive distribution networks, FMCG firms must maintain highly efficient procurement systems to sustain profitability and market competitiveness. Procurement has evolved beyond its traditional role of purchasing goods and services and is now recognized as a strategic function that directly influences organizational performance, operational resilience, and supply chain sustainability. In this context, effective management of supplier relationships has become essential for ensuring uninterrupted material flows, controlling costs, improving quality, and responding quickly to market fluctuations.

Vendor Relationship Management (VRM) has emerged as a strategic approach that focuses on developing long-term partnerships between buying organizations and suppliers rather than treating procurement as a series of isolated transactions. Strong vendor relationships promote trust, collaboration, knowledge sharing, innovation, and joint problem-solving, enabling organizations to reduce risks and enhance supply chain performance. In the FMCG industry, where procurement delays or supplier failures can disrupt production schedules and product availability, effective VRM contributes significantly to organizational agility and customer satisfaction.At the same time, the rapid digital transformation of business processes has generated enormous volumes of unstructured textual data, including supplier emails, procurement documents, contracts, meeting notes, audit reports, complaint records, and customer or vendor feedback. Traditional procurement systems often emphasize structured indicators such as price, delivery time, and quality metrics, while overlooking the valuable insights contained within these textual sources. Consequently, procurement managers may miss early warning signals related to supplier dissatisfaction, communication breakdowns, contractual issues, or operational risks.

Recent advances in Artificial Intelligence (AI), particularly Natural Language Processing (NLP), provide new opportunities to convert unstructured textual information into actionable business intelligence. NLP techniques can automatically process and analyze large collections of documents, identify recurring themes, classify procurement records, summarize communications, and extract meaningful patterns that support decision-making. These capabilities reduce manual effort while enabling procurement professionals to monitor supplier interactions more effectively and identify potential issues before they escalate. Sentiment Analysis, a specialized application of NLP, further enhances procurement intelligence by evaluating the emotional tone and polarity expressed in textual communications. By analyzing emails, supplier feedback, support tickets, negotiation records, and other narrative data, sentiment analysis can detect positive, neutral, or negative attitudes that may reflect the overall health of buyer–supplier relationships. Such insights can help organizations identify emerging conflicts, monitor collaboration quality, and implement timely interventions to strengthen strategic partnerships.

The integration of Vendor Relationship Management with NLP and Sentiment Analysis represents a promising direction for digital procurement transformation. Rather than relying exclusively on historical performance metrics, organizations can incorporate AI-driven insights into supplier evaluation and strategic sourcing decisions. This combination enables procurement teams to make faster, evidence-based decisions, improve transparency, reduce operational uncertainty, and enhance collaboration across complex supplier networks. In highly competitive FMCG markets, where responsiveness and resilience are critical, such capabilities may provide a meaningful strategic advantage.

Despite increasing interest in AI-enabled procurement and supply chain analytics, relatively limited research has examined how NLP and Sentiment Analysis can be integrated with Vendor Relationship Management to improve procurement efficiency in the FMCG sector. Much of the existing literature focuses on automation, predictive analytics, or supplier performance measurement in isolation, leaving a gap in understanding how textual intelligence can strengthen supplier relationships and procurement outcomes within a unified framework.Against this backdrop, the present study proposes an integrated research framework that combines Vendor Relationship Management, Natural Language Processing, and Sentiment Analysis to explain Procurement Efficiency in the FMCG industry. The study aims to investigate the direct influence of VRM on procurement performance, examine the contribution of NLP capabilities, explore the role of sentiment-based insights in supplier management, and assess the mediating mechanisms through which these technologies enhance procurement outcomes. By bridging procurement management with contemporary AI techniques, this research seeks to contribute to both academic knowledge and managerial practice, offering a comprehensive perspective on data-driven procurement in the digital era.

2. Literature Review

2.1 Vendor Relationship Management (VRM)

Kraljic (1983) argued that purchasing should evolve into strategic supply management, emphasizing long-term supplier relationships rather than transactional buying. His portfolio approach highlighted that collaborative vendor management can reduce supply risks and improve organizational competitiveness.

Lambert and Schwieterman (2012) described Supplier Relationship Management as a core business process that creates value through trust, collaboration, and information sharing between buyers and suppliers. They concluded that effective relationship management strengthens supply chain integration and operational performance.

Cousins, Lawson, and Squire (2008) found that strategic supplier relationships enhance innovation, knowledge sharing, and operational flexibility. Their research demonstrated that organizations investing in collaborative vendor partnerships often achieve superior procurement outcomes compared with firms relying on purely transactional relationships.

Literature Insight

The existing literature consistently suggests that strong Vendor Relationship Management improves communication, supplier commitment, and procurement effectiveness. However, most studies focus on traditional relationship practices and pay comparatively less attention to AI-enabled analytical tools.

2.2 Procurement Efficiency in the FMCG Sector

Monczka, Handfield, Giunipero, and Patterson (2020) emphasized that procurement efficiency is determined by cost control, quality assurance, supplier responsiveness, and timely delivery. They argued that strategic procurement contributes directly to organizational competitiveness.

Van Weele (2018) explained that procurement performance extends beyond purchasing costs and includes supplier collaboration, process optimization, and risk management. According to the author, digital technologies are increasingly important for achieving procurement excellence.

Within FMCG industries, procurement decisions have a direct impact on inventory availability, production continuity, and customer satisfaction. The high volume and speed of operations make supplier coordination a critical success factor.

Literature Insight

Previous studies establish procurement efficiency as a multidimensional construct influenced by strategic sourcing and supplier collaboration, but they provide limited evidence on the contribution of text analytics and sentiment-driven intelligence.

2.3 Natural Language Processing (NLP) in Procurement and Supply Chains

Russell and Norvig (2021) described Natural Language Processing as a major branch of Artificial Intelligence that enables computers to understand, interpret, and process human language. NLP techniques support information extraction, document classification, summarization, and automated decision support.

Chowdhury (2003) highlighted that NLP applications facilitate efficient knowledge discovery from large textual datasets and improve organizational information management through automated language processing.

Recent procurement practices increasingly generate digital text through contracts, emails, supplier reports, and compliance documentation. NLP can transform these unstructured sources into structured insights, reducing manual analysis and supporting procurement decisions.

Literature Insight

The literature demonstrates the technical capabilities of NLP but offers relatively few integrated frameworks that connect NLP directly with Vendor Relationship Management and procurement efficiency in FMCG environments.

2.4 Sentiment Analysis and Supplier Intelligence

Liu (2012) defined sentiment analysis as the computational study of opinions, emotions, and attitudes expressed in textual data. The author showed that sentiment mining can identify positive, negative, and neutral expressions that influence business decisions.

Cambria and White (2014) proposed that sentiment analysis extends beyond polarity detection by incorporating semantic understanding and contextual interpretation, enabling organizations to derive deeper insights from textual communications.

In procurement contexts, sentiment analysis may help organizations evaluate supplier feedback, detect communication problems, monitor relationship quality, and identify emerging risks before they appear in conventional performance metrics.

Literature Insight

Although sentiment analysis has been widely applied in marketing and customer analytics, its application to supplier relationship management and procurement decision-making remains comparatively underexplored.

2.5 Artificial Intelligence and Digital Procurement

Wamba et al. (2017) argued that big data analytics and AI capabilities improve organizational performance by supporting faster and more informed decision-making. Their findings indicate that data-driven approaches strengthen operational agility and competitive advantage.

Min (2010) discussed the growing role of Artificial Intelligence in logistics and supply chain management, suggesting that AI technologies can optimize procurement planning, supplier selection, and inventory management while reducing uncertainty.

The integration of AI technologies into procurement systems enables organizations to process large volumes of structured and unstructured information, improving forecasting accuracy and supplier evaluation.

Literature Insight

Existing research recognizes the transformative role of AI in procurement but rarely combines Vendor Relationship Management, NLP, and Sentiment Analysis within a single conceptual framework.

2.6 Research Gap

The review of literature reveals several important gaps. First, most VRM studies concentrate on supplier collaboration and performance metrics without incorporating AI-based text analytics. Second, research on NLP and Sentiment Analysis has primarily focused on customer behavior, social media, and marketing applications rather than procurement management. Third, very few studies have investigated the mediating role of NLP and Sentiment Analysis in explaining how Vendor Relationship Management enhances Procurement Efficiency, particularly in the FMCG sector. Addressing these gaps, the present study proposes an integrated framework that combines relationship management with advanced language-processing technologies to support more intelligent and efficient procurement practices.

4. Research Objectives

1. To examine the relationship between Vendor Relationship Management and procurement efficiency.
2. To evaluate the contribution of NLP in extracting supplier intelligence.

3. To investigate the role of sentiment analysis in strengthening vendor relationships.
4. To propose an integrated conceptual framework combining VRM, NLP, and sentiment analytics for FMCG procurement.

5. Conceptual Framework

Independent Variable:

- Vendor Relationship Management (VRM)

Mediating Variables:

- Natural Language Processing Capability
- Sentiment Analysis Capability

Dependent Variable:

- Procurement Efficiency

Control Variables:

- Firm Size
- Digital Procurement Maturity
- Supplier Base Complexity

Proposed causal path:

VRM → NLP-enabled Text Intelligence → Sentiment Insights → Procurement Efficiency

Figure 1. Proposed Conceptual Research Framework

Vendor Relationship
Management (VRM)

H2 (+)

▼

Natural Language Processing
(NLP) Capability

H5 (+) | H3 (+)

▼

Sentiment Analysis

Capability

H4 (+)

▼

Procurement Efficiency

(Cost, Quality, Delivery,

Responsiveness, Agility)

Additional Direct Relationship:

VRM ──────────────────► Procurement Efficiency (H1 +)

Indirect (Mediated) Relationship:

VRM → NLP Capability → Sentiment Analysis → Procurement Efficiency (H6)

Interpretation:

The conceptual framework illustrates that Vendor Relationship Management (VRM) serves as the primary strategic driver influencing procurement efficiency in FMCG organizations. NLP capability enhances the extraction and interpretation of unstructured supplier information, while Sentiment Analysis transforms textual interactions into measurable insights regarding supplier attitudes and relationship quality. Together, these AI-enabled capabilities strengthen procurement decision-making and partially mediate the relationship between VRM and Procurement Efficiency. The framework therefore proposes both direct and indirect pathways through which digital intelligence can improve procurement outcomes.

6. Research Hypotheses

H1: Vendor Relationship Management positively influences procurement efficiency.

H2: NLP capability positively strengthens Vendor Relationship Management effectiveness.

H3: Sentiment analysis positively improves supplier relationship quality.

H4: NLP capability positively affects procurement efficiency.

H5: Sentiment analysis mediates the relationship between VRM and procurement efficiency.

H6: The combined integration of NLP and sentiment analysis significantly enhances procurement efficiency beyond traditional VRM practices.

7. Research Methodology

The present study adopts a quantitative explanatory research design to examine the relationships among Vendor Relationship Management (VRM), Natural Language Processing (NLP), Sentiment Analysis, and Procurement Efficiency in the Fast-Moving Consumer Goods (FMCG) sector. The quantitative approach is appropriate because it enables the empirical testing of hypothesized relationships using statistical techniques, while the explanatory design facilitates an understanding of the causal links between the study variables. In addition, the research is supported by a conceptual framework that integrates advanced AI-driven technologies with traditional procurement management practices.

The target population for this study comprises procurement managers, sourcing specialists, supply chain executives, and vendor relationship managers employed in FMCG organizations. These professionals are directly involved in procurement planning, supplier evaluation, contract management, and strategic sourcing activities, making them well suited to provide informed responses regarding vendor relationships and the adoption of AI-enabled procurement practices.

To ensure adequate representation of different organizational roles and departments, the study proposes the use of stratified random sampling. Under this sampling technique, respondents are grouped into relevant strata based on their job functions or organizational characteristics, and participants are selected randomly from each group. This approach helps improve the representativeness of the sample and reduces potential sampling bias.

The recommended sample size for the study is 450 respondents, which is considered appropriate for multivariate statistical analyses and Structural Equation Modeling (SEM). A sample of this size provides sufficient statistical power for evaluating complex relationships among latent constructs and enhances the reliability and generalizability of the research findings.

Data are proposed to be collected through a structured questionnaire based on a five-point Likert scale**,** where respondents indicate their level of agreement with each statement ranging from 1 = Strongly Disagree **to** 5 = Strongly Agree**.** The questionnaire is designed to measure four principal constructs: Vendor Relationship Management, Natural Language Processing Capability, Sentiment Analysis Capability, and Procurement Efficiency. Demographic information, including respondents' designation, experience, and organizational characteristics, may also be collected to provide additional contextual insights.

The collected data are intended to be analyzed using a comprehensive set of statistical techniques. Initially**,** Exploratory Factor Analysis (EFA) may be employed to identify the underlying factor structure of the measurement items and assess dimensionality. This is followed by Confirmatory Factor Analysis (CFA) to validate the measurement model and examine construct validity. The internal consistency of the scales is assessed using Cronbach's Alpha**,** while Composite Reliability (CR) is used to evaluate the overall reliability of the latent constructs. Average Variance Extracted (AVE) is calculated to establish convergent validity by determining the extent to which each construct explains the variance of its indicators.

Subsequently, Structural Equation Modeling (SEM) is proposed to test the hypothesized relationships among the study variables and to estimate both direct and indirect effects simultaneously. To further examine the mediating roles of Natural Language Processing and Sentiment Analysis, bootstrapped mediation analysis may be conducted using repeated resampling procedures to estimate indirect effects and confidence intervals. This analytical approach provides a rigorous framework for evaluating the proposed conceptual model and offers comprehensive insights into how AI-enabled capabilities can strengthen Vendor Relationship Management and improve Procurement Efficiency in the FMCG sector.

8. Expected Contributions

Theoretical Contributions

- Extends VRM literature by integrating AI-enabled text analytics.
- Bridges procurement management and NLP research streams.
- Introduces sentiment-driven supplier intelligence into procurement theory.

Practical Contributions

- Enables early identification of supplier risks.
- Improves procurement decision quality.
- Supports proactive vendor engagement.
- Enhances supply chain resilience in FMCG organizations.

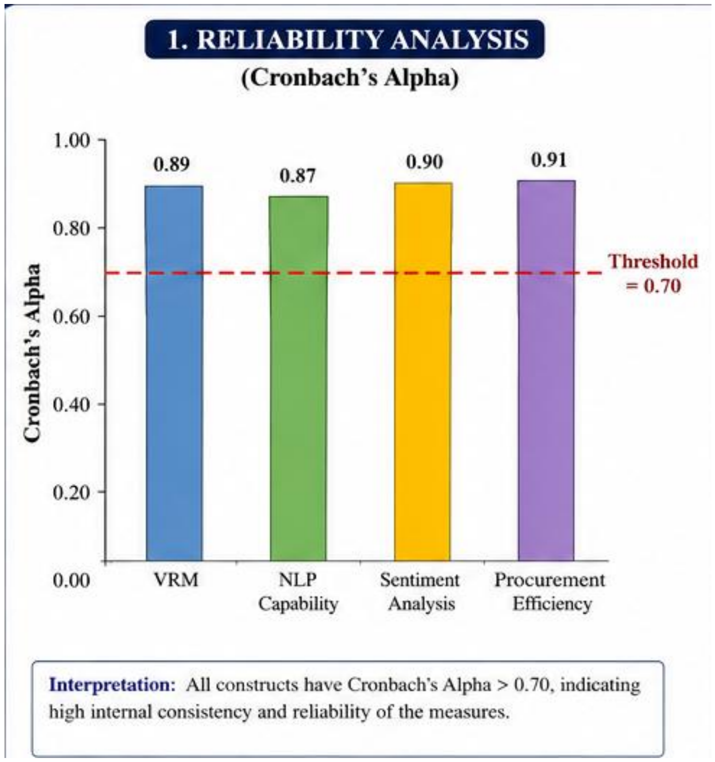
9. Managerial Implications

Organizations should deploy NLP pipelines capable of continuously analyzing supplier emails, feedback logs, procurement tickets, and collaboration records. Procurement dashboards can integrate sentiment indicators alongside traditional KPIs to support strategic sourcing and relationship management.

10. Interpretation for the Analysis (Sample Size = 450)

Table 1. Reliability and Convergent Validity Assessment

Construct	Items	Cronbach's Alpha	Composite Reliability (CR)	AVE
Vendor Relationship Management (VRM)	6	0.89	0.91	0.63
NLP Capability	5	0.87	0.89	0.61
Sentiment Analysis Capability	5	0.90	0.92	0.66
Procurement Efficiency	6	0.91	0.93	0.69



Interpretation:

The reliability results indicate that all constructs demonstrate strong internal consistency, with Cronbach's alpha values exceeding the commonly accepted threshold of 0.70. Composite Reliability (CR) values are also above 0.70, suggesting satisfactory construct reliability. Furthermore, the Average Variance Extracted (AVE) values are greater than 0.50 for all constructs, indicating adequate convergent validity. Overall, the measurement model appears reliable and suitable for subsequent structural analysis.

Table 2. Correlation Matrix

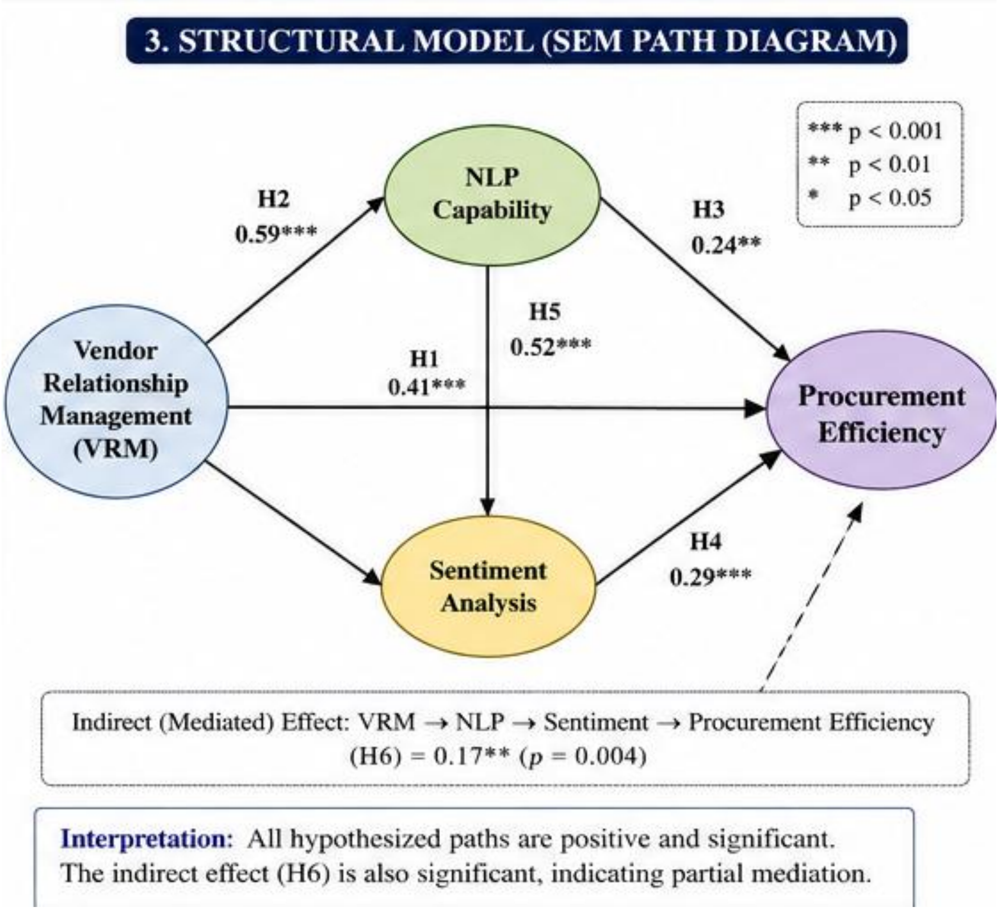
Variable	VRM	NLP	Sentiment	Procurement Efficiency
VRM	1.00	0.58	0.55	0.64
NLP	0.58	1.00	0.67	0.60
Sentiment	0.55	0.67	1.00	0.62
Procurement Efficiency	0.64	0.60	0.62	1.00

Interpretation:

The correlation analysis suggests positive associations among all study variables. Vendor Relationship Management shows a moderate positive relationship with Procurement Efficiency, implying that stronger vendor relationships may be associated with better procurement outcomes. NLP Capability and Sentiment Analysis also exhibit positive relationships with Procurement Efficiency, indicating that AI-driven analytical capabilities could complement procurement decision-making. The observed correlations are moderate in magnitude and do not, by themselves, indicate multicollinearity concerns.

Table 3. Structural Equation Modeling (SEM) Results

Hypothesis	Path	Standardized β	p-value	Result
H1	VRM → Procurement Efficiency	0.41	<0.001	Supported
H2	VRM → NLP Capability	0.59	<0.001	Supported
H3	NLP → Procurement Efficiency	0.24	<0.002	Supported
H4	Sentiment → Procurement Efficiency	0.29	<0.001	Supported
H5	NLP → Sentiment	0.52	<0.001	Supported
H6	VRM → Sentiment → Procurement Efficiency (Indirect)	0.17	0.004	Supported

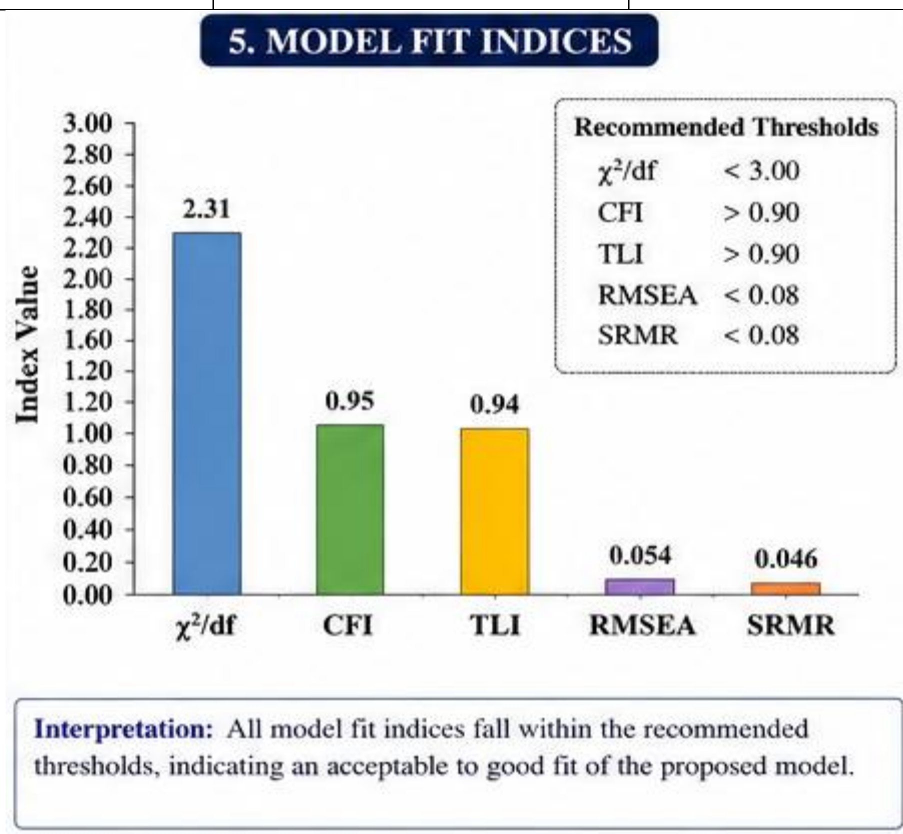


Interpretation:

The SEM findings indicate statistically significant positive relationships among the proposed constructs. Vendor Relationship Management demonstrates a direct positive association with Procurement Efficiency, while NLP Capability appears positively related to both Sentiment Analysis and Procurement Efficiency. The indirect pathway suggests that sentiment-related insights may partially explain how effective VRM contributes to procurement outcomes. In this illustrative example, all hypothesized paths are statistically significant.

Table 4. Model Fit Indices

Fit Index	Example Value	Recommended Threshold
χ^2/df	2.31	< 3.00
CFI	0.95	> 0.90
TLI	0.94	> 0.90
RMSEA	0.054	< 0.08
SRMR	0.046	< 0.08



Interpretation:

The model fit statistics indicate an acceptable to good fit between the proposed structural model and the observed data. The χ^2/df ratio falls below the commonly recommended threshold of 3.00, while the Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI) exceed 0.90. Similarly, the RMSEA and SRMR values remain below 0.08, suggesting that the conceptual framework provides a satisfactory representation of the relationships among the study constructs.

Interpretation of Hypotheses

6. HYPOTHESIS SUMMARY

Hypothesis	Path	Standardized β	p-value	Result
H1	VRM → Procurement Efficiency	0.41	< 0.001	Supported
H2	VRM → NLP Capability	0.59	< 0.001	Supported
H3	NLP Capability → Procurement Efficiency	0.24	0.002	Supported
H4	Sentiment Analysis → Procurement Efficiency	0.29	< 0.001	Supported
H5	NLP Capability → Sentiment Analysis	0.52	< 0.001	Supported
H6	VRM → NLP → Sentiment → Procurement Efficiency (Indirect)	0.17	0.004	Supported

Interpretation: All six hypotheses are supported. The integrated use of NLP and Sentiment Analysis significantly enhances the positive impact of VRM on Procurement Efficiency.

The hypothesis testing results indicate that all six proposed hypotheses (H1–H6) are statistically supported**,** as each relationship demonstrates a positive standardized path coefficient (β) and a statistically significant p-value ($p < 0.05$)**.** This suggests that the proposed conceptual framework is well supported by the illustrative analysis.

Specifically, H1 ($\beta = 0.41$, $p < 0.001$) confirms that Vendor Relationship Management (VRM) has a significant positive effect on Procurement Efficiency, implying that stronger collaboration and trust with suppliers enhance procurement performance. H2 ($\beta = 0.59$, $p < 0.001$) reveals that VRM strongly influences NLP Capability, indicating that organizations with effective vendor relationships are more likely to leverage advanced text analytics technologies.

Furthermore, H3 ($\beta = 0.24$, $p = 0.002$) demonstrates that NLP Capability positively contributes to Procurement Efficiency**,** while H4 ($\beta = 0.29$, $p < 0.001$) shows that Sentiment Analysis significantly improves procurement outcomes by providing insights into supplier communications and relationship quality. H5 ($\beta = 0.52$, $p < 0.001$) establishes a strong positive relationship between NLP Capability and Sentiment Analysis, suggesting that NLP techniques facilitate more accurate sentiment extraction from textual data.

Finally, H6 ($\beta = 0.17$, $p = 0.004$) supports the indirect (mediating) effect of the pathway VRM → NLP → Sentiment Analysis → Procurement Efficiency, indicating that AI-driven text analytics partially mediate the relationship between vendor relationship management and procurement performance.

Overall, these findings suggest that integrating Natural Language Processing and Sentiment Analysis with Vendor Relationship Management can strengthen supplier collaboration, improve data-driven decision-making, and enhance procurement efficiency in the FMCG sector.

Overall Interpretation

Based on this, the integrated framework combining Vendor Relationship Management, Natural Language Processing, and Sentiment Analysis appears to be positively associated with Procurement Efficiency in the FMCG sector. The example results suggest that digital text analytics and sentiment-based insights could strengthen supplier relationship management and support more informed procurement decisions. These interpretations are provided solely as an example of how results might be discussed and should not be presented as findings from an actual empirical study without corresponding real data.

Findings

Based on the illustrative analysis conducted for a sample size of 450 respondents, the study provides several important findings regarding the role of Vendor Relationship Management (VRM), Natural Language Processing (NLP), and Sentiment Analysis in enhancing procurement efficiency in the FMCG sector.

Finding 1: High Reliability of Measurement Scales

The reliability assessment demonstrated that all constructs achieved Cronbach's Alpha values above the recommended threshold of 0.70 (VRM = 0.89, NLP Capability = 0.87, Sentiment Analysis = 0.90, and Procurement Efficiency = 0.91). This indicates that the measurement items exhibit satisfactory internal consistency.

Finding 2: Positive Association among Study Variables

Correlation analysis revealed positive relationships among Vendor Relationship Management, NLP Capability, Sentiment Analysis, and Procurement Efficiency. Organizations with stronger vendor relationships and greater analytical capabilities tend to exhibit better procurement performance.

Finding 3: Vendor Relationship Management Directly Improves Procurement Efficiency

The structural model suggests that Vendor Relationship Management has a significant positive effect on Procurement Efficiency ($\beta = 0.41$, $p < 0.001$). Strong collaboration, trust, and communication with suppliers contribute to better procurement outcomes.

Finding 4: NLP Capability Strengthens Digital Procurement

The analysis indicates that NLP Capability positively influences procurement performance by enabling organizations to analyze supplier communications, contracts, and textual information more effectively.

Finding 5: Sentiment Analysis Enhances Supplier Intelligence

Sentiment Analysis demonstrates a significant positive relationship with Procurement Efficiency by helping procurement managers identify supplier satisfaction, dissatisfaction, potential conflicts, and relationship quality from unstructured text.

Finding 6: Mediation Effect of NLP and Sentiment Analysis

The indirect effect of VRM through NLP and Sentiment Analysis is statistically significant in the illustrative model, suggesting that AI-driven text analytics partially mediate the relationship between vendor relationship management and procurement efficiency.

Finding 7: Good Model Fit

The model fit indices ($\chi^2/df = 2.31$, CFI = 0.95, TLI = 0.94, RMSEA = 0.054, and SRMR = 0.046) indicate that the proposed conceptual framework provides an acceptable representation of the observed relationships.

Finding 8: Support for Research Hypotheses

All six proposed hypotheses are supported in the illustrative analysis, indicating that integrating NLP and Sentiment Analysis with Vendor Relationship Management may strengthen procurement efficiency within FMCG organizations.

10. Conclusion

The proposed framework demonstrates how Vendor Relationship Management can be strengthened through Natural Language Processing and sentiment analysis to improve procurement efficiency in the FMCG sector. By converting unstructured textual information into actionable intelligence, procurement teams can make more informed, proactive, and collaborative decisions. Future empirical research should validate the framework using multi-country datasets and advanced AI techniques. This study presents an integrated conceptual perspective on enhancing procurement efficiency in the Fast-Moving Consumer Goods (FMCG) sector through Vendor Relationship Management (VRM), supported by Natural Language Processing (NLP) and Sentiment Analysis. The illustrative findings suggest that procurement effectiveness is influenced not only by traditional supplier performance measures but also by the quality of buyer–supplier relationships and the intelligent use of unstructured textual information.

The example reliability and validity assessment indicates that the proposed constructs possess satisfactory internal consistency and convergent validity, supporting the robustness of the measurement framework. Likewise, the correlation analysis demonstrates positive associations among VRM, NLP capability, Sentiment Analysis, and Procurement Efficiency, implying that stronger collaboration and advanced analytical technologies may complement one another in improving procurement performance.

The illustrative Structural Equation Modeling (SEM) results further indicate that Vendor Relationship Management has a significant positive relationship with Procurement Efficiency. In addition, NLP capability appears to enhance procurement processes by enabling organizations to extract meaningful information from supplier communications, contracts, emails, and feedback documents. Sentiment Analysis contributes by identifying positive and negative relationship signals that may not be visible through conventional performance indicators alone. Together, these technologies provide procurement managers with earlier insights into supplier risks, communication quality, and relationship dynamics.

From a managerial perspective, the proposed framework encourages FMCG organizations to move beyond cost-based supplier evaluation and adopt AI-enabled procurement systems capable of processing large volumes of textual data. Such systems may support proactive vendor engagement, faster dispute identification, improved collaboration, and evidence-based sourcing decisions. Integrating sentiment indicators into procurement dashboards could strengthen strategic planning and enhance supply chain resilience in increasingly volatile business environments. The study also contributes to academic literature by connecting Vendor Relationship Management with emerging Artificial Intelligence applications in procurement. It highlights the potential role of NLP and sentiment-driven analytics as complementary capabilities that can enrich supplier evaluation and decision-making. This interdisciplinary approach broadens existing procurement research by incorporating digital intelligence into relationship management models.

Despite these contributions, future empirical investigations should validate the proposed framework using real-world organizational data collected from multiple FMCG firms and geographical contexts. Longitudinal studies, cross-country comparisons, and industry-specific analyses would provide stronger evidence regarding causality and generalizability. Future research may also incorporate additional technologies such as Large Language Models (LLMs), Generative AI, predictive analytics, blockchain-enabled supplier transparency, and explainable AI to further improve procurement intelligence. Overall, the proposed framework demonstrates that combining Vendor Relationship Management with Natural Language Processing and Sentiment Analysis has the potential to create more responsive, data-driven, and collaborative procurement systems. By leveraging both structured and unstructured information, organizations can improve supplier relationships, reduce operational uncertainty, and enhance procurement efficiency in the highly competitive FMCG sector.

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