RACE: The Role of Anchor Characteristics in E-Commerce Success

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Live streaming technology has created a new career called e-commerce anchors in the ever-changing world of e-commerce. These anchors play an important role in promoting products and promoting e-commerce expertise. This paper examines the precise e-commerce anchor attributes that most successfully influence purchase intentions, including competence, charm, credibility, communication, fame, affinity, and promptness. This paper proposes the role of anchor characteristics in an e-commerce success (RACE) algorithm to identify key characteristics of e-commerce anchors that have a major impact on purchase intention. The results demonstrate that characteristics such as Affinity, Promptness, and Communication have the greatest effects on changing consumer intentions and increasing purchase intentions. This paper highlights the important role of providing practical information on customer behavior, customer engagement, and e-commerce marketers and advertisers in optimizing these attributes for e-commerce success.

Keywords: E-commerce anchors, Product Promotion, Anchor attributes, Purchase Intentions.

1. Introduction

The incorporation of live streaming technologies has resulted in a revolutionary phenomenon in the quickly changing world of e-commerce nowadays: e-commerce anchors [1]. These anchors are essential characters in digital marketing because they use real-time communications to communicate directly with customers, introduce products, and sway their decisions [2]. In contrast to conventional marketing strategies, e-commerce anchors provide a dynamic environment where customers can interact and learn the details about products directly, ask questions, and get prompt feedback, making the purchasing experience more engaging and personalized [3].

E-commerce anchors offer several benefits [4]. First, they serve as a link between virtual and actual retail environments by offering real-time demos that mimic in-store encounters. By providing openness and genuineness, this feature not only increases customer trust but also allays any fears that customers might have about making blind purchases. Additionally, e-commerce anchors help firms connect emotionally with customers and successfully communicate the benefits of their products—which are critical in motivating consumers to make purchases in situations where competition is fierce.

The efficacy of e-commerce anchors in shaping customer behavior is determined by several characteristics [5]. These characteristics comprise competence, which includes the skill to provide data simply and competently; charm, which connects to the anchor's physical attraction; trustworthiness, demonstrating reliability and knowledge in products that are being offered; communication, highlighting the interaction and attentiveness to questions from viewers; fame, demonstrating the anchor's impact and audience reach; affinity, denoting to the anchor's capacity to link with particular consumer groups; and promptness, indicating how quickly and well customer problems are addressed during live encounters.

Although e-commerce anchors are influential, it is still unclear which specific characteristics have the greatest impact on consumer decisions. This paper tackles the primary issue of discovering and ranking the characteristics of e-commerce anchors that have the greatest impact on customer behavior.

This paper proposes the Role of Anchor Characteristics in E-commerce Success (RACE) algorithm to address this problem. An analysis of a dataset comprising e-commerce anchor characteristics and their effect on purchase intentions is conducted using the RACE algorithm. The RACE algorithm uses rigorous statistical approaches including classifier evaluation and correlation analysis to determine which characteristics have the greatest influence on consumers' perceptions of e-commerce anchoring.

The main contribution of this paper is a thorough investigation of how different characteristics of e-commerce anchors influence customer behavior. By clarifying the roles of characteristics, this paper provides practical suggestions for e-commerce anchors to improve these important characteristics and improve buying intentions. In the end, the results should guide strategic choices meant to optimize e-commerce anchors' capacity to propel e-commerce success.

This paper seeks to provide a thorough understanding of the processes by which e-commerce anchors influence consumer behavior. This facilitates better judgment in using e-commerce anchors within techniques for digital marketing. E-commerce sites and marketers want to effectively use live-streaming technology to increase customer engagement and gain a competitive edge in the e-commerce industry.

This paper is organized as follows: Section 2 analyses related works on the developing characteristics of e-commerce anchors and their influence on customer behavior. The methodology for feature selection and analysis using the RACE algorithm is described in Section 3. Section 4 showcases the empirical results, accompanied by an analysis of the impact of selected anchor characteristics on purchase intention. The paper is finally concluded in Section 5, which summarizes important findings and suggests directions for further research in the quickly developing subject of e-commerce marketing.

2. Related works

The incorporation of live-streaming technology into e-commerce has transformed online shopping experiences by allowing real-time communications between vendors and buyers. This technical advancement has resulted in the rise of e-commerce anchors, who serve as real-time broadcasters who explain products, engage with audiences, and influence buying decisions. Prior research has emphasized the favorable effect of live streaming on customer pleasure and confidence. For example,

Wang et al. [6] investigate how different communication tactics employed by e-commerce anchors impact customers' recurrence buying intents. The study classifies tactics such as tailored suggestions and captivating narratives, analyzing their impact on customer engagement measures like length of viewing, live chat involvement, and overall fulfillment. Using a combination of quantitative and qualitative approaches comprising surveys and data interpretation, the authors detect important factors driving recurring purchases, highlighting faithfulness and perceived value.

Zhang et al. [7] debated that live streaming is changing e-commerce and impacting customer behavior. They concentrate on the psychological strategies used by Taobao Live anchors to incite impulsive purchasing. These strategies comprise generating directed shopping knowledge, employing supplementary products to enhance the attractiveness of the main product, providing temporary discounts, using anchoring bias to establish a price reference point, and establishing credibility to earn the confidence of viewers.

Li et al. [8] investigate the emerging trend of live-streaming e-commerce in China, prioritizing well-known anchor Li Jiaqi. They gather and examine speech information from Li's live broadcasts creating a speech-to-text corpus, using phonetic analytics, application of linguistic units, and rhetorical methods based on phonetic principles, Corpus Linguistics, and Natural Language Processing. Their hypothesis indicates that linguistic characteristics present in these broadcasts impact on consumer buying intentions, which they authenticate via surveys using questionnaires, emphasizing the significance of the anchor speech on customer behavior in this new business strategy.

Dang et al. [9] examined the influence of e-commerce anchors on customers' instinctive purchasing behaviors. Emphasizing live streaming e-commerce, the authors investigate how dynamic data given by e-commerce anchors impacts consumer emotions related to loneliness and the flow experience, which subsequently affects instinct purchasing. Their survey of 466 customers in China indicates substantial inverse relationships between customer loneliness and the dynamism of e-commerce anchor data sources and strong positive relationships with customer flow. They additionally discover adverse associations between lonely and impulsive purchases and favorable connections between flow and impulsive purchases. These results recommend consequences for the business concerning the efficient usage of e-commerce anchors to improve customer engagement and buying behavior.

Chen et al. [10] centered on the new tendency of leading anchor live streaming in e-commerce, highlighting its role in raising customer buying fulfillment by prompt communication with influencers. The study targeted customers who are happy with the merchandise permitted by leading e-commerce anchors, utilizing quantitative techniques.

Using ideas of perceived value, perceptual engagement, perceived excellence, presence in society, and experiential value, the study examined how high-end anchor e-commerce operations affect customer opinions and customer pleasure, thus discovering the fundamental methods underlying this occurrence.

Chen et al. [11] investigate how viewers' purchasing decisions are greatly influenced by anchors in the live-streaming business. They reviewed the literature to determine the essential personality traits of anchors, like charisma, popularity, competence, and interpersonal abilities. These characteristics favorably affect consumer views, thereby influencing decisions about what to buy. The purpose of the study is to offer live-streaming businesses information to improve anchor training techniques and develop plans that enhance customer satisfaction and eventually boost business profitability in the competitive world of live-streaming.

Peng [12] examines the use of AI-powered virtual anchors in real-time e-commerce broadcasts that impact the desire of people to make purchases. Utilizing a structure of perceived value ideas, they polled 307 people for their survey and used SPSS analytics to pinpoint important elements. According to their research, consumers' perceptions of virtual anchoring significantly affect consumers' desire to buy, frequently mediated by advantages perceived. The study shows that the main factor influencing the intention to buy is the language competence of virtual anchors via the mediation of apparent advantages, however, these impacts are mitigated by their conformity to product categories and level of expertise.

Qi et al. [13] investigate how consumer behavior is influenced by anchor traits such as competence, involvement, appearance, and credibility during live broadcasts for e-commerce. Using the Stimulus-Organism-Response (SOR) approach, they determine that the flow experience and customer's perception value are important mediators. Their results highlight how improving these traits can successfully keep clients in settings for live broadcasting, build a loyal consumer base, and make marketing tactics more effective for long-term interaction and successful results in e-commerce environments.

Wen et al. [14] analyzed how customers' intent to buy on international live-streaming e-commerce sites is influenced by the fame of internet celebrity anchors. Their research combined early trust theory and the Technology Acceptance Model (TAM), using the moderator of gender. By utilizing regression techniques and structural equation modeling, they discovered that customers' purchasing behavior is significantly influenced by the reputation of internet celebrity anchors. Initial trust plays a partial mediator in this relationship, accounting for 73.59% of the overall influence. It was also shown that the relationship between initial trust and intentions to buy was moderated by gender.

Chen et al. [15] explored how anchor attributes use the SOR method to impact buy desires in TikTok E-commerce live broadcasts in China. They discovered that characteristics like fame, competence, and product participation have a positive influence on perceived trust and playfulness among Chinese TikTok users, thus increasing their desire to make purchases. These revelations aid in the comprehension of online marketing tactics and emphasize the applicability of the SOR method to live broadcasts of e-commerce on sites like TikTok.

Despite the wealth of study regarding the function and consequences of e-commerce anchors, there is a significant research gap in the methodical identification and prioritization of the particular characteristics that most strongly affect buying decisions. Previous research has frequently concentrated on a single characteristic alone or offered qualitative findings without doing a thorough quantitative study. This gap emphasizes the necessity of a strong technological method to ascertain the relative significance of different e-commerce anchor characteristics.

To address this gap, the RACE algorithm is presented as an innovative approach to feature selection within the realm of e-commerce. The RACE algorithm incorporates various feature selection techniques, such as Chi-Squared attribute evaluation, ReliefF attribute evaluation, and Gain Ratio attribute evaluation. This broad strategy enables a methodical ranking of e-commerce anchor characteristics, giving a clear picture of the characteristics that have the biggest influence on customers' intentions to make purchases.

The utilization of the RACE algorithm in this paper aims to offer practical insights for e-commerce anchors. By figuring out the essential characteristics that influence customer engagement and purchasing choices, the results will guide tactics to maximize e-commerce anchors' efficacy, eventually improving customer experiences and promoting the development of e-commerce.

3. Methodology

This section delineates the methods utilized in discerning the pivotal characteristics of e-commerce anchors that impact customer buying behavior. The paper employs the Role of anchor characteristics in an e-commerce success (RACE) algorithm to methodically assess characteristics like competence, charm, credibility, communication, fame, affinity, and promptness, drawn from an extensive dataset that was acquired from Taobao, a significant e-commerce site in China. Utilizing RACE, the methodology involves a thorough preparation of the data, succeeded by feature selection by Chi-Squared, ReliefF, and Gain Ratio. By combining the outcomes of these techniques, the study calculates average rankings to identify the most influential characteristics. These findings aim to enable e-commerce anchors with doable tactics to enhance customer involvement and boost purchase intents, thus improving the effectiveness of e-commerce overall.

3.1 Data Gathering

The procedure for gathering data entailed compiling an extensive dataset from Taobao, one of the biggest e-commerce sites in China renowned for having strong live-streaming abilities. This dataset contains thorough e-commerce anchor profiles, concentrating on characteristics that are essential for examining how they affect customer purchase decisions.

The following columns are included in the dataset:

1. ID of Anchor: A distinct number assigned to every e-commerce anchor.
2. Whereabouts: China's geographical location where the anchor functions.
3. Age: The anchor's age.
4. Sex: The anchor's gender (male or female).

5. Years of professional background: The duration of the anchor's e-commerce activity.

6. Competence: Representing the perceived competence of the anchor, rated on a scale from 1 to 5.

7. Charm: Representing how appealing the anchor is to consumers, rated on a scale of 1 to 5.

8. Credibility: Representing the anchor's honesty and trustworthiness, Rated on a scale of 1 to 5.

9. Communication: Representing the degree of communication the anchor keeps with viewers, Rated on a scale of 1 to 5.

10. Fame: Quantity of followers the anchor has on Taobao.

11. Affinity: Representing the anchor's affinity, Rated on a scale of 1 to 5.

12. Promptness: Average promptness rating to evaluate the anchor's responsiveness and efficiency in answering questions or comments from viewers, rated on a scale of 1 to 5.

13. Intention to Purchase: Average customer intention rating to buy goods that the anchor promotes.

The dataset's sample entries are shown here:

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ID of Anchor, Whereabouts, Age, Sex, Years of professional background, Competence, Charm, Credibility, Communication, Fame, Affinity, Promptness, Intention to Purchase

1, Shanghai, 38, Female, 4, 3, 4, 4, 5, 12000, 5, 4, 3.6

2, Beijing, 22, Male, 4, 2, 5, 3, 4, 19000, 4, 5, 3.4

3, Guangzhou, 36, Female, 3, 4, 4, 4, 4, 20000, 4, 5, 3.9

4, Chengdu, 20, Male, 5, 5, 4, 4, 3, 13000, 4, 4, 4.2

5, Shenzhen, 37, Female, 4, 4, 5, 5, 4, 19000, 5, 4, 4.9

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The dataset offers a thorough look at e-commerce anchors functioning on Taobao, containing demographic information like years of experience, sex, and age. Additionally, it collects characteristics ratings such as competence, charm, credibility, communication, fame, affinity, and promptness.

For instance, Anchor ID 1 from Shanghai is a 38-year-old female with 4 years of experience, rated 3 for competence, 4 for charm, and credibility, and 5 for communication, with a fame of 12,000 followers. She has an affinity rating of 5 and has a promptness rating of 4 and a purchase intention rating of 3.6. These characteristics are vital for comprehension of their impact on customer buying intentions while live-streaming.

3.2 System Architecture

The system architecture for the RACE algorithm to determine important characteristics of e-commerce anchors begins with entering the data set, removing demographic characteristics such as the ID of Anchor, whereabouts, Age, Sex, and Years of professional background. Missing values are managed utilizing hybrid regression imputation using Random Forest and Multilayer perceptron, and numerical features are normalized using Min-Max normalization. The class label is set to “Intention to Purchase”. Three feature selection techniques are applied: Chi-Squared Attribute Evaluation, ReliefF Attribute Evaluation, and Gain Ratio Attribute Evaluation. These techniques' rankings are averaged, and the top K features with the largest influence on decisions made about purchases are chosen. The final result detects these top K important features (characteristics) for e-commerce anchors on the Taobao platform. Figure 1 shows the system architecture of the RACE algorithm.

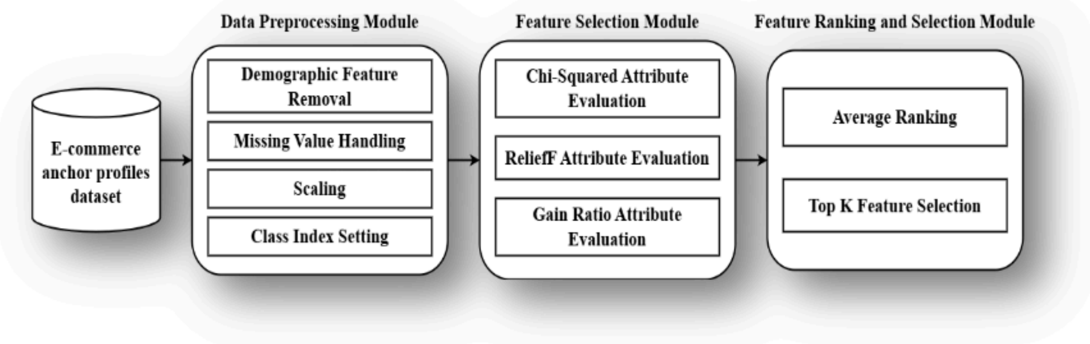

Figure 1: System architecture of the RACE algorithm

3.3 Implementation of RACE algorithm

The RACE Algorithm identifies the top K characteristics of e-commerce anchors that most strongly impact consumers' choice to buy. First, it eliminates non-relevant demographic characteristics and addresses missing data by hybrid regression imputation. Normalized numerical features are used to guarantee uniformity, and feature selection methods like Chi-Squared, ReliefF, and Gain Ratio are utilized to rank features. The algorithm chooses the top K features using their average rank across evaluation techniques, offering perceptions into which features have the biggest influence on buying decisions in e-commerce situations. Algorithm 1 shows the RACE algorithm.

Algorithm 1: RACE		
Input	:	Dataset (D)
Output	:	Top K features
Step 1	:	Exclude Demographic Attributes: • Remove demographic features like ID of Anchor, whereabouts, Age, Sex, and Years of professional background from D.
Step 2	:	Impute Missing Values in D using hybrid regression imputation: • RF_{ij} = Missing values imputation using Random Forest. • MLP_{ij} = Missing values imputation using Multilayer Perceptron. $IMV_{ij} = \frac{RF_{ij} + MLP_{ij}}{2}$ • Where, • RF_{ij} is the imputed value using Random Forest for attribute j in instance i. • MLP_{ij} is the imputed value using MLP for attribute j in instance i. • IMV_{ij} is the average imputed value for attribute j in instance i.
Step 3	:	Scaling using Min-Max Normalization:

$$p'_{ij} = \frac{p_{ij} - \mathrm{Min}}{\mathrm{Max} - \mathrm{Min}}$$

- Where,
- p_{ij} is the original value of attribute j in instance i.
- Min is the minimum value of attribute j.
- Max is the maximum value of attribute j.
- p'_{ij} is the normalized value

Step 4 : Set Class Index:

- Set the feature representing the class label, typically "Intention to Purchase".

Step 5 : Feature Selection Techniques:

- CS_FR = Features ranking using Chi-Squared Attribute Evaluation with Ranker Search.
- RF_FR = Features ranking using ReliefF Attribute Evaluation with Ranker Search.
- GR_FR = Features ranking using Gain Ratio Attribute Evaluation with Ranker Search.

$$\mathrm{AVG\_FR}_j = \frac{\mathrm{CS\_FR}_j + \mathrm{RF\_FR}_j + \mathrm{GR\_FR}_j}{3}$$

- Where,
- $\mathrm{CS\_FR}_j$ is the rank of feature j based on Chi-Squared.
- $\mathrm{RF\_FR}_j$ is the rank of feature j based on ReliefF.
- $\mathrm{GR\_FR}_j$ is the rank of feature j based on the Gain Ratio.
- $\mathrm{AVG\_FR}_j$ is the average rank of feature j.

Step 6 : Select Top K Features:

- Sort features based on their average ranking.
- Return Top K Features.

3.3.1 Random Foret-based Missing Data Imputation

Random Forest-based missing data imputation is an efficient method that successfully handles incomplete datasets by utilizing ensemble learning. This technique includes training numerous decision trees on the complete data, where features with missing values are forecasted using the observed values of other features. The imputation procedure could be denoted as:

$$\widehat{X}_{\mathrm{missing}} = \frac{1}{A}\sum_{a=1}^{A}\widehat{X}^{a}_{\mathrm{missing}} \tag{1}$$

Where $\widehat{X}_{\mathrm{missing}}$ denotes the imputed missing values, A is the number of trees in the Random Forest ensemble, and $\widehat{X}^{a}_{\mathrm{missing}}$ are the predictions from each tree a. This method not only imputes missing values but also collects intricate relationships and connections among features, thus improving the accuracy of ensuing analysis and modeling efforts.

3.3.2 Multilayer Perceptron-based Missing Data Imputation

Multilayer Perceptron-based missing data imputation is a strong technique utilizing neural networks to manage incomplete datasets efficiently. This technique contains training an MLP technique on the complete dataset, where features with missing values are forecasted employing learned relationships from other features. The imputation procedure could be mathematically denoted as:

$$\widehat{X}_{\mathrm{missing}} = \sigma(P.X_{\mathrm{missing}} + a) \tag{2}$$

where $\widehat{X}_{missing}$ denotes the imputed missing values, $X_{missing}$ are the features equivalent to missing values, P represents the weights, a is the bias term, and σ is the activation function (For instance, ReLU) utilized in the output layer of the MLP technique. This technique exploits MLP's ability to collect multifaceted non-linear associations between features, guaranteeing strong imputations that maintain data integrity. Despite the processing requirements, MLP-based imputation provides adaptability in modeling different data patterns and enhancing dataset completeness for succeeding studies and modeling tasks.

3.3.3 Chi-Squared Attribute Evaluation with Ranker Search-based Features Ranking

Chi-Squared Attribute Evaluation with Ranker Search-based Features Ranking is a technique for evaluating the importance of features in datasets, mainly in feature selection tasks. It includes calculating the chi-squared statistic for each feature concerning the target feature and gauging the independence between the feature and the target. The chi-squared value X^2 for a feature P_i and target Q is calculated as:

$$X^2(P_i, Q) = \sum_{p_i} \frac{(O_{p_i} - E_{p_i})^2}{E_{p_i}} \tag{3}$$

where O_{p_i} and E_{p_i} denotes the observed and expected frequencies of P_i correspondingly. The ranker search then sorts features using their chi-squared scores, detecting those most likely pertinent for predictive modeling. This technique not only helps to lower the dimensionality and computational expenses but also improves model interpretability by choosing features with noteworthy correlations with the target feature.

3.3.4 ReliefF Attribute Evaluation with Ranker Search-based Features Ranking

Regarding feature selection procedures, ReliefF is one of the strong feature selection methods. It functions by determining the significance of each feature by the comparison of instances in proximity, changing weights using their difference in class values. The ReliefF formula is described as:

$$W^{ReliefF}(p, q) = \sum_{i=1}^{k} \frac{-diff(x_i, x_i')}{k} \tag{4}$$

Where, $W^{ReliefF}(p, q)$ represents the ReliefF weight for feature p regarding class q. K is the number of nearest neighbors. $diff(x_i, x_i')$ denotes the absolute difference between the feature value x_i of the instance x and the equivalent feature value x_i' of a neighboring instance x'.

The ReliefF formula calculates feature pertinence by repeatedly sampling instances and updating weights based on their influence on nearest neighbor classification. This recurrent procedure successfully ranks features by their capability to differentiate between classes, making ReliefF a strong tool in feature selection tasks.

3.3.5 Gain Ratio Attribute Evaluation with Ranker Search-based Features Ranking

Gain Ratio Attribute Evaluation with Ranker Search-based Features ranking computes the gain ratio (GR) for each feature to rank features. The GR for a feature F is calculated utilizing the equation:

$$GR(F) = \frac{IV(F)}{SplitInfo(F)} \tag{5}$$

where IV(F) is the intrinsic value of feature F and SplitInfo(F) is the amount of data required to split on feature F. This technique employs a Ranker Search technique to repeatedly assess and rank features using their gain ratio, seeking to determine features that present the higher information gain relative to the possible data content and splitting necessities in the dataset.

4 Results and Discussions

The RACE Algorithm was employed to determine important characteristics of e-commerce anchors that strongly influence the intention to buy. This paper concentrated on characteristics such as competence, charm, credibility, communication, fame, affinity, promptness, and Purchase Intention, seeking to identify the most significant characteristics. For execution, Java and the Weka tool were utilized to implement the RACE algorithm. The predictive performance of a Naïve Bayes classifier was then evaluated on a test dataset, using features selected by each feature selection model.

In evaluating model performance, crucial metrics with Accuracy, Precision, Recall, and F1-score were used. These metrics cooperatively assess the model's predictive ability, guaranteeing a complete evaluation of its efficiency.

Accuracy: Accuracy is the proportion of accurate results among all cases.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

Precision: Precision is the proportion of true positives among forecasted positives.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{7}$$

Recall: Recall is the proportion of actual positives correctly predicted.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{8}$$

F1-score: The F1-score balances precision and recall into a solitary evaluation metric for classifier effectiveness.

$$F1 - \text{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

Where:

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

Comparative analysis across various feature selection models including Chi-Squared

Attribute Evaluation, ReliefF Attribute Evaluation, and Gain Ratio Attribute Evaluation with Ranker Search demonstrated impressive outcomes which is demonstrated in Table 1. However, the RACE algorithm reliably outperformed these individual models. It attained an Accuracy of 93%, Precision of 92%, Recall of 95%, and an F1-score of 93%, representing its sturdiness in detecting features with noteworthy influence on buying intention.

Table 1: Performance Comparison

Feature Selection Model	Accuracy	Precision	Recall	F1-score
Chi-squared attribute Evaluation with Ranker	86	85	88	86
ReliefF Attribute Evaluation with Ranker	89	88	91	89
Gain Ratio Attribute Evaluation with Ranker	87	86	89	87
RACE Algorithm	93	92	95	93

The advantage of the RACE algorithm lies in its capability to combine numerous feature selection models, including Chi-Squared, ReliefF, and Gain Ratio. By combining rankings from these various models, RACE efficiently detects the most important characteristics of e-commerce anchors. This thorough approach guarantees that the chosen features together improve predictive accuracy and model performance, exceeding the results attainable through singular models. Figure 2 shows the line chart of this performance comparison.

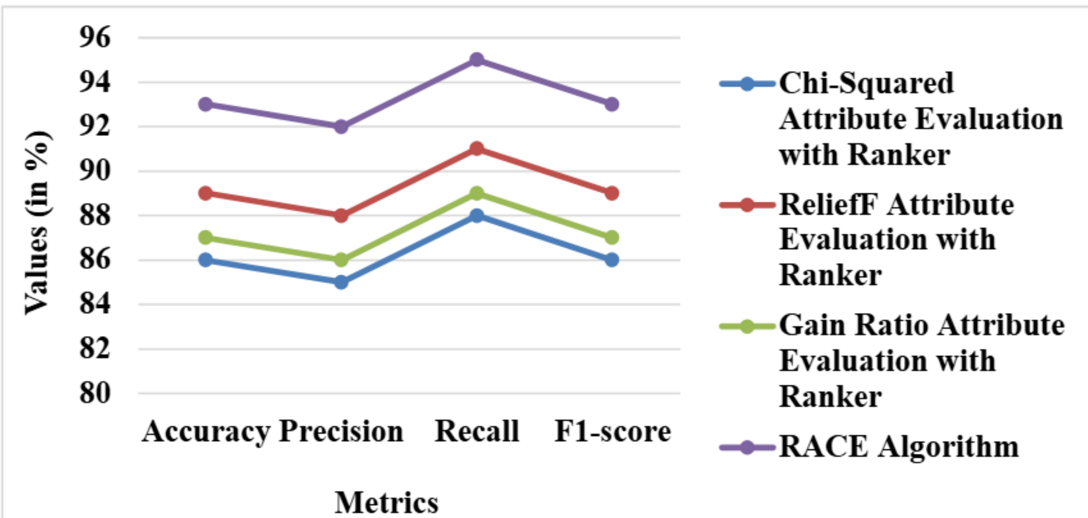

Figure 2: Performance Comparison

Using the RACE algorithm's examination, the top 3 characteristics of e-commerce anchors discovered as most significant for intention to buy are Affinity, Promptness, and Communication. These characteristics appeared steadily across various evaluation models, highlighting their crucial role in impacting customer buying decisions.

Overall, the RACE algorithm is shown to be a successful method for detecting important characteristics of e-commerce anchors that drive buying intention. Its comprehensive strategy not only improves predictive accuracy but also presents actionable insights for e-commerce platforms to enhance their tactics. To improve Affinity, Promptness, and Communication, e-commerce anchors should strengthen personalized communication tactics tailored to customer desires, guarantee efficient and timely consumer service across all platforms, and engage actively with consumers through collaborative content and real-time replies, thus enhancing consumer satisfaction and trustworthiness.

5. Conclusion

The paper effectively utilized the RACE algorithm to detect the top characteristics of e-commerce anchors that significantly influence customer buying intention, particularly Affinity, Promptness, and Communication. Implemented using Java and Weka tools, the RACE algorithm proved excellent output compared to other feature selection models, attaining the highest accuracy, precision, recall, and F1 scores with a Naïve Bayes classification model. These results present actionable insights for e-commerce platforms to improve personalized communication, guarantee quick customer service, and actively engage customers, thus improving satisfaction and trustworthiness. The RACE algorithm's robust strategy demonstrates its potential as a beneficial tool for feature selection, providing notable advantages for e-commerce platforms. Future work could explore the application of the RACE algorithm in the healthcare domain to confirm its efficacy and increase its usefulness.

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