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BUSINESS ANALYTICS ON ACTUAL ONLINE PURCHASE: AN APPROACH USING SENTIMENT ANALYSIS BASED ON ONLINE REVIEWS

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ABSTRACT

This paper investigates the relationship between online reviews and online purchase intention, with a focus on the electronic products industry in America. While regression and other analytics are commonly used for such analyses, there is a scarcity of research on the impact of online reviews on actual online purchases in this specific industry. The study uses KDD methodology and Tableau for insights, with Python handling data pre-processing and building a sentiment predictive model using both unsupervised and supervised techniques. The findings highlight that review quantity significantly influences actual online purchases compared to other online review elements. Bernoulli Naïve Bayes model performed well in predicting the online review sentiments towards the actual purchase (62.54%). Logistic Regression well classified the sentiment of online reviews polarity with minor errors (85.46%). Positive online reviews greatly impact Amazon purchases, especially for electronics. Sentiment analysis is crucial for businesses to grasp market trends and consumer needs, guiding effective marketing strategies. Utilizing the HEARD technique enhances sentiment analysis, boosting brand awareness, popularity, and online business revenue.

Keywords: Online Reviews; Actual Online Purchase; Purchase Intention; Sentiment Analysis; Big Data; Machine Learning.

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INTRODUCTION

In the era of digital transformation, the internet, a technology used by 5.2 billion people globally (Internet World Stats, 2021a), plays a pivotal role. America boasts 1 billion internet users, with 9.6% from Latin America and 6.3% from North America (Internet World Stats, 2021b). Urban (2015) and CIA World Factbook (2018) reveal that 71% of American consumers, encompassing digital immigrants and natives, rely extensively on the internet. Amazon, the leading e-commerce platform, recorded a staggering $263 billion in annual net sales in 2020 (Statista, 2021). Valera (2018) and Chinabrands (2019) note that electronic products dominated these sales. The internet's omnipotence enables users to swiftly gather information and make online purchases, a phenomenon explored by Middlebrook (2015) and Stankevich (2017).

Understanding purchase intention is crucial for businesses, with online shopping carts acting as valuable tools (Serrano, 2019). Close and Kukar-Kinney (2010) emphasize the significance of products in the shopping cart. However, the Baymard Institute (2019) reports a rising shopping abandonment rate, reaching 68% annually, impacting over 69% of online businesses in 2019. Online reviews, crucial for pre-purchase decisions, are heavily relied upon by consumers. Murphy (2018) highlights that 86% of American online consumers trust local businesses after reading over 10 reviews. Factors such as length, recentness, polarity, volume, and sentiment influence decision-making (Murphy, 2018). Zhen Li and Shimizu (2018) suggest that analyzing online review aspects can offer insights into market trends and aid in formulating marketing strategies.

Given the inconsistency between review polarity and star ratings, sentiment analysis emerges as a crucial method. This paper seeks to explore the effectiveness of online reviews on actual online purchases, particularly in the realm of electronic products. The subsequent sections delve into related works, methodology, results, findings, and conclusion.

RELATED WORKS

Actual Online Purchase

According to Ajzen (1985, 1991), the process of purchasing a desired product online, termed an "actual purchase," mirrors traditional in-store purchases but occurs through the internet. Analyzing actual purchase data, as suggested by Ismail and Mokhtar (2016), proves valuable for understanding market trends, evaluating consumer behavior, assessing satisfaction, and formulating effective marketing strategies.

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Perceived risks, encompassing brand reputation, customer services, transaction security, and trust in the product or seller, significantly influence consumers' pre-purchase and actual purchase decisions (Cheng et al., 2012; Indiani et al., 2015). Ismail and Mokhtar (2015) highlighted a positive and significant correlation between online purchase intention and actual purchase, emphasizing the importance of aligning perceived risk with consumer acceptance levels for successful sales.

D'Alessandro et al. (2012) and Shareef et al. (2013) demonstrated the predictability of actual purchases through online purchase intention. In the herbal product industry, online reviews emerge as a critical factor influencing Malaysians' actual purchase decisions (Rezai et al., 2013; Ismail and Mokhtar, 2015). However, Thongpapanl and Ashraf (2011) and Hashjin et al. (2014) presented contrasting findings, indicating minor effects or imperfect utilization of online purchase intention in predicting actual purchases. Additionally, Brown et al. (2009) asserted that attitudes wield a greater impact on actual purchases than online purchase intentions.

Online Reviews

Electronic word of mouth (eWOM) stands out as a rapid and cost-free means of disseminating information on the internet (Sutanto & Aprianingsih, 2016). Comparative analyses by Sutanto and Aprianingsih (2016) indicated that eWOM exerts more significant influence than traditional word of mouth. Sung et al. (2015) emphasized that online reviews, shaped by consumers' past experiences with a product, surpass company-provided reviews in persuasiveness and trustworthiness.

In the realm of online review studies focused on purchase behavior, researchers commonly assessed elements such as quality, valence, length, credibility, quantity, and recentness (Sung et al., 2015; Utrillas, 2016; Fan et al., 2017; Zhen Li & Shimizu, 2018). The escalating volume of data has led to increased automation and a greater reliance on descriptive and predictive analytics. Fan et al. (2017) demonstrated that sentiment analysis, specifically using the Boss Model, significantly enhances the accuracy of predicting automobile sales within a condensed timeframe, especially when dealing with vast datasets. Sung et al. (2015) further asserted that review valence, length, quality, and quantity exhibit a noteworthy correlation with book sales in Korea.

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Review Timeliness

Several studies emphasized the importance of review timeliness in influencing consumer decisions. Somohardjo (2017) defined review timeliness as the timing of posted online reviews. Zhao et al. (2015) argued that the latest online reviews provide up-to-date information to readers, while Sa'ait et al. (2016) found that referring to outdated reviews can lead to confusion and poor decisions among online consumers. Contrarily, Madu and Madu (2002) contended that outdated reviews deliver invalid and unreliable references.

In specific contexts, Sung et al. (2015) discovered a significant positive correlation between online book reviews posted within the first six months after publication and book sales in Korea. Similarly, Zhao et al. (2015) found that many updated online reviews positively correlate with hotel booking intention in China. Hu et al. (2008) and Jin et al. (2014) supported these findings, highlighting that 60% of actual purchases and intentions are influenced by updated reviews, thereby increasing consumer attention, and indirectly impacting sales. Additionally, Jin et al. (2014) and Cheong et al. (2019) argued that updated reviews offer more critical, reliable, and informative information than older reviews.

However, Pan and Zhang (2011) found that online consumers commonly used outdated reviews to assess product performance and quality. Cheung et al. (2008) discovered that Hong Kong consumers prioritize relevant and comprehensive online reviews for restaurant and food selection over review timing. Somohardjo (2017) concluded that Dutch consumers do not evaluate restaurants based on review timeliness, as this element has a negative relationship but is insignificant toward booking intention.

In summary, while numerous studies focus on review timeliness and its impact on purchase intention, few explore its influence on actual online purchases, especially for electronic products in the United States.

Review Length

Online consumers often assume that shorter reviews provide less information about a product compared to longer ones. Sung et al. (2015) discovered that online reviews containing fewer than 40 words had a diminished impact on book sales in Korea. Conversely, reviews spanning 100 to 500 words were found to offer meaningful and abundant information for purchase decisions. Chevalier and Mayzlin (2006), found that longer reviews had a lesser impact on actual purchases, as consumers were more inclined to read shorter reviews. Research by Bone (1995) and Chatterjee (2001) revealed that the length of reviews did not influence restaurant booking intentions in the Netherlands and showed insignificant correlation. In summary, the influence of review length on online purchases varies across countries, cultures, and backgrounds, emphasizing the dynamic nature of purchase patterns and review evaluations.

Review Quantity

According to Zhao et al. (2015), review quantity, defined as the number of online reviews, serves as a metric for assessing the popularity and trendiness of goods or services (Davis and Khazanchi, 2008; Tsao et al., 2015). Fu et al. (2011) and Cui et al. (2012) discovered that positive online reviews significantly influence the sales of experience products, as opposed to search products. A substantial volume of similar online reviews has a persuasive impact on consumer purchasing decisions (Huyen and Costello, 2017), as supported by Tsao et al. (2015), highlighting the role of review quantity in assessing product or service demand.

Peng (2017) and Zhao et al. (2015) established a positive and significant correlation between review quantity and online hotel booking intentions, though no correlation was found with hotel revenues. Chevalier and Mayzlin (2006) observed a similar pattern in online book sales, where the influence of review quantity on actual consumer purchases depended on the valence of the reviews.

Duan et al. (2008) summarized that the number of movie reviews has a significant and positive relationship with ticket sales. Increased online discussions and reviews lead to higher exposure and awareness, contributing to elevated movie ticket sales. In the electronic products industry, Cui et al. (2012) found that recent electronic product reviews have a more substantial impact on product revenues.

Review Valence

Online reviews, containing subjective information, play a crucial role in influencing consumers' purchase decisions. Positive reviews positively impact, while negative reviews negatively impact, the decision-making process (Ye et al., 2013; Zhen Li & Shimizu, 2018). In the United States electronics market, Cui et al. (2012) emphasized the significant influence of review valence on purchase decisions. Across various industries, a positive and significant correlation exists between review valence, online consumers' purchase intention, and business revenues. This correlation is evident in the automobile industry (Fan et al., 2017), electronic products industry (Cui et al., 2012; Ketelaar et al., 2015), health and beauty industry (Sutanto & Aprianingsih, 2016), hotel industry (Tsao et al., 2015; Peng, 2017; Zhen Li & Shimizu, 2018), and food industry (Somohardjo, 2017).

However, the impact of positive and negative online reviews on consumers' purchase decisions and sales varies inconsistently. Therefore, understanding the specific degree of review valence influencing American consumers' electronic products' online purchases is crucial for contemporary online retailers (Ye et al., 2013; Cui et al., 2012).

Sentiment Analysis

Sentiment analysis plays a crucial role in classifying emotions and predicting subjective information as positive, negative, or neutral. Sasikala and Sheela (2018) emphasized its significance for businesses in understanding consumer emotions and experiences, aiding in the formulation of comprehensive business strategies. Additionally, sentiment analysis is employed in deciphering market trends through text mining techniques such as bag of words, tokenization, and POS tagging, facilitating the classification of online reviews for better decision-making. Polarity detection methods, including supervised, unsupervised, and hybrid approaches, were employed to categorize subjective information into positive or negative categories (Sasikala and Sheela, 2018b). The Negation Phrase Identification algorithm became essential in dealing with fraudulent online reviews that may distort consumers' decision-making processes by identifying words altering the meaning of statements (Fang and Zhan, 2015).

Various classification algorithms like Support Vector Machine (SVM), Sequential Minimal Optimization, Naive Bayes (NB), Decision Trees (DT), and Logistic Regression (LR) are employed for sentiment analysis. SVM, according to Fang and Chen (2011), demonstrated superior accuracy in sentiment analysis. Naive Bayes and Logistic Regression models are commonly used for large datasets (Sasikala and Sheela, 2018b; Singh and Kaur, 2015). Multinomial Naive Bayes was highlighted as a better classifier for discrete counting in text documents and dictionary development (Ray, 2017). Logistic Regression (LR) was praised for its binary output representation and s-shaped graph (Gandhi, 2018).

Safrin et al. (2017) conducted sentiment analysis on DVD player online reviews, achieving accuracy, precision and recall values were 90.47%, 87% and 90% respectively. They found that the use of POS tagging and Negation Phrase Identification algorithms maximized word classification performance. While SVM performed lower than Artificial Neural Networks

(ANN) in some cases (Zheng et al., 2013), it was generally supported as a superior classifier. In the food industry, Logistic Regression outperformed Multinomial Naive Bayes (MNB) and Bernoulli Naive Bayes (BNB) in terms of accuracy (Sasikala and Sheela, 2018b).

Text mining techniques are crucial for improving predictive accuracy and reducing errors in sentiment analysis, especially when reviews may begin with negative words despite conveying a positive overall sentiment towards products or services. Overall, sentiment analysis proves indispensable in deciphering consumer sentiments and guiding strategic decision-making for businesses.

Table 1. Summary of Past Research Results

Papers	Classification Algorithms	Accuracy (%)
Sasikala and Sheela (2018)	MNB BNB LR	92.90 92.40 93.30
Elmurngi and Gherbi (2018)	NB DT LR SVM	80.61 81.45 81.61 80.90
Singh and Kaur (2015)	MNB	94.97
Zheng, et al (2013)	ANN SVM with sigmoid function SVM with radial basis function	93.13 54.00 53.89
Fang and Chen (2011)	SVM	78.00

METHODOLOGY

According to Panke (2018), the philosophical worldviews component encompasses constructivism, postpositivism, advocacy, and pragmatism. Among these beliefs, the pragmatic approach, characterized by its incorporation of mixed methods, emerges as the most suitable for seamlessly integrating quantitative and qualitative approaches, utilizing diverse methods, procedures, and techniques to effectively fulfill the objectives of the paper. Panke (2018)

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emphasizes that the pragmatic approach not only prioritizes methodological applications but also comprehensively grasps research problems through diverse perspectives. Considering this, the correlation examination between online reviews and actual purchases necessitates a deductive approach, while sentiment analysis using online reviews calls for an inductive approach. Hence, the design component of the pragmatic approach aligns seamlessly with these requirements.

Conceptual Framework

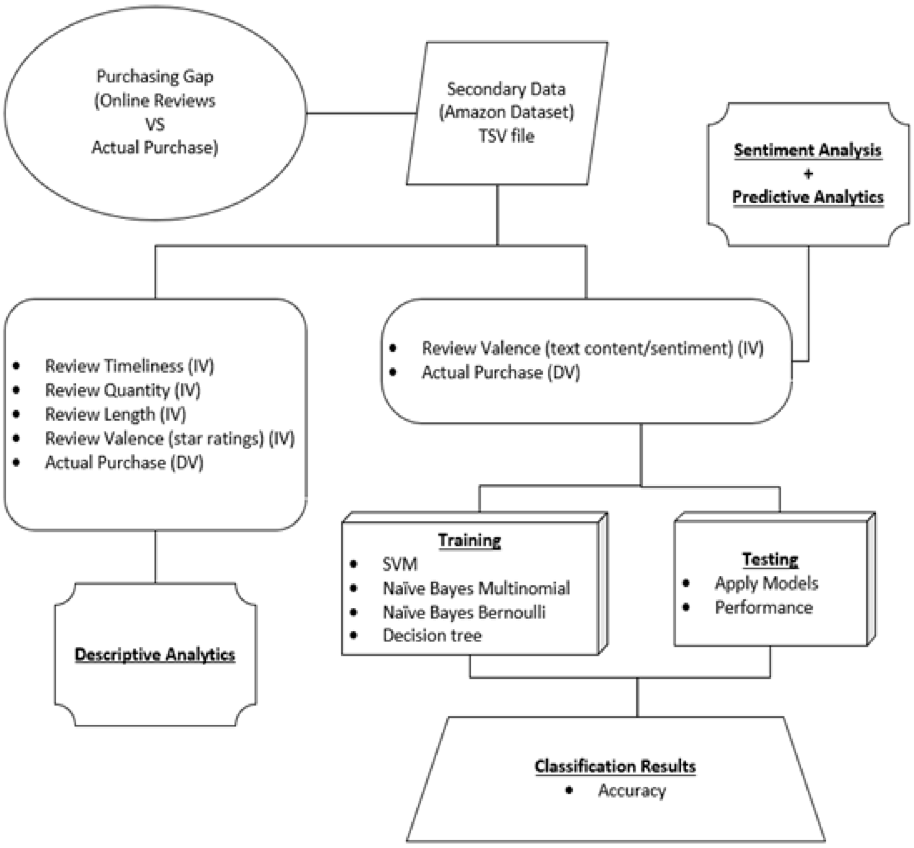

Figure 1. Conceptual Framework

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Data

The Amazon shopping platform serves as a vast online marketplace, particularly prominent in countries across the Americas. According to Statista (2021), Amazon United States stands out as the leading online marketplace, commanding the highest net sales and market share percentages. The dataset used in this study was sourced from the open-access Amazon website and comprises 15 fields and 3,093,869 records. Refer to Table II for a concise summary of the data specifics.

Table 2. Variable Explanatio

Name of Variable	Description	Data Type	Sample Data
marketplace	Country code of the marketplace	character	US
customer_id	Unique ID for Amazon user	number	41409413
review_id	Unique ID for each online review	character	R2MTG1GCZLR2DK
product_id	Unique ID for each product	character	B00428R89M
product_parent	Unique ID for the same product	number	112201306
product_title	Product name	character	yoomall 5M Antenna WIFI RP-SMA
product_category	Category of the product	character	Electronics
star_rating	Rating ranges from 1 to 5	number	5
helpful_votes	The vote for each review (0 or 1)	number	0
total_votes	Total number of votes received	number	380
vine	Review under Vine Program (N or Y)	character	N
verification_purchase	Verified purchase on the reviews (N or Y)	character	Y
review_headline	Review title	character	Five Stars
review_body	Review content	character	It works as advertising.
review_date	Date posted reviews	date	8/31/2015

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Data Analysis

Data preprocessing is a pivotal step in any data analytics undertaking. The complete preprocessing procedures were executed through the Tableau Prep Builder tool. For descriptive analytics and the creation of a compelling dashboard, the Tableau Desktop tool was employed. Additionally, predictive analytics was conducted using Python, leveraging appropriate libraries for constructing Logistic Regression, SVM, Naive Bayes (Multinomial and Bernoulli), and Decision Tree models. The model development process was augmented by techniques such as stop words removal, tokenization, n-grams, and TFIDF utilizing the Natural Language Toolkit (NLTK). The predictive machine learning models underwent evaluation using pertinent performance metrics, including accuracy, recall, precision, and F1 Score, in conjunction with AUC and ROC values.

DATA PROCESSING, ANALYSIS AND RESULTS

Data Understanding and Sampling

An Exploratory Data Analysis (EDA) was conducted to comprehensively assess and determine the appropriateness of the data for the project at hand. The dataset encompasses 15 fields, encompassing both continuous and categorical variables. Through a meticulous process, six fields were excluded from the analysis, four underwent essential pre-processing, while the remaining five fields were retained in their original state. To manage the considerable volume of data, Random Sampling was employed, strategically selecting a subset to facilitate more streamlined analytics, given the overall dataset size of three million records.

Data Cleaning and Processing

The pre-processing of a data sample containing nine fields and spanning 645,000 observations was carried out. Initially, the date range was restricted to January 1, 2011, to January 1, 2016, resulting in a reduction of total observations to 554,000. Subsequently, various cleaning actions were performed, including standardizing word case, removing punctuation, and eliminating null values. Specifically addressing the "product_title" field, a grouping action was applied to reduce the number of unique values. The pronunciation grouping function utilized the Metaphone3 algorithm to group similar words, employing a key-based grouping approach. Conversely, the Spelling grouping function employed the Levenshtein distance to measure the similarity

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between two strings, functioning as a distance-based grouping method. The edit operation encompassed deletion, insertion, and substitution.

In a study conducted by Badi and Kaur in 2019, a hybrid grouping method was proposed as a combination of spelling and pronunciation to optimize accuracy and reduce computation duration. The research compared this hybrid approach with two other methods, namely Levenshtein Distance and Metaphone3, using a visual representation in Figure 2. The results indicated that while the accuracy of the Hybrid method was slightly lower than that of Levenshtein Distance, its overall performance was superior. Consequently, the researchers opted to use the Hybrid method for subsequent processing (Badi and Kaur, 2019).

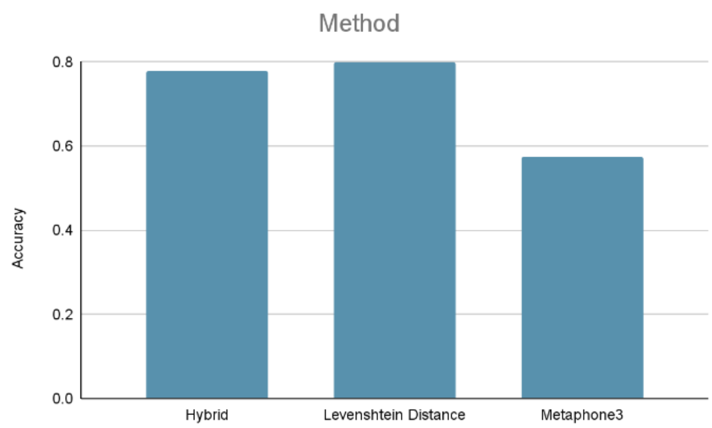

Figure 2. First Comparison between Hybrid, Levenshtein Distance and Metaphone3 (Badi and Kaur, 2019)

Approximately 79% of the distinct values within the product_title field were consolidated into a sub-category. However, despite the high consolidation rate, the total number of unique values remained significant. Consequently, a manual grouping process was undertaken, resulting in the identification of 12 categories associated with related product_titles.

Descriptive Analytics

Descriptive analytics was applied through the creation of a well-designed dashboard, presenting a comprehensive overview of online reviews for electronic products.

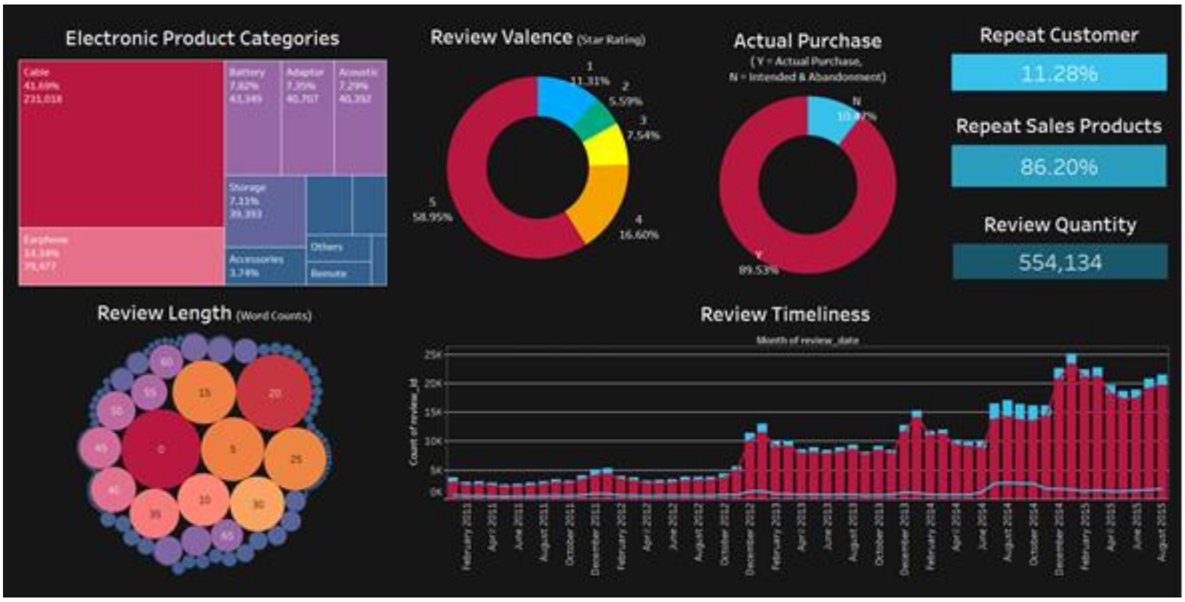

Figure 3. Dashboard

The data presented in Figure 3 indicates that cables are the top-selling electronic product on Amazon, constituting 41.69% of total sales, followed by earphones, batteries, adaptors, and acoustics. This suggests that low-cost and substitutable electronic products have higher sales compared to more expensive and less frequently changed items like machines, laptops, cameras, and mobile phones. The paper focuses on the top three selling electronic products, revealing that over 50% of Amazon users were satisfied with their purchases, giving five/four-star ratings. However, 16.9% of users expressed dissatisfaction, assigning one/two-star ratings to the electronic products.

Approximately 10.47% of Amazon users write online reviews even if they don't complete the purchase of electronic products. The data also reveals that 11.28% of users make repeat purchases, contributing to 86.20% of repeat sales products, and a total of 554,134 reviews. Additionally, 85% of popular electronic products on Amazon are purchased by multiple users, emphasizing the widespread popularity of certain product types on the platform.

The review length with five words in a bin was illustrated where seven bins were highlighted which include 0 (0 - 4 words), 20 (20 - 24 words), 5 (5 - 9 words), 15 (15 - 19 words), 25 (25 - 29 words), 30 (30 - 34 words) and 10 (10 - 14 words). Amazon users commonly write comments within these specified word ranges, each accounting for at least 5% of the total. Examining the timeline and monthly review creation, it was observed that the number of online

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reviews is consistently growing annually. Notably, December and January stand out as turning points, marked by a significant increase in both online reviews and sales.

Correlation Map

The study utilized a correlation map to assess the impact of various elements in online reviews on the actual online purchase behavior of American consumers for electronic products. The primary focus was on the target variable of actual online purchase, with independent variables including review quality, review length, review timeliness, and review valence. Certain transformations were applied, such as converting star ratings (float64), review dates (date), and review content (string) to integers. Descriptive analytics revealed predominantly positive online reviews, prompting the use of under-sampling to prevent biased results.

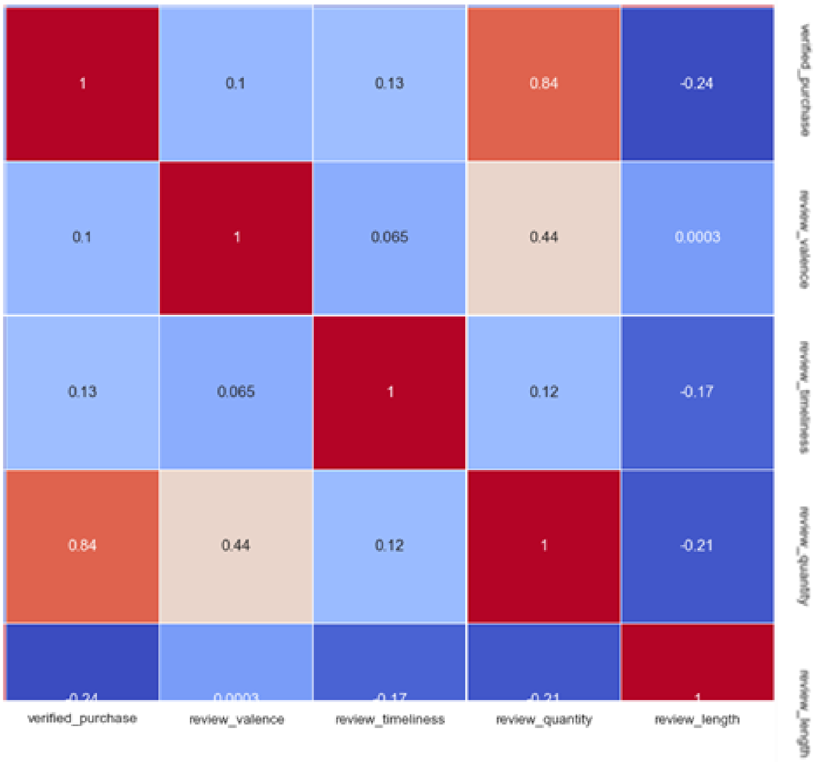

Figure 4. Correlation Map Output

The key factor influencing the actual online purchase of electronic products among American consumers on Amazon is the quantity of online reviews, showing a strong positive relationship (0.84). The second most impactful element is the length of reviews, albeit with a

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negative relationship (-0.24). Following this, review timeliness (0.13) and review valence (0.1) also play a role in influencing consumer purchases. These results suggest a crowd mentality phenomenon, indicating that a higher number of reviews contribute to increased product awareness and popularity, leading to a higher likelihood of actual purchases.

Predictive Analytics

The section focuses on sentiment prediction for electronic product reviews on the Amazon platform among American consumers, utilizing Support Vector Machine (SVM), Naive Bayes (Multinomial and Bernoulli), and Decision Tree algorithms. The "review_body" variable is used for sentiment analysis, and to ensure unbiased predictions, the binary values of the "verified_purchase" variable are balanced, resulting in a reduced dataset of 11 thousand observations. The classification process involves implementing stop words, tokenization, n-grams, and TFIDF to enhance performance. The dataset is split into an 80% training set and a 20% test set. Five models are built and executed to assess accuracy, precision, and recall.

Table 3. Results of the Prediction of Sentiment Review Content towards Actual Online Purchase

Models	Recall	Precision	Accuracy
SVM	65.50%	60.17%	60.52%
Logistic Regression	66.23%	60.18%	60.66%
Multinomial Naive Bayes	68.73%	60.13%	61.04%
Bernoulli Naive Bayes	85.79%	58.97%	62.54%
Decision Tree	67.53%	56.70%	57.39%

Table 3 shows that among various models, Bernoulli Naive Bayes achieved the highest recall rate at 85.79%, indicating superior retrieval performance. Despite Logistic Regression having the highest precision rate at 60.18%, Bernoulli Naive Bayes outperformed in overall accuracy, with a rate of 62.54%, making it the most suitable model for prediction. Additionally,

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Bernoulli Naive Bayes demonstrated the highest Area Under the Curve (AUC-ROC) value at 67%, further supporting its effectiveness in the context of the study.

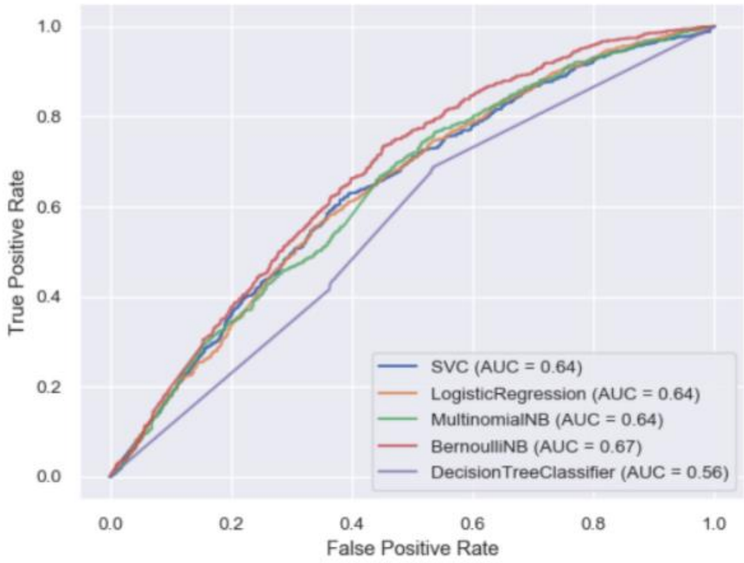

Figure 5. AUC-ROC Results for Review Content (Sentiment) towards Actual Purchase

The project achieved a highest accuracy rate of 62.54% and the highest AUC-ROC value of 67%, which are considered acceptable. While typical model building involves considering three to four factors, this project specifically focuses on the sentiment of online reviews in relation to actual online purchases. The correlation map indicates that review content is not the sole influencing factor; instead, review quantity has the most significant impact on actual purchases. Consequently, the relatively lower percentages for accuracy and AUC-ROC values are justified. Importantly, all models demonstrated good performance as no threshold points fell under incorrectly classified proportions, confirming overall acceptability.

Sentiment Analysis

Researchers aimed to assess the precision of sentiment classification by substituting the target variable with "review_sentiment." They utilized TextBlob to predict whether each review's sentiment was positive or negative. Machine learning models were then constructed and assessed using these sentiment predictions as the target variable, as detailed in Table IV.

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Table 4. Results of the Prediction of Sentiment Review Content towards Review Sentiment

Models	Recall	Precision	Accuracy
SVM	99.67%	85.51%	84.45%
Logistic Regression	99.28%	85.71%	85.46%
Multinomial Naive Bayes	99.83%	84.65%	84.57%
Bernoulli Naive Bayes	92.47%	87.25%	82.23%
Decision Tree	94.52%	86.87%	83.30%

In a comparative analysis of models, Multinomial Naive Bayes demonstrated the highest recall rate at 99.83%, making it the most suitable model with superior retrieval capabilities. The Bernoulli Naive Bayes achieved the highest precision rate of 87.25%. While Logistic Regression showed lower recall and precision, it still yielded an overall accuracy of 85.46% and an AUC-ROC value of 85%.

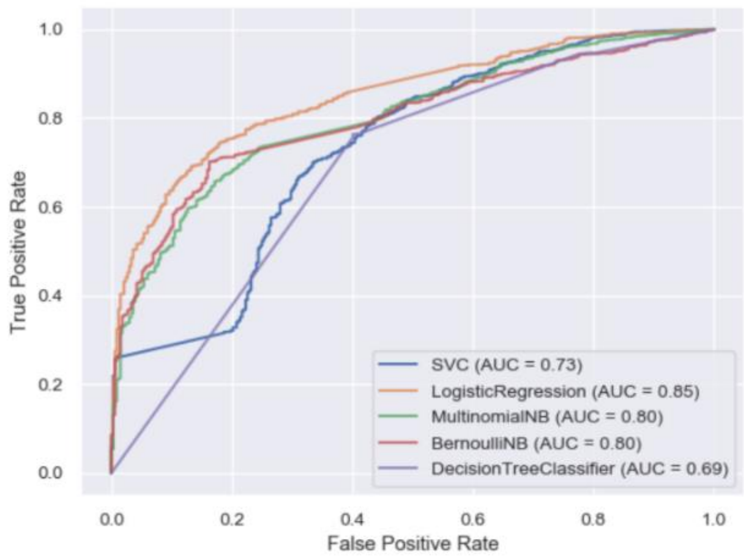

Figure 6. AUC-ROC Results for Review Content towards Review Sentiment

A word cloud analysis was employed to depict the prevalent words in reviews of electronic products on Amazon. The top 5 popular words, including "sound," "good," "TV,"

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"mini," and "love," encapsulate the opinions expressed by customers regarding these electronic products. Figure 7 visually represents the significant terms reflecting customer sentiments.

Figure 7. Word Cloud Output

PROJECT FINDINGS AND CONCLUSION

Overall Findings

The study reveals that several aspects of online reviews significantly influence the online purchase of electronic products. The quantity, length, timeliness, and polarity of reviews play crucial roles. The correlation analysis indicates positive linear relationships between review quantity, timeliness, and valence with actual online purchases, with respective correlation coefficients of 0.84, 0.13, and 0.1. In contrast, review length shows a negative linear relationship with a correlation coefficient of -0.24. In summary, the popularity and influence of electronic products in online purchases are positively correlated with increased discussions about them. Higher numbers of updated reviews on Amazon contribute to the perceived reliability of these products. Positive reviews play a significant role in shaping consumer decisions, while negative reviews receive less attention. Longer reviews provide detailed information for reference, but there is a negative relationship between review length and actual online purchases, as lengthy content may confuse readers with critical information.

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Status of Findings

Review Quantity and Review Valance

In examining both the quantity and sentiment of reviews, a thorough analysis reveals that the prevalence of positive reviews tends to drive a greater number of actual online purchases compared to negative reviews overall. Noteworthy is the finding that around 9.7% of repeat customers have made multiple electronic product purchases, attributing their decisions to positive reviews. In contrast, a mere 1.7% of repeat customers expressed dissatisfaction with product performance or quality, resulting in unfavorable reviews.

Review Timeliness

The analysis of online reviews reveals a consistent annual increase in both positive and negative responses for electronic products. December and January consistently witness a surge in electronic product sales, contributing to record gaps. Common date ranges for specific electronic product categories are January to November and December to August. December to November is considered standard, accounting for products with varying popularity throughout the year. Shopping cart abandonment cases are on the rise annually, with positive reviews tripling and negative reviews doubling since July 2014. Despite fluctuations, the minimum monthly records for positive and negative reviews remain at an average of 1000 and 300, respectively. This suggests active expression of opinions online since 2014.

Review Length

American consumers exhibit specific writing patterns in online reviews based on their post-purchase experiences. Positive reviews tend to range from 0 to 30 words, with common lengths being 0, 5, 20, 25, and 30 words. For negative reviews, consumers typically use 15, 20, or 25 words, occasionally incorporating 0, 5, 10, and 30 words. Interestingly, negative reviews for products not purchased often consist of a minimum of 20 words expressing disapproval. Additionally, consumers who have not bought electronic products may still post positive reviews with similar word lengths as those based on actual purchases. In summary, American consumers commonly use 20 words to convey both positive and negative sentiments in online reviews, particularly for electronic products on platforms like Amazon.

Accuracy for Prediction and Sentiment Analysis

In this project, the Bernoulli Naive Bayes machine learning technique was employed to predict

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sentiment in online purchase reviews. The model's performance was enhanced through tokenization, n-grams, stop-words, and TFIDF. The AUC-ROC curve demonstrated a substantial 67% coverage, bolstering the effectiveness of Bernoulli Naive Bayes. With only one independent variable considered, the accuracy rate was 62.54%, indicating that review content alone does not solely determine electronic product online purchases. Other factors likely contribute to the decision-making process.

Table 5. Overall Summary on Prediction of Sentiment Review Content towards Actual Online Purchase

Model	Accuracy	AUC
SVM	60.52%	64%
Logistic Regression	60.66%	64%
Multinomial Naïve Bayes	61.04%	64%
Bernoulli Naïve Bayes	62.54%	67%
Decision Tree	57.39%	56%

Logistic Regression is a well-trained machine learning technique that is used to predict the review content towards review sentiment which is used to obtain the highest accuracy for the sentiment classification (Sasikala and Sheela, 2018b). In this study, Logistic Regression obtained 85.46% of accuracy with the highest AUC value of 85% than the other models.

Table 6. Overall Summary on the Prediction of Sentiment Review Content towards Review Sentiment

Model	Accuracy	AUC
SVM	85.45%	73%
Logistic Regression	85.46%	85%
Multinomial Naïve Bayes	85.57%	80%
Bernoulli Naïve Bayes	82.23%	80%
Decision Tree	83.30%	69%

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Implication of the project

The number of online reviews significantly influences the purchase decisions of electronic products on Amazon, with factors such as length, recentness, and polarity also playing a role. Businesses can enhance awareness and revenue by emphasizing the importance of maximizing online reviews, particularly positive ones. A key strategy is providing prompt and tactful responses to reviews, especially negative ones, as this encourages consumers to share their experiences and fosters a positive relationship between buyers and sellers. Educating and encouraging consumers to post reviews right after purchase is also crucial for maintaining up-to-date information and monitoring product/service performance. The project suggests that positive reviews are often brief (less than 10 words), while negative ones tend to be more detailed (more than 15 words), providing opportunities for retailers to address issues and improve. Tactfully handling negative reviews is deemed essential to avoid potential damage to business reputation.

Limitations of the project

This project specifically centers around electronic products acquired by American consumers through the Amazon platform. Consequently, the results obtained herein should be considered primarily as references or guidance for related subjects. One key factor is the exclusive focus on a dataset comprising online reviews of electronic products posted by American consumers on the Amazon platform. Additionally, the project concentrated on just four online review elements, limiting its ability to comprehensively assess the impact of these elements on the actual online purchase of electronic products.

Recommendations

Online retailers are advised to promptly respond to all online reviews, particularly negative ones. This not only showcases the retailer's commitment to exceptional after-sales service, prioritizing customer satisfaction over financial gains, but also indirectly enhances the likelihood of garnering support from online users, thereby bolstering business awareness and reputation. According to research, online retailers can glean valuable insights for performance improvement from negative reviews, given that online consumers and reviewers tend to express their dissatisfaction succinctly in 15 to 25 words. Additionally, when crafting responses to negative reviews, retailers must ensure the use of polite, rational language that avoids offending any

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parties, highlighting the importance of tactful handling of such feedback.

Furthermore, online retailers can leverage positive reviews by sharing them on various social media and review platforms, including Google reviews, blogs, and social review platforms. This strategy contributes to building business awareness and reputation, fostering increased discussion, popularity of products or services, and trust in the business. In conclusion, American consumers exhibit a crowd mentality, making positive reviews a powerful tool to maximize business reputation and revenue.

In addition, it is recommended that online retailers regularly monitor their online presence to ensure alignment with business objectives. Utilizing sentiment analysis allows retailers to track market trends based on sentiment, facilitating the formulation of more effective marketing strategies. By employing specific keywords or critical sentiment analysis, online retailers can directly address issues and implement efficient solutions.

Moreover, the HEARD technique, coupled with sentiment analysis, is recommended for all businesses. This technique involves listening to clients (hear), empathizing with customers' situations/perspectives (empathize), apologizing for any shortcomings (apologize), resolving issues effectively (resolve), and diagnosing the root causes of mistakes for prevention (diagnose).

Lastly, online retailers are encouraged to incentivize customers who leave reviews after their initial or subsequent purchases. Encouraging customers to use business hashtags on social media or blogs capitalizes on the potency of electronic Word-of-Mouth (eWOM). This method harnesses the strong marketing potential of online consumers, simultaneously boosting popularity, awareness, and business reputation.

CONCLUSION

In summary, the chosen elements in online reviews exhibit a significant correlation with the actual online purchases of electronic products among American consumers. Additionally, sentiment analysis was employed to anticipate the sentiments expressed in online reviews regarding the actual online purchase of electronic products.

Upon conducting descriptive analytics on review quantity and valence, it was found that 79.26% of online consumers express satisfaction with the performance of electronic products on the Amazon platform. Moreover, 9.7% of online consumers are repeat customers with positive responses, while 1.7% are extremely dissatisfied with the products. Descriptive

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analytics on review length revealed that the most common word count used to convey satisfaction is 20 words. Notably, positive feedback tends to be concise (below 10 words), whereas negative feedback tends to be more extensive (above 20 words). Analyzing review timeliness highlighted December and January as crucial months that significantly boost revenues and set new records.

The results indicate that review valence has the least impact (0.1) on actual online purchases, while review quantity (0.84) has the highest impact, followed by review length (-0.24) and review timeliness (0.13). In essence, a substantial volume of short, positively worded reviews can strongly influence actual online purchases of electronic products on the Amazon platform, showcasing the phenomenon of crowd mentality in identifying American consumer buying behavior.

Bernoulli Naive Bayes emerged as the most effective machine learning classifier for predicting sentiment in online reviews toward actual online purchases. Leveraging tokenization, stopwords removal, n-grams, and TFIDF, it achieved an accuracy rate of 62.54% and an AUC value of 67%, outperforming other classifiers. While these values may not be exceptionally high, further improvement is possible through deeper analysis.

Furthermore, Logistics Regression proved to be the optimal machine learning classifier for predicting sentiment in online reviews. With an accuracy rate of 85.46% and an AUC value of 85%, it outshone other classifiers. Consequently, sentiment analysis stands out as a critical technique for online retailers, enabling them to comprehend market trends and fulfill the needs of online consumers, thereby devising effective marketing strategies. Finally, the HEARD technique, coupled with sentiment analysis, offers a strategic approach to maximize brand awareness, popularity, and revenues for online businesses.

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