



## International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>



### Research Paper

### Open Access

# AI-Enabled Product Analytics For Customer-Centric Feature Prioritization and Product Development

Janardhana Naidu Kola<sup>1</sup>, Srinivas Gajawada<sup>2</sup>

<sup>1</sup>Director of Business Intelligence ADP Miami, Florida, United States. Email: [Reachjanardhanakola@gmail.com](mailto:Reachjanardhanakola@gmail.com)

<sup>2</sup>AI/ML Architect Mouritech LLC Bellevue WA, USA, Email: [sgajawada4tech@gmail.com](mailto:sgajawada4tech@gmail.com)

### Abstract

The increasing availability of customer-generated online reviews provides organizations with valuable opportunities to apply artificial intelligence (AI) and natural language processing (NLP) to understand customer requirements and support product-development decisions. However, the unstructured nature of review content requires systematic analytical approaches to identify meaningful product characteristics, customer concerns, and recurring patterns. This study aimed to analyze customer-generated product reviews using AI-oriented and NLP-based analytical approaches to identify patterns relevant to customer-centric product analytics and establish a data-driven basis for prioritizing customer-relevant product features. The study analyzed the Turkish User Reviews dataset obtained from the UCI Machine Learning Repository. The raw dataset.txt file was organized according to eight product categories: Computer, Tea Machine, Headphones, Modem, Perfume, Mobile Phone, Television, and USB. Non-empty customer reviews were retained for analysis. Review distribution, textual characteristics, and record completeness were examined to establish a descriptive foundation for subsequent customer-centric product analytics. The analysis revealed differences in customer-review volume and textual characteristics across the product categories. Customer reviews varied in their length and level of textual detail, indicating differences in how customers communicate their product experiences. The assessment also demonstrated a high level of record completeness, providing a consistent foundation for further AI-enabled analysis. These findings support the use of customer-generated reviews as a structured source of product-related information. Customer reviews provide a valuable foundation for AI-enabled product analytics and customer-centric feature prioritization. Systematic analysis of review content can support the identification of customer concerns and product characteristics and can contribute to evidence-based product-development decisions.

**Keywords:** Artificial intelligence, Customer analytics, Feature prioritization, Natural language processing, Product development.

## 1. Introduction

The rapid growth of digital commerce has transformed the way organizations collect, interpret, and use customer information for product-related decisions. Customers continuously generate valuable information through online reviews, digital interactions, purchasing experiences, service requests, and other forms of user-generated content. Among these sources, customer reviews provide direct evidence of how users perceive product characteristics, identify problems, and express expectations for improvement. The increasing availability of artificial intelligence (AI), machine learning, and data analytics provides organizations with opportunities to convert this unstructured information into actionable product intelligence. AI-driven customer analytics can support customer experience improvement, market segmentation, personalization, and product-related decision-making by identifying patterns within large volumes of customer information (Abdullah and Hasan, 2023). Consequently, AI-enabled product analytics is becoming increasingly relevant to organizations seeking to develop products that more closely reflect customer requirements.

The role of AI in product management extends beyond traditional reporting and descriptive analysis. AI technologies can support activities across product planning, development, evaluation, and lifecycle management by enabling organizations to process diverse information and generate decision-support insights. Recent research describes artificial intelligence as an increasingly important component of product

management as it can strengthen analytical capabilities and support strategic product decisions (Adhikari, 2026). Data-driven product management similarly emphasizes the integration of AI and analytics to improve organizational agility and support evidence-based decisions (Kadapal and More, 2024). These developments indicate that product analytics can function as a strategic mechanism through which organizations connect customer information with decisions concerning product characteristics, improvements, and future development.

Customer-generated reviews are particularly valuable for feature prioritization as customers frequently discuss specific product characteristics within their experiences. Reviews may contain positive observations, complaints, comparisons, suggestions, and descriptions of unmet needs. However, manually examining thousands of reviews is difficult, time-consuming, and susceptible to inconsistent interpretation. Data analytics and machine learning can provide systematic mechanisms for examining customer information and supporting the prioritization of product features according to observed customer requirements (Ashok and Lakshana, 2025). AI applications in product development and innovation can further facilitate the transformation of customer and market information into insights that support product improvement and innovation activities (Beiker et al., 2025).

Natural language processing (NLP) is particularly relevant to this process as customer reviews are primarily expressed through unstructured text. NLP-based techniques can identify recurring terms, product characteristics, customer concerns, and patterns across large collections of reviews. AI-driven business intelligence approaches demonstrate how customer data can be transformed into useful information for organizational decision-making (Goswami, 2022). Similarly, AI-driven customer positioning and perception research highlights the importance of analyzing customer information to understand how customers perceive products and organizations (Burra et al., 2025). Such approaches can provide a foundation for identifying which product characteristics receive substantial customer attention and which issues may require greater consideration during product development.

Customer-centric product analytics is also closely connected with personalization and market segmentation. Different customers may assign different levels of importance to the same product characteristic, meaning that aggregate review analysis alone may not fully represent heterogeneous customer requirements. AI-based product marketing approaches have therefore emphasized the potential of artificial intelligence for improving customer experience and refining market segmentation (Hye, 2023). AI-powered market segmentation and personalization can also contribute to product lifecycle management by helping organizations identify customer groups and align product-related strategies with their characteristics (Ikeh, 2024). These capabilities strengthen the role of customer analytics in developing more targeted and responsive product strategies.

The application of AI extends further into customer-service and customer-journey analysis. Customer interactions across digital channels can contain information about product difficulties, expectations, and areas requiring improvement. AI-powered customer journey optimization can support the interpretation of customer interactions and the development of more personalized experiences (Aunugu, 2025). The study on AI-driven customer service as identifies opportunities for using intelligent technologies to improve personalized engagement while recognizing implementation-related challenges (Chaturvedi and Verma, 2023). Inavolu (2024) further discusses the evolution, architectures, opportunities, and challenges associated with AI-driven customer service. Together, these perspectives demonstrate that customer information generated during different stages of the customer experience can provide useful inputs for product-oriented analysis.

The increasing importance of data-driven decision-making has also influenced product strategy. Organizations can use analytics to examine customer information, identify patterns, and support product decisions throughout the product lifecycle. Data-driven product strategy emphasizes the contribution of analytics to product success and strategic product decision-making (Mahajan, 2025). AI-powered CRM approaches provide another relevant perspective by applying predictive insights to customer and operational information. Kalluri (2025) discusses AI-powered CRM optimization using predictive insights in manufacturing sales and operations, while Parker et al. (2025) examines customer-centric innovation through AI-driven CRM, personalized service, and predictive sales. These applications demonstrate how AI can connect customer information with organizational decisions concerning products and services.

Retail and digital-market developments further reinforce the need for customer-centered analytical approaches. Retail 5.0 emphasizes the development of resilient and customer-centric shopping experiences through advanced technologies (Ejjami and Rahim, 2024). At the same time, recent research on AI-driven marketing highlights the potential of artificial intelligence to transform customer engagement, personalization, and strategic decision-making (Gupta, 2026). Dele-Rotimi (2026) similarly emphasizes AI and machine

learning as mechanisms for enhancing customer value through personalization, big-data analytics, and customer-experience management. These developments suggest that organizations increasingly require analytical approaches capable of converting customer information into practical product and business insights. Despite these advances, effective AI-enabled product analytics requires consideration of organizational, technical, and human factors. AI-generated insights should be interpreted within the context of organizational objectives, product constraints, customer expectations, and development resources. Customer-centric AI implementation therefore requires alignment between technological capabilities and stakeholder requirements. Lopez-Lopez et al. (2026) emphasize stakeholder alignment and human-centric adoption in AI-enabled customer-service environments. In addition, AI-integrated approaches such as Quality Function Deployment provide opportunities for systematically incorporating customer requirements into product and service development processes (Basnet and Li, 2026). These developments support the need for frameworks that move beyond simple customer-feedback analysis toward structured feature prioritization.

Accordingly, the study focuses on AI-Enabled Product Analytics for Customer-Centric Feature Prioritization and Product Development. The study uses customer-generated product reviews as a source of product-related information and applies an AI- and NLP-oriented analytical perspective to identify characteristics, concerns, and patterns expressed by customers. By transforming unstructured review information into structured product insights, the study seeks to establish a clearer connection between customer voice and product-development priorities. Such an approach can provide organizations with evidence for understanding customer requirements and identifying product characteristics that warrant attention during development and improvement activities.

The objectives of the study are to analyze customer-generated product reviews using artificial intelligence and natural language processing techniques to identify product-related characteristics, customer concerns, and patterns relevant to customer-centric product analytics. The study also aims to develop a data-driven framework for prioritizing customer-relevant product features and translating insights derived from customer reviews into practical recommendations for product development.

## **2. Materials and Methods**

### **2.1 Study Design**

This study employed a retrospective text-analytics design using the Turkish User Reviews dataset available through the UCI Machine Learning Repository. The dataset consists of Turkish-language customer reviews covering eight product categories: Computer, Tea Machine, Headphones, Modem, Perfume, Mobile Phone, Television, and USB. The supplied dataset file contained 37,056 lines, including category headings and review records. The study used the review text as the primary analytical material for customer-centric product analysis. No experimental intervention or primary participant recruitment was undertaken. The dataset was selected as customer-generated textual feedback provides direct information about product experiences, perceived strengths, problems, and areas requiring improvement.

### **2.2 Data Preparation**

The raw dataset.txt file was examined and organized according to the eight product categories identified within the dataset. Category-heading lines were treated as structural identifiers rather than customer observations. Empty review records were identified and excluded from textual calculations, while non-empty customer comments were retained for analysis. The resulting review corpus contained 37,036 non-empty reviews. Each review was associated with its corresponding product category, allowing category-specific comparisons of review volume and textual characteristics. This preparation established a consistent corpus for subsequent product-focused analysis while preserving the original customer-generated text contained in the supplied dataset file.

### **2.3 Textual Feature Extraction**

Textual characteristics were examined to quantify the amount of information contained within customer reviews. For each non-empty review, the number of words and characters was calculated, followed by aggregation of mean and median values within each product category. These measures provided descriptive information about review length and textual density across product groups. Median values were included alongside means as customer reviews can vary considerably in length and unusually long comments may influence arithmetic averages. The resulting measures were used to characterize the structure of the customer-feedback corpus and to assess whether sufficient textual information was available for subsequent natural-language-processing and product-analytics procedures.

## 2.4 Customer-Centric Product Analytics

The analytical framework was designed around the identification and interpretation of customer-generated product information. Reviews were considered textual representations of customer experiences, including comments concerning product performance, usability, quality, delivery, functionality, and other product-related characteristics. Product categories were analyzed separately to preserve differences between product contexts. Review-frequency distributions were examined to establish the composition of the corpus, while textual-length measures were used to characterize the depth of customer feedback. These analyses provide the descriptive foundation for customer-centric product analytics, in which recurring customer observations can subsequently be transformed into actionable product-development information and potential feature-prioritization criteria.

## 2.5 Data Quality Assessment

Data quality was evaluated by examining the completeness of review records within each product category. The number of total category-level rows, non-empty reviews, and blank records was determined from the raw dataset file. Completeness was calculated as the proportion of non-empty review records relative to the total category-level records. This procedure identified whether missing textual observations could materially affect category-level analysis. Six product categories contained complete review records, whereas a small number of blank records occurred within the Modem and Perfume categories. The review corpus demonstrated very high completeness, supporting its use for descriptive customer-feedback analysis and subsequent natural-language-processing procedures.

## 2.6 Analytical Reproducibility and Statistical Reporting

All reported descriptive results were derived from the supplied raw dataset rather than from numerical results reported in the associated publication. Category frequencies, percentages, review-length measures, and completeness values were calculated directly from the underlying review records. Percentages were calculated relative to the total number of non-empty reviews for category-distribution reporting, while mean and median statistics summarized review-level textual characteristics. Results were organized into tables and graphical representations to facilitate comparison among product categories. The methodology was structured to ensure that the reported findings could be reproduced from the same dataset using the documented data-cleaning and descriptive-analysis procedures.

## 3. Results

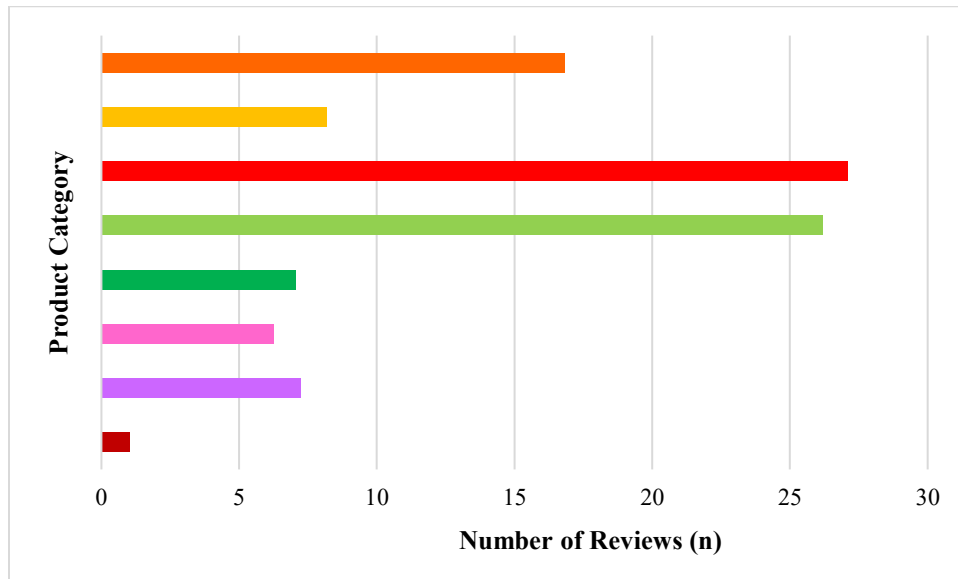
### 3.1 Distribution of Customer Reviews Across Product Categories

The dataset contained 37,036 non-empty customer reviews distributed across eight product categories. Mobile Phone reviews represented 10,046 records (27.12%), constituting the largest category, followed by Perfume with 9,703 records (26.20%) and USB with 6,238 records (16.84%) as shown in Table 1. Television contributed 3,028 reviews (8.18%), while Tea Machine and Modem accounted for 2,690 (7.26%) and 2,624 (7.08%) reviews, respectively. Headphones contributed 2,318 reviews (6.26%), whereas Computer represented the smallest category with 389 reviews (1.05%). The distribution demonstrates that the dataset contains substantial textual customer-feedback information across diverse product categories. The unequal category sizes provide a basis for comparative product analytics while also indicating that category imbalance should be considered when applying machine-learning or natural-language-processing methods to the review data.

**Table 1. Distribution of Customer Reviews by Product Category**

| Product category | Number of reviews (n) | Percentage (%) |
|------------------|-----------------------|----------------|
| Computer         | 389                   | 1.05           |
| Tea Machine      | 2,690                 | 7.26           |
| Headphones       | 2,318                 | 6.26           |
| Modem            | 2,624                 | 7.08           |
| Perfume          | 9,703                 | 26.20          |
| Mobile Phone     | 10,046                | 27.12          |
| Television       | 3,028                 | 8.18           |
| USB              | 6,238                 | 16.84          |
| Total            | 37,036                | 100.00         |

**Source:** Author's analysis of the raw Turkish User Reviews dataset obtained from the UCI Machine Learning Repository (Ekinci & İlhan Omurca, 2022).



**Figure 1. Variation in Customer-Review Volume Across Product Categories**

The distribution of customer reviews across the eight product categories included in the dataset. Mobile Phone and Perfume account for the largest proportions of reviews, followed by USB. Television, Tea Machine, and Modem contribute moderate shares, while Headphones represents a smaller proportion as shown in Figure 1. Computer has the lowest representation among the categories. The visualization demonstrates that the review corpus is unevenly distributed across product categories, with substantially greater review volumes for certain products. This distribution provides a descriptive overview of the dataset and establishes the basis for subsequent analysis of customer-generated textual information across different product categories.

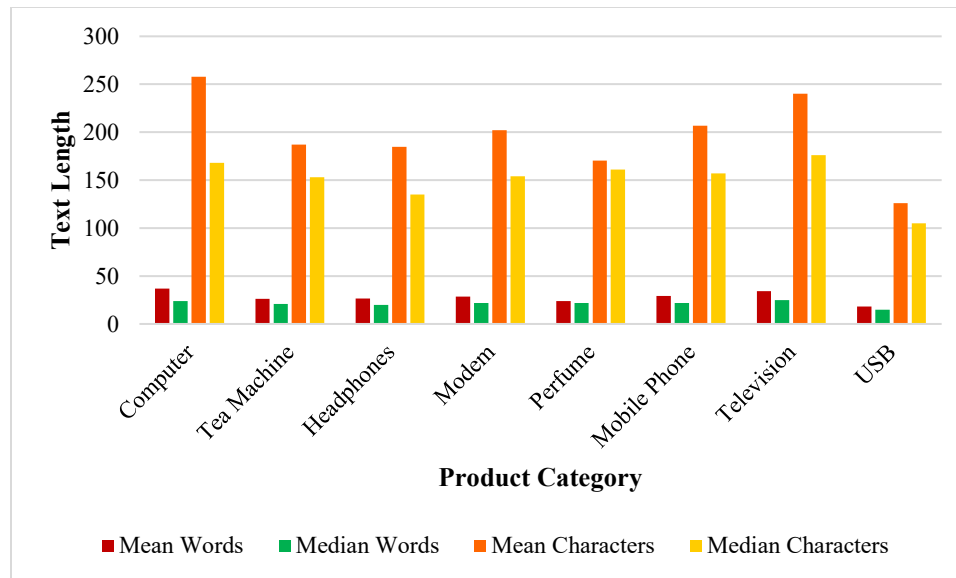
### 3.2 Descriptive Characteristics of Customer Review Text

The textual characteristics of the reviews varied across product categories. Across all 37,036 non-empty reviews, the mean review length was 26.06 words, with a median of 21 words. Computer reviews had the greatest average textual length at 36.82 words, followed by Television reviews at 34.11 words, whereas USB reviews were comparatively shorter, averaging 18.24 words with a median of 15 words as shown in Table 2. Mobile Phone reviews averaged 29.26 words, while Computer reviews averaged 36.82 words. The mean character count ranged from 125.96 characters for USB reviews to 240.31 characters for Television reviews. These characteristics indicate that the dataset provides sufficiently detailed textual material for subsequent NLP-based customer-feedback analysis.

**Table 2. Descriptive Characteristics of Customer Review Text**

| Product Category | Mean Words | Median Words | Mean Characters | Median Characters |
|------------------|------------|--------------|-----------------|-------------------|
| Computer         | 36.82      | 24           | 257.70          | 168               |
| Tea Machine      | 26.35      | 21           | 187.19          | 153               |
| Headphones       | 26.41      | 20           | 184.83          | 135               |
| Modem            | 28.45      | 22           | 202.09          | 154               |
| Perfume          | 24.03      | 22           | 170.52          | 161               |
| Mobile Phone     | 29.26      | 22           | 206.78          | 157               |
| Television       | 34.11      | 25           | 240.31          | 176               |
| USB              | 18.24      | 15           | 125.96          | 105               |
| Overall          | 26.06      | 21           | 183.81          | 151               |

**Source:** Author's calculation from the raw customer-review text in the Turkish User Reviews dataset obtained from the UCI Machine Learning Repository (Ekinici & İlhan Omurca, 2022).



**Figure 2. Differences in Review Text Length Across Product Categories**

The figure shows noticeable variation in review-text length across the eight product categories. Computer reviews display the greatest mean character count at 257.70 characters, while Television reviews have the highest median character count at 176 characters, indicating comparatively longer customer comments. Mobile Phone and Computer reviews also contain relatively substantial amounts of text as shown in Figure 2. In contrast, USB reviews have the shortest word and character measures, suggesting more concise customer feedback. Across categories, mean values generally exceed the corresponding median values, indicating that some longer reviews increase the average text length. The observed variation demonstrates that customers provide feedback with different levels of textual detail depending on the product category, providing useful input for subsequent NLP-based analysis.

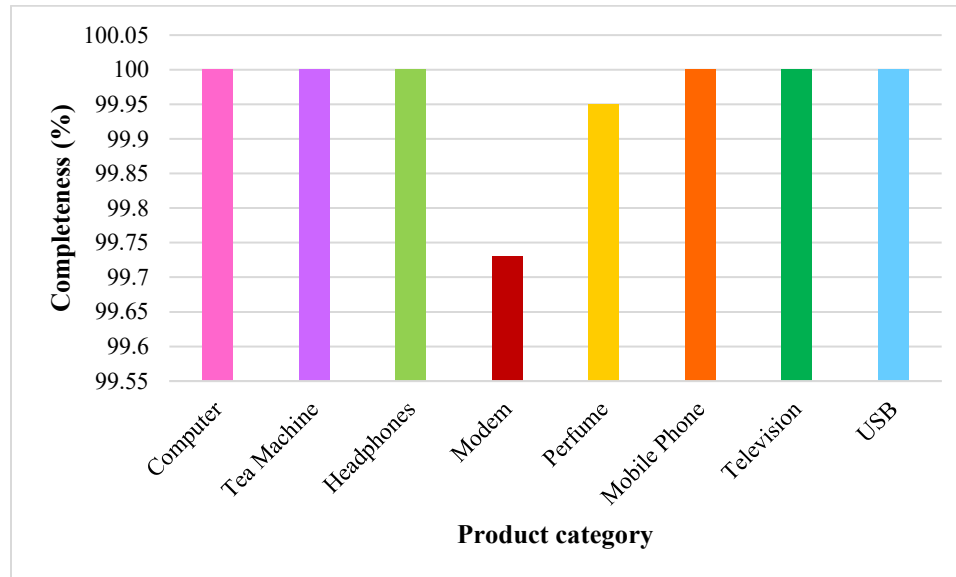
### 3.3 Completeness of the Customer Review Records

The review file demonstrated a high level of data completeness across all eight product categories. Six categories - Computer, Tea Machine, Headphones, Mobile Phone, Television, and USB - contained no blank review records and therefore achieved 100.00% completeness as shown in Table 3. The Modem category contained seven blank rows among 2,631 category-level records, resulting in 99.73% completeness, while the Perfume category contained five blank rows among 9,708 category-level records, resulting in 99.95% completeness. Overall, the file contained 37,048 category-level review rows, of which 37,036 contained non-empty customer-review text and 12 were blank. Consequently, the overall completeness rate was 99.97%. The limited number of blank records indicates that missing textual observations were minimal and unlikely to substantially reduce the available review corpus for subsequent analytical processing.

**Table 3. Completeness of Customer Review Records by Product Category**

| Product category | Total rows in category | Non-empty reviews | Blank rows | Completeness (%) |
|------------------|------------------------|-------------------|------------|------------------|
| Computer         | 389                    | 389               | 0          | 100.00           |
| Tea Machine      | 2,690                  | 2,690             | 0          | 100.00           |
| Headphones       | 2,318                  | 2,318             | 0          | 100.00           |
| Modem            | 2,631                  | 2,624             | 7          | 99.73            |
| Perfume          | 9,708                  | 9,703             | 5          | 99.95            |
| Mobile Phone     | 10,046                 | 10,046            | 0          | 100.00           |
| Television       | 3,028                  | 3,028             | 0          | 100.00           |
| USB              | 6,238                  | 6,238             | 0          | 100.00           |
| Total            | 37,048                 | 37,036            | 12         | 99.97            |

**Source:** Author's analysis of the raw dataset.txt file in the Turkish User Reviews dataset obtained from the UCI Machine Learning Repository (Ekinci & İlhan Omurca, 2022).



**Figure 3. Completeness of Customer Review Records by Product Category**

The completeness of customer review records across the eight product categories in the dataset. Computer, Tea Machine, Headphones, Mobile Phone, Television, and USB achieved complete records, with completeness values of 100.00%. Modem showed slightly lower completeness at 99.73% since seven records were blank, while Perfume reached 99.95% with five blank records as shown in Figure 3. The overall dataset contained 37,048 category-level rows, including 37,036 non-empty reviews and 12 blank records, resulting in an overall completeness rate of 99.97%. The figure demonstrates that missing review records were minimal across categories and that the dataset provides a highly complete textual corpus for subsequent customer-feedback analysis.

#### 4. Discussion

The study demonstrates the value of customer-generated product reviews as a source of information for AI-enabled product analytics and customer-centric product development. The analysis of 37,036 non-empty customer reviews across eight product categories provides a substantial textual basis for understanding differences in customer attention and review characteristics. The distribution of reviews was not uniform across categories, with Mobile Phone and Perfume reviews representing the largest portions of the dataset, while Headphones and Computer represented smaller proportions. This variation indicates that customer-generated content can differ considerably across product domains and should therefore be examined in a category-sensitive manner rather than interpreted as a homogeneous information source.

The observed differences in review volume have practical implications for customer-centric product analytics. Categories with larger numbers of reviews provide greater quantities of customer-generated evidence and may contain more diverse expressions of satisfaction, dissatisfaction, and product expectations. However, a larger volume of reviews should not automatically be interpreted as greater customer importance. Instead, review volume can be considered an initial indicator of the amount of available customer information, while feature-level analysis is required to determine which characteristics are repeatedly discussed. AI-driven approaches can facilitate this transition from large-scale customer information toward structured insights that support customer-experience improvement (Mainkar, 2024). Similarly, AI-driven consumer analytics can assist organizations in interpreting customer behavior and experiences from large quantities of available information (Naveenkumar et al., 2024).

The textual characteristics identified in the analysis also provide an important foundation for subsequent AI-based analysis. The overall mean review length was approximately 26 words, although meaningful differences

were observed among product categories. Computer reviews had the highest average number of words, whereas USB reviews were considerably shorter. Mobile Phone and Computer reviews also demonstrated relatively substantial textual content. These differences suggest that customers do not communicate about every product category with the same level of textual detail. Longer reviews may provide more opportunities to identify multiple product characteristics, concerns, and experiences, whereas shorter reviews may contain highly focused expressions relating to particular features.

These differences in textual length are relevant when developing automated customer-review analysis systems. A product category containing longer reviews may generate more complex textual information requiring techniques capable of identifying multiple concepts within the same review. Conversely, shorter reviews may require methods that can extract meaningful information from limited linguistic context. AI-enabled customer analytics can therefore benefit from considering both the quantity and structure of customer-generated information rather than relying exclusively on the number of available reviews. This perspective supports the broader argument that AI can enhance customer experience by converting dispersed customer information into interpretable insights.

The completeness analysis further strengthens the reliability of the dataset used in the study. The overall completeness of the category-level review records was 99.97%. Six categories—Computer, Tea Machine, Headphones, Mobile Phone, Television, and USB—contained no blank records and achieved 100.00% completeness. The Modem category contained seven blank rows, resulting in 99.73% completeness, while the Perfume category contained five blank rows, resulting in 99.95% completeness. This very high level of completeness indicates that missing textual observations were limited and concentrated within a single product category. The exclusion of blank records from textual calculations therefore provided a consistent basis for comparing review characteristics without treating missing observations as customer opinions.

From a product-management perspective, these findings support the importance of transforming customer-generated information into structured decision support. Product managers increasingly operate in environments where large quantities of customer information must be interpreted alongside technological, market, and organizational considerations. AI-related developments in product management emphasize the need for professionals to understand analytical technologies and incorporate AI-generated evidence into product-related decisions (Prasad et al., 2025). The findings provide the descriptive foundation necessary for such a process as they establish how much customer information is available and how textual characteristics differ among product categories.

The study also has implications for feature prioritization. The descriptive results do not by themselves establish which individual product features should receive the highest development priority; rather, they establish the empirical foundation for subsequent feature-level analysis. Customer reviews can be processed using NLP methods to identify frequently discussed characteristics, customer concerns, and recurring requirements. These extracted signals can then be organized into a prioritization framework. Such an approach is consistent with the broader development of AI-supported quality and product-management systems, in which customer requirements are systematically connected with product improvement activities. AI-enabled quality-management frameworks have been proposed as mechanisms for integrating intelligent analytics into broader business-excellence processes (Reginald, 2026).

The connection between customer reviews and structured product-development decisions is particularly relevant to Quality Function Deployment (QFD). Traditional QFD provides a systematic approach for translating customer requirements into technical and product-development considerations. AI-enabled QFD can extend this concept by using automated analytical methods to process larger quantities of customer information. Recent research has examined AI-driven QFD for product-service systems, demonstrating the potential for intelligent approaches to support the transformation of customer-oriented information into structured quality and development decisions (Salvatori et al., 2026). In the context of the study, customer-review analytics can therefore be regarded as an upstream information source that may subsequently support feature prioritization and product-development planning.

The findings should nevertheless be interpreted within the scope of the available analysis. The descriptive results establish review distributions, textual characteristics, and record completeness, but they do not independently demonstrate causal relationships between customer feedback and product success. The review frequency does not necessarily represent customer preference, and textual length does not necessarily indicate the importance of a product feature. Future analytical stages should therefore combine review frequency with NLP-based feature extraction, sentiment or opinion analysis, and appropriate prioritization criteria before making product-development recommendations.

The study supports the usefulness of customer-generated reviews as an empirical foundation for AI-enabled product analytics. The substantial review corpus, differences in category-level textual characteristics, and high record completeness provide a suitable basis for more advanced analysis. The findings suggest that AI can help organizations move from simply collecting customer feedback toward systematically interpreting customer-generated evidence and connecting it with product decisions. When combined with appropriate product-management processes and quality-oriented frameworks, such analysis can contribute to a more structured approach to customer-centric feature prioritization and product development.

## 5. Conclusion

This study highlights the potential of AI-enabled product analytics for transforming customer-generated reviews into structured information that can support customer-centric product development. Analysis of the Turkish User Reviews dataset identified 37,036 non-empty customer reviews distributed across eight product categories: Computer, Tea Machine, Headphones, Modem, Perfume, Mobile Phone, Television, and USB. The distribution of reviews varied substantially between categories, demonstrating that customer-generated information is not evenly represented across product domains. Differences in review length were also observed, with customers providing varying levels of textual detail depending on the product category. These variations indicate that customer reviews contain heterogeneous information that can provide a useful foundation for product-oriented analysis. The assessment of record completeness further demonstrated that the dataset was highly consistent, with 99.97% completeness across category-level records. A total of 12 blank records were identified, comprising seven records in the Modem category and five records in the Perfume category, and these were excluded from textual calculations. These findings establish a reliable descriptive foundation for subsequent AI and natural language processing applications. By systematically analyzing customer-generated text, organizations can identify recurring product characteristics, customer concerns, and areas requiring further investigation. The study therefore supports the development of data-driven approaches for customer-centric feature prioritization and product development. Future studies can extend this framework through automated feature extraction, sentiment analysis, topic modeling, and quantitative feature-prioritization methods to translate customer feedback into more specific and actionable product-development decisions.

## References

1. Abdullah, M. S., & Hasan, R. (2023). AI-driven insights for product marketing: Enhancing customer experience and refining market segmentation. *American Journal of Interdisciplinary Studies*, 4(04), 80-116.
2. Adhikari, A. (2026). Artificial Intelligence in Product Management. In *Strategic Product Management: A Complete Perspective of Strategizing, Developing and Managing Products* (pp. 539-566). Singapore: Springer Nature Singapore.
3. Ashok, P., & Lakshana, S. (2025, July). Harnessing Data Analytics and Machine Learning to Optimize Product Decisions and Prioritize Features. In *2025 6th International Conference on Data Intelligence and Cognitive Informatics (ICDICI)* (pp. 210-215). IEEE.
4. Aunugu, D. R. (2025). AI-Powered customer journey optimization: Personalizing user experience in BPM systems. *Partners Universal International Innovation Journal*, 3(3), 49-58.
5. Basnet, P., & Li, L. (2026). Enhancing product and service development through AI-integrated Quality Function Deployment. *Research in Engineering Design*, 37(1), 4.
6. Beiker, S. A., Waidringer, J., & Giri, C. (2025, August). Artificial Intelligence in Product Development and Innovation. In *2025 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA)* (pp. 1-9). IEEE.
7. Burra, R., Wu, T. Y., Chang, K., & Huang, C. F. (2025). AI-Driven Customer Positioning and Perception: Strategies, Challenges and Insights. *Digital Technologies Research and Applications*, 4(2), 96-108.
8. Chaturvedi, R., & Verma, S. (2023). Opportunities and challenges of AI-driven customer service. *Artificial Intelligence in customer service: The next frontier for personalized engagement*, 33-71.
9. Dele-Rotimi, A. O. (2026). Enhancing customer value through artificial intelligence and machine learning: Personalization, big data analytics, and customer experience management. *International Journal of Applied Resilience and Sustainability*, 2(2), 1290-1321.
10. Ejjami, R., & Rahim, N. (2024). Retail 5.0: creating resilient and customer-centric shopping experiences through advanced technologies. *International Journal For Multidisciplinary Research*, 6(4).

11. Ekinci, E., & İlhan Omurca, S. (2022). Turkish user reviews [Data set]. UCI Machine Learning Repository. <https://doi.org/10.24432/C5HK72>
12. Goswami, D. (2022). Harnessing ai-driven business intelligence from customer data. *Review of Applied Science and Technology*, 1(03), 10-63125.
13. Gupta, A. K. (2026). AI-Driven Marketing: Transforming Customer Engagement, Personalization, and Strategic Decision-Making in the Digital Era.
14. Hye, A. (2023). Artificial intelligence in product marketing: Transforming customer experience and market segmentation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 3(1), 132-159.
15. Ikeh, C. O. (2024). AI-powered market segmentation and personalization strategies for enhancing digital product lifecycle management. *International Journal of Research Publication and Reviews*, 6(6), 21107.
16. Inavolu, S. M. (2024). Exploring AI-driven customer service: Evolution, architectures, opportunities, challenges and future directions. *International Journal of Engineering and Advanced Technology*, 13(3), 156-163.
17. Kadapal, R., & More, A. (2024). Data-Driven Product Management Harnessing AI and Analytics to Enhance Business Agility. *Journal Of Public Administration And Management*, 3(6), 1-10.
18. Kalluri, V. S. (2025). AI-Powered CRM Optimization: Transforming Manufacturing Sales and Operations with Predictive Insights. Available at SSRN 5225506.
19. Lopez-Lopez, D., Fondevila-Gascón, J. F., Torres-Peregrina, B. M., & Marco-Simó, J. M. (2026). Aligning stakeholders in AI-enabled customer service: Toward human-centric adoption in electronic marketplaces. *Electronic Markets*, 36(1), 42.
20. Mahajan, S. (2025). Data-Driven Product Strategy: Evaluating the Impact of Data Analytics on Product Success. *JIMS81 International Journal of Information Communication and Computing Technology*, 13(2), 867-879.
21. Mainkar, S. D. (2024, October). Role of Artificial Intelligence in Customer Experience Enhancement: Present Scenario and Future Prospects. In *International Conference On Data Mining And Information Security* (pp. 451-478). Singapore: Springer Nature Singapore.
22. Naveenkumar, N., Rallapalli, S., Sasikala, K., Priya, P. V., Husain, J., & Boopathi, S. (2024). Enhancing consumer behavior and experience through AI-driven insights optimization. In *AI impacts in digital consumer behavior* (pp. 1-35). IGI Global Scientific Publishing.
23. Parker, N., Morris, N., Reed, C., Russell, A., Srinivas, C., & Nishil, S. (2025). Leveraging Generative AI to Transform CRM Workflows and Customer Interaction.
24. Prasad, S., Deshmukh, R., & Narasimha, M. (2025, August). Strategic Product Management Education in the Era of Artificial Intelligence. In *2025 IEEE Technology and Engineering Management Society Conference-Global (TEMSCON Global)* (pp. 1-6). IEEE.
25. Reginald, P. J. (2026). AI-Enabled Quality Management Framework for Achieving Sustainable Business Excellence. *National Journal of Quality, Innovation, and Business Excellence*, 10-19.
26. Salvatori, E., Haber, N., & Tronci, M. (2026). AI-Driven Quality Function Deployment for Product Service Systems: A Comparative Study in the Photovoltaic systems' Sector. *Engineering Management Journal*, 1-18.