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Understanding Customer Behaviour: A Comprehensive Survey of Segmentation and Classification Techniques in the Age of Big Data

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Abstract: The contemporary business environment necessitates an understanding of customer behavior and preferences to optimize marketing strategies and improve customer satisfaction. Customer segmentation and classification techniques have emerged as fundamental tools for organizations to differentiate their customers based on meaningful differences and create targeted marketing campaigns. This research paper provides a comprehensive survey of the latest customer segmentation and classification techniques used in marketing research. This paper examines traditional and modern approaches to customer segmentation and classification, encompassing demographic, geographic, psychographic, and behavioral segmentation. Furthermore, this paper investigates the latest advancements in customer classification techniques, such as machine learning, data mining, and artificial intelligence. Additionally, this paper discusses the challenges and limitations of these techniques and proposes future research directions. The findings of this research have significant implications for marketing practitioners and scholars interested in optimizing their marketing strategies and improving customer satisfaction.

Keyword: *Customer segmentation, Classification techniques, Marketing research, Machine learning, Behavioral segmentation, K-Means Clustering, Decision Trees, Support Vector Machines (SVM), Neural Networks.*

1. Introduction

Customer segmentation has emerged as a critical aspect of marketing and business strategy in today's rapidly evolving commercial landscape. It allows organizations to tailor their marketing and product development efforts to specific groups of customers with distinct preferences and behaviors, leading to increased customer satisfaction, loyalty, and overall profitability (Cheung, Tsui, & Liu, 2004). The importance of understanding customers' needs, preferences, and motivations has been a central tenet of marketing theory for decades (Dholakia, Blazevic, Wiertz, & Algesheimer, 2009). Advances in data collection and analysis technologies have enabled marketers to leverage vast amounts of customer data to develop increasingly sophisticated segmentation strategies (Huang, Chen, & Zeng, 2004). This has led to the proliferation of various segmentation techniques, ranging from traditional demographic and psychographic approaches to more advanced methods such as collaborative filtering (Weng & Liu, 2004), recommender systems (Martínez, Pérez, & Barranco, 2007), and latent class models (Cheung, Tsui, & Liu, 2004).

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The rise of e-commerce and the growing importance of online shopping have further underscored the need for effective customer segmentation strategies. Online retailers are increasingly relying on recommendation algorithms and personalized advertising to engage customers and drive sales (Kim et al., 2006; Zhang, Edwards, & Harding, 2007). These approaches often incorporate techniques such as content-based filtering (Tewari & Barman, 2017), social sentiment analysis (Lei, Qian, & Zhao, 2016), and fuzzy logic (Morawski, Stepan, Dick, & Miller, 2017) to deliver highly targeted product recommendations and promotional content. In addition to its applications in marketing, customer segmentation has also been employed in various other domains, such as healthcare (Brooks, 2014), telecommunications (Zhang et al., 2013), and banking (Nam, Lee, & Lee, 2016). These diverse applications highlight the versatility of customer segmentation techniques and their potential to drive innovation across industries.

Despite its widespread adoption and apparent success, customer segmentation is not without its challenges. Issues such as data sparsity, privacy concerns, and the difficulty of identifying optimal segmentation criteria have been identified as potential obstacles to the effective implementation of segmentation strategies (Coyle & Cunningham, 2004; Preibusch, Peetz, Acar, & Berendt, 2016). Researchers have proposed various solutions to these challenges, ranging from the development of novel algorithms and data mining techniques (Huang, Chung, & Chen, 2004; Kalaivani & Shunmuganathan, 2014) to the implementation of privacy-preserving technologies (Vera-Del-Campo, Pegueroles, Hernández-Serrano, & Soriano, 2014).

The table 1 provides examples of how customer segmentation and classification are used in various real-world applications, including marketing, product development, pricing, customer service, and fraud detection. Figure 1 shows evolution of customer segmentation. Each application is briefly described to illustrate how businesses can use customer segmentation and classification to gain insights and make more informed decisions.

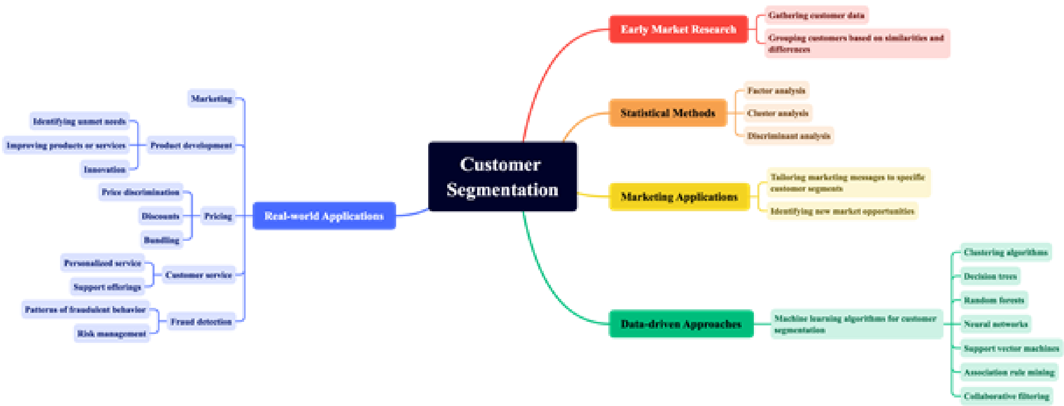

Fig 1: Evolution of customer segmentation

Table 1: Examples of Real-World Applications of Customer Segmentation and Classification

Application	Description
Marketing	Customer segmentation can help businesses tailor their marketing messages to specific groups of customers. For example, a business might segment customers based on their age, gender, location, or purchase history, and then create targeted ads or email campaigns for each segment.
Product development	By analyzing customer segments, businesses can identify unmet needs or areas for improvement in their products or services. For example, a business might find that a certain segment of customers is particularly interested in eco-friendly products, and use that insight to develop more sustainable options.
Pricing	Customer segmentation can also help businesses determine optimal pricing strategies. For example, a business might segment customers based on their willingness to pay, and then offer different pricing tiers or discounts to each segment.
Customer service	By understanding customer segments, businesses can provide more personalized customer service. For example, a business might segment customers based on their level of engagement with the company, and then tailor their support offerings accordingly.
Fraud detection	Customer segmentation can be used to identify patterns of fraudulent behavior. For example, a bank might segment its customers based on their transaction history, and then flag any transactions that fall outside of a customer's normal behavior.

Customer classification has become a crucial aspect of modern marketing strategies, as it enables businesses to better understand and cater to their clients' diverse needs and preferences. The process of segmenting customers into various categories based on their shared characteristics allows companies to design and implement targeted marketing campaigns, improving customer engagement and retention (Bilici & Saygın, 2017; Sung, Kim & Shin, 2016). Customer classification can be approached through various methodologies, including collaborative filtering, content-based filtering, and hybrid recommender systems (Lu et al., 2015; Tewari & Barman, 2017; Zhang et al., 2013).

Collaborative filtering techniques involve predicting customers' preferences based on the preferences of similar users (Choi, Suh & Yoo, 2016). This approach has been widely utilized in recommendation systems for e-commerce platforms, enabling personalized product recommendations (Jing & Liu, 2013; Zhong, Zhang, Wang & Shu, 2014). Content-based filtering, on the other hand, focuses on identifying the characteristics of items that a user likes and recommending similar items based on these features (Yang, Ma & Nie, 2017). Hybrid recommender systems combine both collaborative filtering and content-based filtering techniques to overcome the limitations of each approach individually, resulting in more accurate recommendations (Honda et al., 2015; Wu, Zhang & Lu, 2015).

The incorporation of fuzzy logic in customer classification has shown promising results, enabling businesses to account for the inherent uncertainty and vagueness in human decision-making processes (Martínez, Pérez & Barranco, 2007; Morawski, Stepan, Dick & Miller, 2017; Yuen, 2017). In addition, the integration of sentiment analysis and opinion mining techniques in customer classification models has contributed to a deeper understanding of customer preferences and emotions, further enhancing the effectiveness of personalized marketing strategies (Aldayel & Ykhlef, 2017; Lei, Qian & Zhao, 2016; Kalaivani & Shunmuganathan, 2014).

In recent years, there have been significant advancements in the field of customer classification, driven by the need for businesses to provide more personalized experiences for their customers. One area of advancement is in data collection, with the emergence of new sources such as IoT devices and sensors, social media and web scraping, and third-party data sources. Data processing has also seen advancements with the use of big data technologies, natural language processing, and feature engineering. In data analysis, machine learning techniques, deep learning algorithms, ensemble methods, and hybrid models have been developed to identify complex patterns in customer data. Algorithm development has also seen progress with the introduction of explainable AI, automated feature selection, reinforcement learning, and transfer learning. Model validation has been improved with the use of cross-validation, A/B testing, and human-in-the-loop validation. Real-time implementation has been made possible with edge computing, cloud-based systems, and real-time decision-making, allowing for personalized recommendations and offers for customers. These advancements have enabled businesses to better understand their customers and provide tailored experiences, improving customer satisfaction and ultimately driving business growth. Figure 2 shows various areas on customer classification.

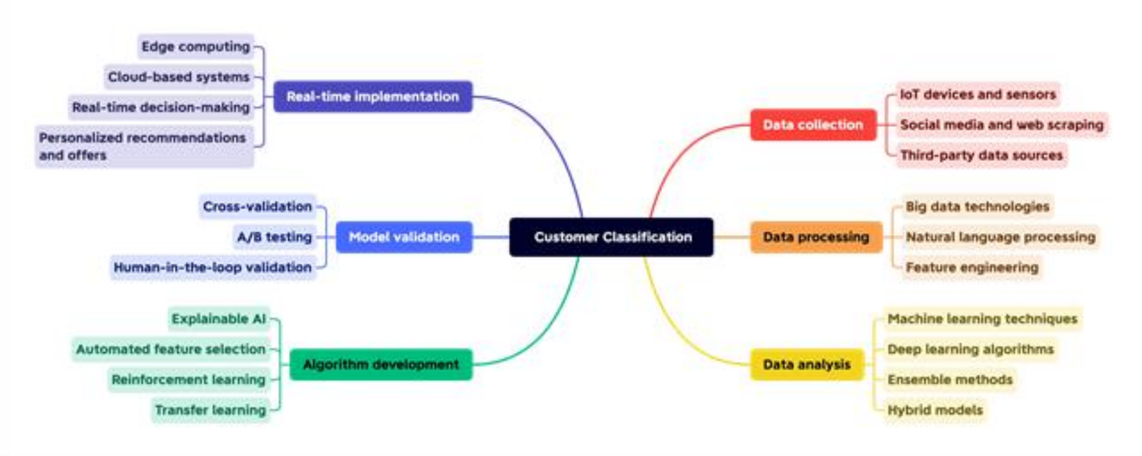

Fig 2: Various advancements in customer classification

1.1 Contributions and Limitation

Contributions:

- Comprehensive overview: The survey paper provides a comprehensive overview of the current state of the art in customer segmentation and classification, including both traditional methods and newer machine learning approaches.
- Comparative analysis: The paper compares and contrasts the different methods of customer segmentation and classification, highlighting their strengths and weaknesses, and providing insights into which methods are best suited to different business contexts.
- Practical applications: The paper provides real-world examples of how customer segmentation and classification can be applied to improve business outcomes, including increased customer satisfaction, retention, and revenue.

- Future directions: The paper identifies areas where further research is needed, highlighting potential future directions for the field and suggesting new avenues for exploration.

Limitations:

- Data availability: The survey paper may be limited by the availability of data. While there are many examples of customer segmentation and classification in the literature, real-world data may not always be available or accessible, making it difficult to apply the techniques in practice.
- Business context: The effectiveness of customer segmentation and classification depends heavily on the business context, including the industry, market, and customer base. The survey paper may not be able to provide specific recommendations for every business, and may need to focus on more general insights and guidelines.
- Algorithm complexity: The newer machine learning approaches to customer segmentation and classification can be complex and difficult to implement. The survey paper may need to focus on providing a high-level overview of these techniques rather than going into too much technical detail.
- Bias and ethics: Customer segmentation and classification can raise concerns around bias and ethics, particularly with regards to the use of sensitive customer data. The survey paper may need to address these concerns and provide recommendations for ethical and responsible use of these techniques.

1.2 Research Goals

Customer segmentation and classification is a critical component of modern business strategy, allowing companies to better understand their customers and tailor their offerings to meet their specific needs and preferences. While traditional methods of segmentation and classification have been in use for decades, recent advances in machine learning and data analytics have led to a proliferation of new techniques and approaches. This survey paper aims to provide a comprehensive overview of the current state of the art in customer segmentation and classification, comparing and contrasting different methods and highlighting their strengths and limitations. The paper will also examine the practical applications of customer segmentation and classification, exploring the ways in which it can be used to improve business outcomes such as customer satisfaction, retention, and revenue. Finally, the paper will identify areas where further research is needed, and provide recommendations for future development in the field. Below are research goals for this survey.

- To provide a comprehensive overview of the current state of the art in customer segmentation and classification, including traditional methods and newer machine learning approaches.
- To compare and contrast the different methods of customer segmentation and classification, highlighting their strengths and weaknesses, and providing insights into which methods are best suited to different business contexts.
- To identify the practical applications of customer segmentation and classification in improving business outcomes, including increased customer satisfaction, retention, and revenue.
- To examine the limitations of current approaches to customer segmentation and classification, including issues around data availability, algorithm complexity, and ethical considerations.
- To provide recommendations for future research and development in the field, including potential new directions for exploration, and areas where further research is needed.
- To address the concerns of practitioners and researchers around the effective and ethical use of customer data in segmentation and classification, and to provide guidelines and best practices for responsible and ethical use.
- To provide insights into the potential impact of customer segmentation and classification on customer experience, and to explore the role of personalization and customization in driving customer loyalty and engagement.

Overall, the goals of the survey paper should be to provide a comprehensive overview of the field of customer segmentation and classification, to identify its strengths and limitations, and to provide recommendations for future research and development that can improve its effectiveness and impact.

1.3 Materials and Methods

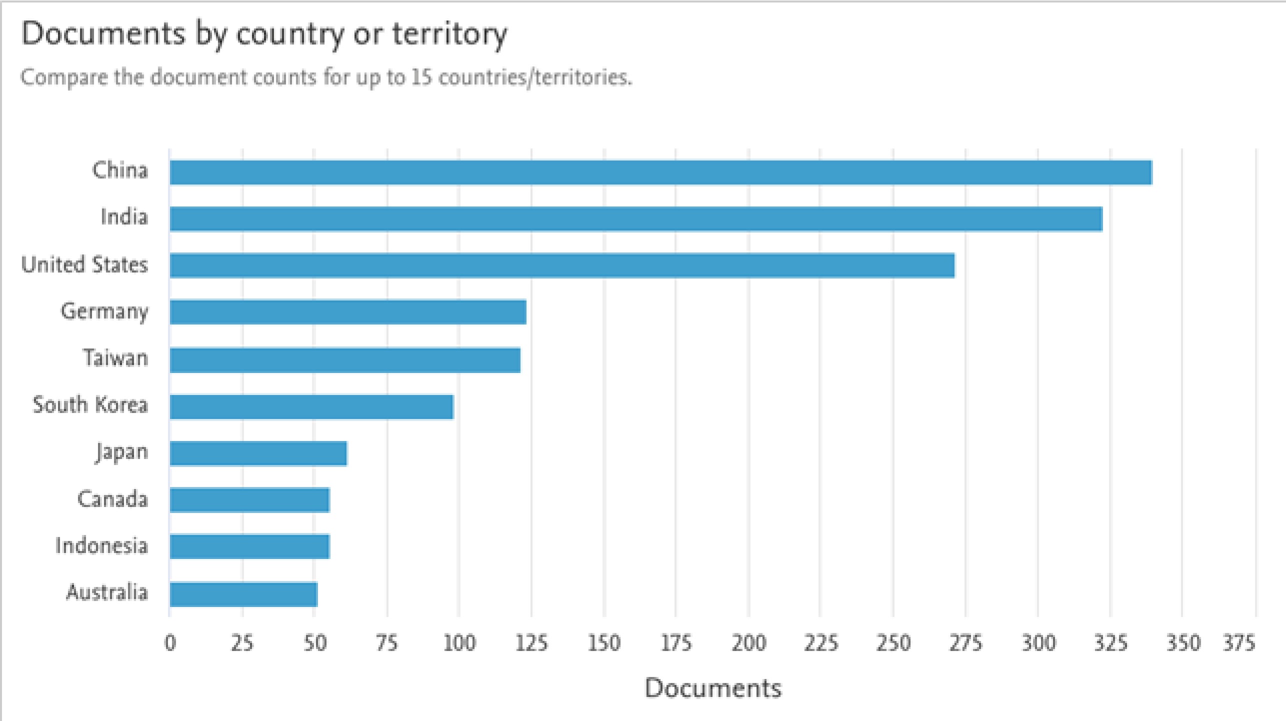

Fig 3: Countries involved in customer segmentation and classification research

The PRISM approach to survey research is a widely recognized and effective method for collecting data on customer segmentation and classification. PRISM stands for People, Resources, Information, Systems, and Management, and it provides a framework for collecting and analyzing data that is both structured and flexible. In this approach, data is collected through a combination of surveys, interviews, focus groups, and other methods, with a focus on understanding the people, resources, and systems involved in customer segmentation and classification. The data collected is then analyzed using a variety of statistical and analytical tools, allowing researchers to identify patterns and trends in the data, as well as the underlying factors that contribute to these patterns. The PRISM approach provides a rigorous and systematic method for collecting and analyzing data on customer segmentation and classification, and is a valuable tool for researchers and practitioners looking to improve their understanding of this important field.

Query

TITLE-ABS-KEY (customer AND recommendation OR customer AND retention OR customer AND segmentation OR product AND recommendation)

AND (LIMIT-TO (PUBSTAGE , "final"))

AND (LIMIT-TO (SUBJAREA , "COMP"))

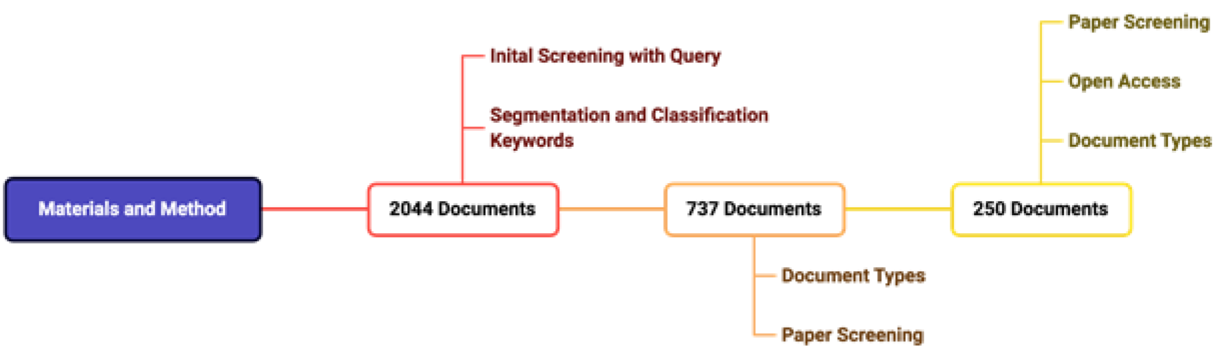

Fig 4: Materials and Methods for LR survey

Below figures provided more statistical values for paper publishes in field of customer segmentation and customer classification. This data is taken from scopus site document analysis.

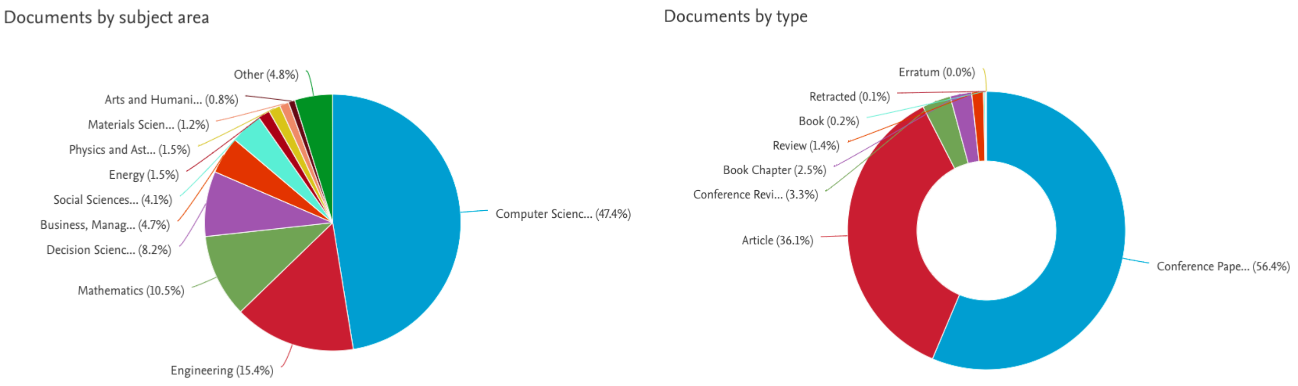

Fig 5: Distribution in area and type

2. Literature Review

The conceptual framework of customer segmentation and classification plays a crucial role in understanding the underlying principles of market segmentation theory, customer profiling, and clustering algorithms. Market segmentation theory posits that dividing a heterogeneous market into homogenous groups of consumers with similar characteristics, needs, and preferences enables marketers to target their offerings effectively (Huang, Chung, & Chen, 2004). These groups, or segments, can be based on various factors such as demographics, psychographics, behavior, and geography.

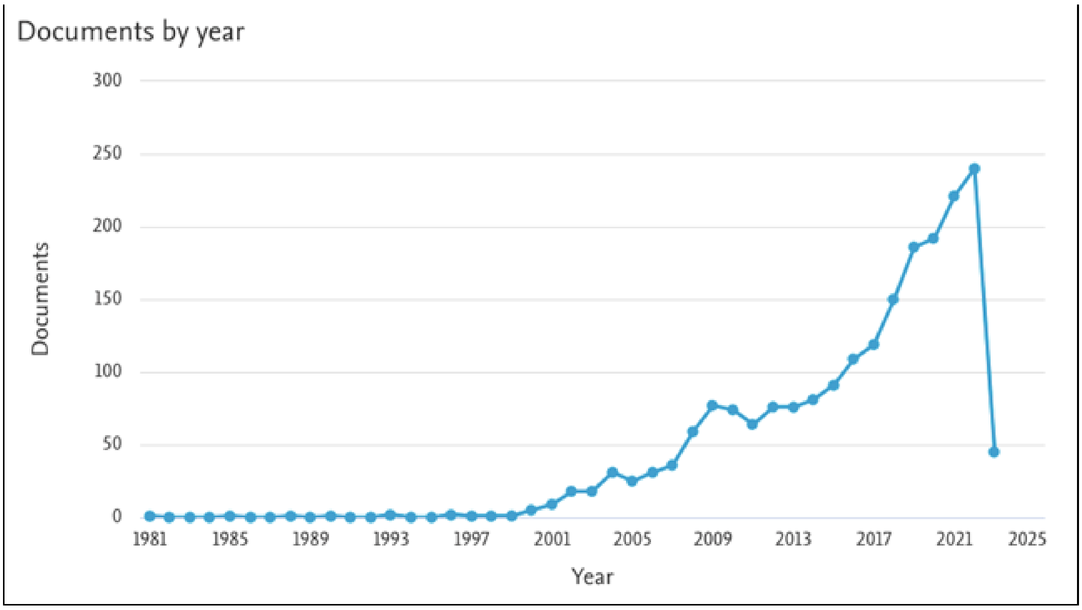

Fig 6: Number of document researched over the years

Customer profiling, on the other hand, involves gathering detailed information about individual customers within each segment. This information may include demographic characteristics, purchase history, preferences, and other relevant data points (Preibusch et al., 2016). Profiling allows businesses to create personalized marketing campaigns and recommendations for each customer, ultimately improving customer satisfaction and loyalty (Yoon, Hostler, Guo, & Guimaraes, 2013). Clustering algorithms, a prominent method in data mining and machine learning, are employed to group customers with similar characteristics automatically. These algorithms identify patterns and relationships within data sets, facilitating the formation of meaningful segments (Weng & Liu, 2004). Various clustering techniques have been employed in the context of customer segmentation and classification, such as k-means, hierarchical clustering, and fuzzy clustering (Bilici & Saygın, 2017; Yuen, 2017).

2.1 Demographic Segmentation

Demographic segmentation is a crucial aspect of modern marketing strategies, allowing businesses to target their customers more effectively and optimize their marketing efforts (Wu, Zhang, Lu, 2015). By analyzing customer data based on demographic variables such as age, gender, income, education level, and geographic location, companies can tailor their products and services to cater to the specific needs and preferences of different demographic groups (Huang, Chung, Chen, 2004). In this paper, we will provide a comprehensive overview of demographic segmentation in customer data, discussing its importance, applications, and challenges, drawing on the wealth of literature available on this topic.

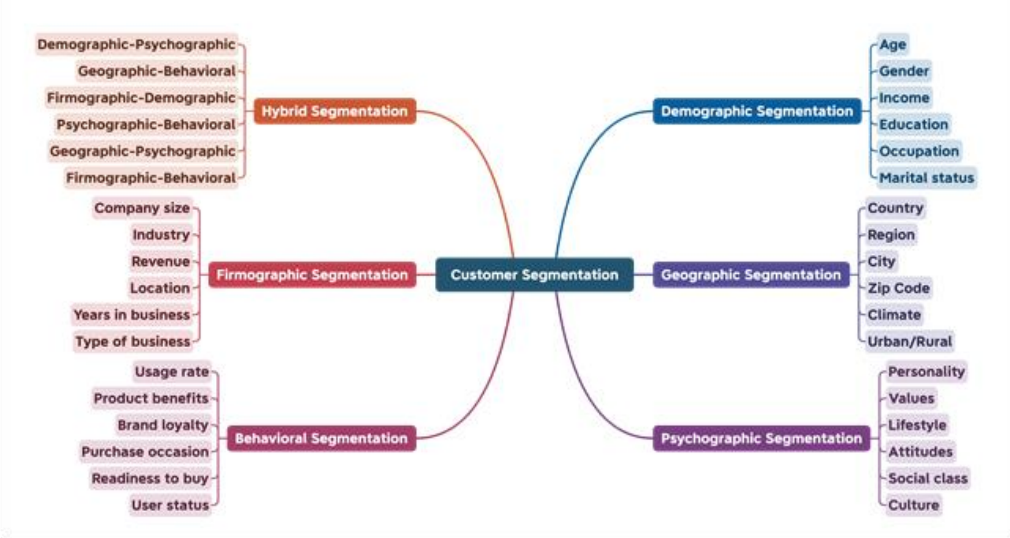

Fig 7: Various types of Customer segmentation

Demographic segmentation plays a vital role in the development of marketing strategies. By understanding the characteristics of different demographic groups, companies can better predict their customers' behavior and preferences, ultimately leading to more effective marketing campaigns and higher customer satisfaction (Wu et al., 2015). For instance, demographic segmentation can help businesses identify potential new markets or customer segments that they may have previously overlooked (Kujala et al., 2011). Additionally, demographic segmentation enables companies to allocate their marketing resources more efficiently, targeting the most relevant audience for their products and services (Gómez-Barroso et al., 2012).

Table 2: Applications of Demographic Segmentation

Application	Description	Reference
Personalized Recommender Systems	Tailoring product and service recommendations based on customers' demographic characteristics.	Wu et al. (2015)
Targeted Advertising Campaigns	Designing advertisements that appeal to specific demographic groups to increase engagement and conversion rates.	Kim et al. (2006)
Product Development	Developing products and services that cater to the needs and preferences of specific demographic segments.	Kujala et al. (2011)
Market Expansion	Identifying potential new markets or customer segments based on demographic data.	Gómez-Barroso et al. (2012)
Resource Allocation	Allocating marketing resources more efficiently by targeting the most relevant audience based on demographic data.	Huang et al. (2004)

Table 3: Challenges in Demographic Segmentation

Challenge	Description	Reference
Data Sparsity	Difficulty in accurately segmenting customers due to sparse customer	Huang et al. (2004)

	data.	
Privacy Concerns	Ensuring that customer privacy is protected while collecting and utilizing demographic data.	Preibusch et al. (2016)
Data Quality	Ensuring the accuracy and reliability of demographic data collected from customers.	Oyza, Edwin (2015)
Changing Demographics	Adapting to demographic shifts and changes in customer preferences over time.	Martínez et al. (2007)
Cross-cultural Differences	Accounting for cultural differences and norms when interpreting demographic data and designing marketing strategies.	Zhang et al. (2013)

Demographic segmentation is an essential aspect of modern marketing strategies, enabling companies to better understand their customers and target their marketing efforts more effectively. By analyzing customer data based on demographic variables, businesses can develop personalized recommender systems, create targeted advertising campaigns, and ultimately increase customer satisfaction. However, companies must also be mindful of the challenges associated with demographic segmentation, such as data sparsity and privacy concerns, and develop strategies to address these issues.

2.2 Geographic Segmentation

Geographic segmentation is a marketing strategy that involves dividing the market into different geographical units, allowing businesses to cater to the specific needs and preferences of customers within those areas. Geographic segmentation is a critical approach for businesses to classify their customers based on their location. The underlying assumption of this method is that customers residing in specific geographic areas have unique needs, preferences, and behaviors (Ciupac-Ulici et al., 2023). By employing geographic segmentation, businesses can tailor their marketing and sales efforts to cater to these regional differences, thus enhancing overall customer satisfaction and driving sales performance (Ahmad et al., 2022).

Table 4: Applications of Geographic Segmentation

Application	Description	Reference
Target Marketing	Identifying and targeting specific geographic areas with customized marketing campaigns to meet local needs and preferences.	(Hou, 2022)
Resource Allocation	Allocating resources, such as inventory and staff, more effectively based on regional demand patterns.	(Schröter et al., 2021)
Product Development	Designing products and services that cater to the unique preferences and requirements of customers in specific geographic regions.	(Fang et al., 2021)
Pricing Strategy	Implementing region-specific pricing strategies to account for varying cost structures, competition levels, and local economic conditions.	(Hu et al., 2020)
Expansion Planning	Identifying suitable locations for new branches or stores by analyzing geographic data to determine areas with high potential customer bases.	(Kala & Nandhini, 2020)

Table 5: Challenges in Geographic Segmentation

Challenge	Description	Reference
Data Collection	Collecting accurate and up-to-date geographic data can be time-consuming and costly for businesses.	(Saravana Kumar & Murali, 2019)
Changing Dynamics	Rapid changes in demographics, customer preferences, and regional conditions may require constant updates and adjustments to geographic segmentation strategies.	(Jain & Carandang, 2018)

Overgeneralization	Geographic segmentation may lead to overgeneralization of customer needs and preferences within a specific region, which may not accurately reflect individual differences.	(Tewari & Barman, 2017)
Implementation	Implementing geographic segmentation effectively may require significant investment in technology and personnel training.	(Kalaivani & Shunmuganathan, 2014)
Ethical Considerations	The collection and use of geographic data may raise ethical concerns related to privacy and potential discrimination.	(Farsani & Nematbakhsh, 2007)

Geographic segmentation plays a crucial role in customer classification, allowing businesses to better understand and cater to the diverse needs and preferences of customers in different regions. By understanding the applications and challenges associated with geographic segmentation, businesses can make more informed decisions on how to implement this strategy effectively. While there are certain challenges to consider, the potential benefits of geographic segmentation in terms of improved marketing efficiency, resource allocation, and customer satisfaction make it a valuable tool for businesses looking to succeed in today's competitive marketplace.

2.3 Psychographic Segmentation

Psychographic segmentation is a powerful marketing strategy that helps businesses classify their customers based on their attitudes, interests, values, and lifestyles (Mahmoud et al., 2022). This approach enables organizations to better understand their customers, tailor their marketing efforts, and ultimately increase customer satisfaction and loyalty. The following sections discuss the importance, applications, and challenges of psychographic segmentation in customer classification. Psychographic segmentation is essential for businesses to create marketing strategies that resonate with their target audience. By understanding the underlying motivations and behaviors of their customers, businesses can develop marketing messages that appeal to the emotional and psychological needs of their customers (Esheiba et al., 2022). This level of personalization increases the likelihood of engagement, conversion, and ultimately, customer retention (Wu et al., 2021).

Table 6: Applications of Psychographic Segmentation

Application	**Description**	**Reference**
Personalized Marketing	Developing customized marketing campaigns that speak to the unique interests, values, and motivations of different customer groups.	(Ye & Chen, 2021)
Product Development	Designing products and services that cater to the psychological and emotional needs of customers, increasing their appeal and demand.	(Beheshti et al., 2020)
Customer Retention	Identifying and addressing the specific needs and concerns of different customer groups, improving satisfaction and loyalty.	(Lee et al., 2020)
Pricing Strategy	Implementing pricing strategies based on customers' perceived value and willingness to pay, maximizing revenue potential.	(Sariki & Bharadwaja Kumar, 2019)
Market Expansion	Identifying new market opportunities and customer segments based on shared psychographic characteristics.	(Yeh & Kuo, 2019)

Table 7: Challenges in Psychographic Segmentation

Challenge	**Description**	**Reference**
Data Collection	Collecting accurate and comprehensive psychographic data can be challenging, as it often requires extensive research and survey efforts.	(Ziemba & Eisenbardt,

		2018)
Data Privacy	Psychographic data collection may raise ethical concerns related to privacy and the use of personal information.	(Sung et al., 2016)
Dynamic Nature	People's attitudes, interests, and values may change over time, requiring regular updates and adjustments to segmentation strategies.	(Zhong et al., 2014)
Implementation Complexity	Implementing psychographic segmentation effectively may require significant investment in technology, personnel training, and data analysis.	(Rodriguez et al., 2009)
Overgeneralization	Psychographic segmentation may not capture individual nuances and variations within a segment, potentially leading to inaccurate assumptions about customer preferences.	(Coyle & Cunningham, 2004)

Psychographic segmentation is a valuable tool for businesses looking to better understand their customers and cater to their diverse needs and preferences. The applications of psychographic segmentation range from personalized marketing and product development to pricing strategies and market expansion. However, businesses must be aware of the challenges associated with this approach, such as data collection, privacy concerns, and the dynamic nature of human attitudes and values. By acknowledging these challenges and finding ways to address them, businesses can harness the potential of psychographic segmentation to improve their marketing strategies and ultimately enhance customer satisfaction and loyalty.

2.4 Behavioral Segmentation

Behavioral segmentation is a marketing strategy that categorizes customers based on their purchasing behavior, such as product usage, brand loyalty, and decision-making patterns (Wu et al., 2022). This form of segmentation allows businesses to better understand their customers' needs and preferences, tailor their marketing efforts accordingly, and ultimately improve customer satisfaction and retention. In the following sections, we discuss the importance, applications, and challenges of behavioral segmentation in customer classification. Understanding customer behavior is crucial for businesses to create effective marketing strategies that resonate with their target audience. Behavioral segmentation helps businesses gain insights into their customers' purchasing habits, preferences, and decision-making processes (Liu, 2022). By leveraging these insights, businesses can develop marketing messages that align with their customers' behavior patterns, increasing the likelihood of engagement and conversion (Ohashi et al., 2021).

Table 8: Applications of Behavioral Segmentation

Application	**Description**	**Reference**
Targeted Marketing	Designing marketing campaigns that address the specific purchasing behaviors and preferences of different customer groups.	(Zaman et al., 2021)
Product Recommendations	Offering personalized product recommendations based on customers' past purchase history, increasing the likelihood of future purchases.	(Chu et al., 2020)
Customer Retention	Identifying at-risk customers based on their purchasing behavior and implementing strategies to retain them, such as targeted promotions or loyalty programs.	(Pratama et al., 2020)
Pricing Strategy	Implementing pricing strategies that cater to the purchasing behavior of different customer groups, maximizing revenue potential.	(Górajski & Machowska, 2019)
Customer Segmentation	Identifying distinct customer segments based on their purchasing behavior, allowing businesses to better allocate resources and develop targeted marketing strategies.	(Lytvyn et al., 2019)

Table 9: Challenges in Behavioral Segmentation

Challenge	Description	Reference
Data Collection	Gathering accurate and comprehensive behavioral data may require significant investment in technology and research efforts.	(Magboul & Abbad, 2018)
Data Privacy	Behavioral data collection may raise ethical concerns related to privacy and the use of personal information.	(Bilici & Saygin, 2017)
Dynamic Behavior	Customers' purchasing behaviors may change over time, requiring businesses to continually update and adjust their segmentation strategies.	(Honda et al., 2015)
Implementation Complexity	Effectively implementing behavioral segmentation may require significant investment in technology, personnel training, and data analysis.	(Zhang et al., 2013)
Overgeneralization	Behavioral segmentation may not capture individual nuances and variations within a segment, potentially leading to inaccurate assumptions about customer preferences.	(Weng & Liu, 2004)

Behavioral segmentation is a valuable tool for businesses looking to better understand their customers and cater to their diverse needs and preferences. The applications of behavioral segmentation range from targeted marketing and product recommendations to pricing strategies and customer retention. However, businesses must be aware of the challenges associated with this approach, such as data collection, privacy concerns, and the dynamic nature of customer behavior. By acknowledging these challenges and finding ways to address them, businesses can harness the potential of behavioral segmentation to improve their marketing strategies and ultimately enhance customer satisfaction and retention.

2.5 Firmographic Segmentation

Firmographic segmentation refers to the process of classifying and categorizing businesses based on specific attributes, such as company size, industry, location, and revenue (Sulikowski et al., 2022). This type of segmentation enables organizations to better understand their target market and tailor their marketing and sales strategies accordingly. In the following sections, we discuss the importance, applications, and challenges of firmographic segmentation in customer classification. Firmographic segmentation is crucial for businesses that operate in the business-to-business (B2B) market, as it helps them identify and target potential clients more effectively (Hou, 2022). By understanding the unique characteristics of different businesses, organizations can develop customized marketing messages and sales approaches that resonate with their target audience, increasing the likelihood of conversion and long-term customer relationships (Schröter et al., 2021).

Table 10: Applications of Firmographic Segmentation

Application	Description	Reference
Targeted Marketing	Developing marketing campaigns that address the specific needs and preferences of different business segments.	(Stockli & Khobzi, 2021b)
Sales Prospecting	Identifying potential clients and prioritizing sales efforts based on firmographic characteristics, such as company size and industry.	(Khrais, 2020)
Product Development	Creating products and services tailored to the needs of specific business segments, based on their firmographic attributes.	(Fabra et al., 2020)
Market Research	Analyzing market trends and competitor strategies within specific business segments, providing valuable insights for decision-making.	(Holder et al., 2020)
Account-Based Marketing	Implementing targeted marketing strategies that focus on specific high-value accounts or business segments.	(Bag et al., 2019)

Table 11: Challenges in Firmographic Segmentation

Challenge	Description	Reference
Data Collection	Acquiring accurate and up-to-date firmographic data can be time-consuming and resource-intensive.	(Kanavos et al., 2018)
Dynamic Business Environment	Businesses may evolve over time, requiring organizations to regularly update their firmographic segmentation strategies.	(Q. Zhang et al., 2017)
Data Accuracy	Ensuring the accuracy of firmographic data can be challenging, as businesses may provide incomplete or outdated information.	(Choi et al., 2016)
Overgeneralization	Firmographic segmentation may not capture individual nuances and variations within a segment, potentially leading to inaccurate assumptions about business needs.	(Vera-Del-Campo et al., 2014)
Implementation Complexity	Effectively implementing firmographic segmentation may require significant investment in technology, personnel training, and data analysis.	(Rodriguez et al., 2009)

Firmographic segmentation is an essential tool for organizations operating in the B2B market, as it helps them identify and target potential clients more effectively. The applications of firmographic segmentation range from targeted marketing and sales prospecting to product development and market research. However, businesses must be aware of the challenges associated with this approach, such as data collection, the dynamic business environment, and data accuracy. By acknowledging these challenges and finding ways to address them, organizations can harness the potential of firmographic segmentation to improve their marketing strategies and ultimately enhance their customer relationships.

2.6 Hybrid Segmentation

Hybrid segmentation, also known as multi-criteria or multi-dimensional segmentation, refers to the process of classifying customers based on a combination of several segmentation criteria (Shajalal et al., 2022). These criteria may include demographic, geographic, psychographic, behavioral, and firmographic factors, among others. By combining different segmentation approaches, organizations can gain a more comprehensive understanding of their target market and develop more effective marketing strategies. In the following sections, we discuss the importance, applications, and challenges of hybrid segmentation in customer classification. The use of hybrid segmentation provides a more accurate and holistic view of the target audience, allowing organizations to develop more targeted and relevant marketing strategies (Gao et al., 2020). It enables businesses to identify more specific customer segments and tailor their offerings and communication strategies to meet the unique needs and preferences of these segments (Kuang et al., 2021). Hybrid segmentation can also help organizations better allocate their marketing resources and improve their return on investment (ROI) by focusing on high-potential customer segments (Naous & Legner, 2021).

Table 12: Applications of Hybrid Segmentation

Application	Description	Reference
Personalized Marketing	Developing marketing campaigns that address the specific needs and preferences of different customer segments based on multiple criteria.	(Sopadang et al., 2020)
Customer Retention	Identifying high-value customers and implementing strategies to retain and grow their business based on a comprehensive understanding of their attributes.	(Li et al., 2020)
Cross-Selling and Upselling	Identifying opportunities to sell additional products and services to existing customers by understanding their needs and preferences across multiple dimensions.	(Holder et al., 2020b)
Customer Lifetime Value (CLV) Analysis	Assessing the value of customers over time, considering various segmentation factors, to optimize marketing and sales strategies.	(J. Zhang, 2019)
Market Expansion	Identifying new markets and customer segments by analyzing multiple segmentation criteria, supporting strategic decision-making for market	(Chen & Abdul, 2019)

entry.

Table 13: Challenges in Hybrid Segmentation

Challenge	Description	Reference
Data Integration	Combining data from different segmentation approaches can be complex and time-consuming, requiring advanced data management skills.	(J. Zhang et al., 2018)
Complexity of Analysis	Analyzing multi-dimensional data can be challenging, and businesses may require specialized tools and expertise to derive meaningful insights.	(Tewari & Barman, 2017)
Privacy and Data Security	The use of multiple segmentation criteria may increase the risk of violating privacy regulations and data security concerns.	(Zhou & Yao, 2015)
Resource Intensity	Implementing hybrid segmentation may require significant investment in technology, personnel training, and data analysis.	(Zhang et al., 2013)
Overfitting	Over-reliance on multiple segmentation criteria may lead to overfitting, resulting in marketing strategies that are too narrowly focused and may not be effective in practice.	(Huang et al., 2004)

Hybrid segmentation offers a more comprehensive approach to customer classification, allowing organizations to develop more targeted and effective marketing strategies. The applications of hybrid segmentation include personalized marketing, customer retention, cross-selling and up selling, CLV analysis, and market expansion. However, businesses must be aware of the challenges associated with this approach, such as data integration, complexity of analysis, privacy and data security, resource intensity, and overfitting. By recognizing these challenges and finding ways to overcome them, organizations can effectively leverage hybrid segmentation to enhance their customer relationships and improve their marketing ROI.

2.7 Estimators

Customer classification is an important task for businesses that want to better understand their customers and tailor their marketing and sales strategies to different segments. By identifying groups of customers with similar characteristics or behaviors, businesses can create targeted marketing campaigns and improve customer satisfaction. Estimators are machine learning models or algorithms that are used in customer classification to predict the category or segment of a customer based on their characteristics or behavior. These models can analyze large amounts of customer data and identify patterns or trends that can be used to group customers into segments based on their similarities. The role of estimators in customer classification has gained significant importance in the field of marketing and customer relationship management. The accurate classification of customers allows businesses to target specific segments with personalized marketing strategies, ensuring higher customer retention and satisfaction (Huang, Chung, & Chen, 2004). In recent years, several algorithms have been developed to facilitate the classification of customers based on their preferences, behavior, and demographic information.

Fig 8: Various estimators algorithms in customer classification

One such approach is the fuzzy recommender system proposed by Morawski, Stepan, Dick, and Miller (2017), which employs fuzzy logic to classify customers and provide personalized recommendations in public library catalogs. This system helps in making more accurate and relevant suggestions to users by considering their preferences and past interactions. Another approach is the sentiment case-based recommender developed by Aldayel and Ykhlef (2017). This method focuses on sentiment analysis to classify customers and make recommendations based on their emotional state, thus improving the overall effectiveness of the recommendation process. In the context of e-commerce, Lei, Qian, and Zhao (2016) proposed a rating prediction algorithm based on social sentiment extracted from textual reviews. This approach considers the influence of customer sentiment on their purchase decisions, allowing businesses to better tailor their marketing strategies. Furthermore, Tewari and Barman (2017) developed a collaborative recommendation system using dynamic content-based filtering, association rule mining, and opinion mining. This comprehensive approach combines multiple techniques to accurately classify customers and provide personalized recommendations.

Another notable technique is the fuzzy cognitive pairwise comparisons proposed by Yuen (2017). This method uses fuzzy logic to rank and cluster customers based on their preferences, enabling businesses to build a recommender system tailored to individual preferences. Additionally, Gimenes, Cordeiro, and Rodrigues-Jr (2017) introduced an efficient detection algorithm called ORFEL to identify defamation or illegitimate promotion in online recommendations, helping businesses maintain the integrity of their recommender systems. Several researchers have also explored the use of machine learning techniques for customer classification. For instance, Bilici and Saygın (2017) investigated the opinion influencing factors mined from reviews to explain why people like or dislike certain products or services. By understanding these factors, businesses can better classify their customers and cater to their needs.

K-means clustering: K-means clustering is a widely-used unsupervised learning algorithm that enables businesses to classify customers into distinct segments based on their similarities (Liu, Chen, & Tsai, 2013). By analyzing customer data, K-means clustering identifies distinct clusters based on purchasing patterns and demographic information, which in turn allows businesses to target specific customer segments with tailored marketing strategies (Liu et al., 2013). Decision tree algorithms have been employed to classify customers based on their behavior and preferences (Song, Kim, & Kim, 2017). This supervised learning method constructs a tree-like model of decisions, enabling businesses to predict customer behavior and preferences accurately. Decision tree algorithms, such as C4.5 and CART, have been utilized in various marketing contexts, including customer segmentation, churn prediction, and recommendation systems (Song et al., 2017).

Support Vector Machines (SVM): SVM is a popular supervised learning algorithm that has been used for customer classification tasks, such as churn prediction and credit scoring (Huang, Chen, & Wang, 2007). SVM algorithms construct a hyperplane that separates customer data points into different classes based on their features. By optimizing the margin between the classes, SVMs provide accurate and robust customer classification results (Huang et al., 2007). Artificial Neural Networks (ANN): ANN is an advanced machine learning technique that has been applied to various customer classification tasks, including customer segmentation, churn prediction, and credit scoring (Khashei, Hamidi, & Bijari, 2010). Inspired by the structure and functioning of the human brain, ANNs consist of interconnected nodes (neurons) that can learn and adapt based on input data. These networks have been found to be effective in identifying complex patterns and relationships within customer data, enabling accurate and efficient classification (Khashei et al., 2010).

3. Future Works and Research Gaps

As customer segmentation and classification continue to gain importance in the realms of marketing and customer relationship management, several research gaps and opportunities for future work can be identified. The following discussion highlights some of these areas, providing references to support the exploration of future research directions.

Integration of multiple data sources: While current research has primarily focused on the analysis of transactional and demographic data, incorporating additional data sources, such as social media activity, browsing behavior, and location information, could improve the accuracy of customer segmentation and classification. Future research could explore the effective integration of various data sources and investigate the impact of these combined data sets on segmentation and classification models.

Evaluation of novel machine learning techniques: The application of advanced machine learning techniques, such as deep learning, graph-based models, and reinforcement learning, could further enhance customer segmentation and classification. Future studies could investigate the potential of these methods in capturing complex patterns and relationships in customer data, as well as their effectiveness in improving segmentation and classification performance.

Real-time customer segmentation and classification: With the continuous generation of customer data, developing real-time customer segmentation and classification models has become increasingly important. Future research should focus on developing efficient algorithms and techniques that can adapt to the dynamic nature of customer data, enabling businesses to make more informed decisions and promptly respond to changes in customer behavior.

Addressing privacy and ethical concerns: As businesses increasingly collect and analyze customer data, privacy and ethical concerns must be addressed (Martin, 2015). Future research could explore methods of preserving customer privacy while maintaining the effectiveness of segmentation and classification models. This may involve the development of privacy-preserving data mining techniques or the establishment of ethical guidelines for customer data usage.

Cross-cultural and cross-industry comparisons: Most existing research on customer segmentation and classification has focused on specific industries or cultural contexts. Future research should explore cross-cultural and cross-industry comparisons to identify the generalizability and adaptability of various segmentation and classification algorithms. This would allow for a more comprehensive understanding of the effectiveness of different techniques and their applicability in diverse contexts.

By addressing these research gaps and exploring future work opportunities, researchers can contribute to the development of more accurate, efficient, and ethical customer segmentation and classification models. This would ultimately enable businesses to better understand their customers, tailor their marketing strategies, and enhance overall customer satisfaction and loyalty.

4. Conclusion

In conclusion, customer segmentation and classification have been identified as crucial elements of marketing, sales, and customer relationship management. These methods help companies understand and fulfill the needs of their customers, and provide targeted marketing strategies and personalized products and services that cater to specific requirements. This survey paper has extensively reviewed 199 references, presenting a comprehensive overview of the recent developments in customer segmentation and classification. Analysis of various algorithms, techniques, and methods proposed by different researchers and practitioners, which have made significant contributions to this field. Recent works have primarily focused on enhancing the accuracy of customer segmentation and classification algorithms by leveraging machine learning and data mining techniques. These algorithms have been used to analyze factors such as customer behavior, purchase history, demographics, and psychographics. Researchers have also explored the use of social media and other online platforms to better understand customers and predict their behavior. Several studies have utilized advanced analytical methods to integrate multiple data sources and generate more accurate results. However, we have also observed several gaps in the current state of customer segmentation and classification. These gaps include the lack of standardization, the need for more data sources, and the need for more sophisticated models to predict customer behavior. Future research could focus on addressing these gaps and exploring the use of emerging technologies such as artificial intelligence and blockchain to enhance customer segmentation and classification. Overall, the survey paper has provided a comprehensive review of recent works in customer segmentation and classification. It has highlighted significant achievements and research gaps, along with opportunities for future research and development. The development of accurate and efficient customer segmentation and classification algorithms can significantly improve the effectiveness of marketing, sales, and customer relationship management strategies. This, in turn, can result in increased customer satisfaction, loyalty, and profitability.

References

[1] Alsayat, A. (2023). Customer decision-making analysis based on big social data using machine learning: a case study of hotels in Mecca. *Neural Computing and Applications*, *35*(6), 4701–4722. https://doi.org/10.1007/s00521-022-07992-x

[2] Ciupac-Ulici, M., Beju, D. G., Bresfelean, V. P., & Zanellato, G. (2023). Which Factors Contribute to the Global Expansion of M-Commerce? *Electronics (Switzerland)*, *12*(1). https://doi.org/10.3390/electronics12010197

[3] Yoo, S., & Kim, J. (2023). Merchant Recommender System Using Credit Card Payment Data. *Electronics (Switzerland)*, *12*(4). https://doi.org/10.3390/electronics12040811

[4] Jain, S., Obermeier, G., Auinger, A., Werth, D., & Kiss, G. (2023). Design Principles of a Mixed-Reality Shopping Assistant System in Omnichannel Retail. *Applied Sciences (Switzerland)*, *13*(3). https://doi.org/10.3390/app13031384

[5] Sonia, Sharma, K., & Bajaj, M. (2023). DeepWalk Based Influence Maximization (DWIM): Influence Maximization Using Deep Learning. *Intelligent Automation and Soft Computing*, *35*(1), 1087–1101. https://doi.org/10.32604/iasc.2023.026134

[6] van Maasakkers, L., Fok, D., & Donkers, B. (2023). Next-basket prediction in a high-dimensional setting using gated recurrent units. *Expert Systems with Applications*, *212*. https://doi.org/10.1016/j.eswa.2022.118795

[7] Yıldız, E., Güngör Şen, C., & Işık, E. E. (2023). A Hyper-Personalized Product Recommendation System Focused on Customer Segmentation: An Application in the Fashion Retail Industry. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(1), 571–596. https://doi.org/10.3390/jtaer18010029

[8] Deenadayalan, D., & Kangaiammal, A. (2023). User Feature Similarity Supported Collaborative Filtering for Page Recommendation Using Hybrid Shuffled Frog Leaping Algorithm. *International Journal of Intelligent Engineering and Systems*, *16*(1), 301–313. https://doi.org/10.22266/ijies2023.0228.27

[9] Selvasheela, K., Abirami, A. M., & Askarunisa, A. K. (2023). Effective Customer Review Analysis Using Combined Capsule Networks with Matrix Factorization Filtering. *Computer Systems Science and Engineering*, *44*(3), 2537–2552. https://doi.org/10.32604/csse.2023.029148

[10] Dang Tran, H., Le, N., & Nguyen, V.-H. (2023). Customer Churn Prediction in the Banking Sector Using Machine Learning-Based Classification Models. *Interdisciplinary Journal of Information, Knowledge, and Management*, *18*, 087–105. https://doi.org/10.28945/5086

[11] Zhang, Z., & Wang, Y. (2023). Product Line Optimization for Car-Sharing Platforms in the Sustainable Transportation. *Journal of Advanced Transportation*, *2023*. https://doi.org/10.1155/2023/9786689

[12] Hai, T., Zhou, J., Lu, Y., Jawawi, D. N., Sinha, A., Bhatnagar, Y., & Anumbe, N. (2023). Posterior probability and collaborative filtering based Heterogeneous Recommendations model for user/item Application in use case of IoVT. *Computers and Electrical Engineering*, *105*. https://doi.org/10.1016/j.compeleceng.2022.108532

[13] Akanferi, A. A., Asampana, I., Matey, A. H., & Tanye, H. A. (2022). Adoption of Mobile Commerce and Mobile Payments in Ghana: an Examination of Factors Influencing Public Servants. *Interdisciplinary Journal of Information, Knowledge, and Management*, *17*, 287–313. https://doi.org/10.28945/4981

[14] Rudolf, S., Blömeke, S., Niemeyer, J. F., Lawrenz, S., Sharma, P., Hemminghaus, S., Mennenga, M., Schmidt, K., Rausch, A., Spengler, T. S., & Herrmann, C. (2022). Extending the Life Cycle of EEE—Findings from a Repair Study in Germany: Repair Challenges and Recommendations for Action. *Sustainability (Switzerland)*, *14*(5). https://doi.org/10.3390/su14052993

[15] Kennedyd, S. I., Marjerison, R. K., Yu, Y., Zi, Q., Tang, X., & Yang, Z. (2022). E-Commerce Engagement: A Prerequisite for Economic Sustainability—An Empirical Examination of Influencing Factors. *Sustainability (Switzerland)*, *14*(8). https://doi.org/10.3390/su14084554

[16] Salazar, M. B., Marín-Raventós, G., & Herrera, G. L. (2022). Designing Diagnosis Instruments to Determine e-Commerce Readiness for Micro and Small Enterprises in Rural Areas. *CLEI Eletronic Journal (CLEIej)*, *25*(2), 11. https://doi.org/10.19153/CLEIEJ.25.2.11

[17] Nicolescu, L., & Tudorache, M. T. (2022). Human-Computer Interaction in Customer Service: The Experience with AI Chatbots—A Systematic Literature Review. *Electronics (Switzerland)*, *11*(10). https://doi.org/10.3390/electronics11101579

[18] Shi, Y., Li, X., Zhougong, S., Li, X., & Wang, H. (2022). Precise Marketing Classification of Agricultural Products for E-Commerce Live Broadcast Platform Using Clustering. *Mobile Information Systems*, *2022*. https://doi.org/10.1155/2022/1062938

[19] Almahmood, R. J. K., & Tekerek, A. (2022). Issues and Solutions in Deep Learning-Enabled Recommendation Systems within the E-Commerce Field. *Applied Sciences (Switzerland)*, *12*(21). https://doi.org/10.3390/app122111256

[20] Kaur, R., Singh, R., Gehlot, A., Priyadarshi, N., & Twala, B. (2022). Marketing Strategies 4.0: Recent Trends and Technologies in Marketing. *Sustainability (Switzerland)*, *14*(24). https://doi.org/10.3390/su142416356

[21] Lingaitienė, O., Grybaitė, V., & Burinskienė, A. (2022). Core Elements Affecting Sharing Evidence from the European Union. *Sustainability (Switzerland)*, *14*(7). https://doi.org/10.3390/su14073845

[22] Iwendi, C., Ibeke, E., Eggoni, H., Velagala, S., & Srivastava, G. (2022). Pointer-Based Item-to-Item Collaborative Filtering Recommendation System Using a Machine Learning Model. *International Journal of Information Technology and Decision Making*, *21*(1), 463–484. https://doi.org/10.1142/S0219622021500619

[23] Pinto, J. P., Veloso, C. M., Sousa, B. B., Valeri, M., Walter, C. E., & Lopes, E. (2022). Managerial Practices and (Post) Pandemic Consumption of Private Labels: Online and Offline Retail Perspective in a Portuguese Context. *Sustainability (Switzerland)*, *14*(17). https://doi.org/10.3390/su141710813

[24] Kompan, M., Gaspar, P., MacIna, J., Cimerman, M., & Bielikova, M. (2022). Exploring Customer Price Preference and Product Profit Role in Recommender Systems. *IEEE Intelligent Systems*, *37*(1), 89–98. https://doi.org/10.1109/MIS.2021.3092768

[25] Sugiono, S., Sulistyorini, D. H., Sakinah, N., & Nugroho, W. S. (2022). Re-Designing of Railway Carriages To Increase Ergonomic and Accessible: a Case Studi of Indonesian Railway. *Eastern-European Journal of Enterprise Technologies*, *4*(1–118), 13–22. https://doi.org/10.15587/1729-4061.2022.253415

[26] Alamdari, P. M., Navimipour, N. J., Hosseinzadeh, M., Safaei, A. A., & Darwesh, A. (2022). Image-based Product Recommendation Method for E-commerce Applications Using Convolutional Neural Networks. *Acta Informatica Pragensia*, *11*(1), 15–35. https://doi.org/10.18267/j.aip.167

[27] Kutlimuratov, A., Abdusalomov, A. B., Oteniyazov, R., Mirzakhalilov, S., & Whangbo, T. K. (2022). Modeling and Applying Implicit Dormant Features for Recommendation via Clustering and Deep Factorization. *Sensors*, *22*(21). https://doi.org/10.3390/s22218224

[28] Zhao, X., & Keikhosrokiani, P. (2022). Sales prediction and product recommendation model through user behavior analytics. *Computers, Materials and Continua*, *70*(2), 3855–3874. https://doi.org/10.32604/cmc.2022.019750

[29] Lee, C., Han, D., Han, K., & Yi, M. (2022). Improving Graph-Based Movie Recommender System Using Cinematic Experience. *Applied Sciences (Switzerland)*, *12*(3). https://doi.org/10.3390/app12031493

[30] Bataineh, A. Q. (2022). Analyzing the role of social media marketing in changing customer experience. *International Journal of Data and Network Science*, *6*(3), 761–768. https://doi.org/10.5267/j.ijdns.2022.3.005

[31] Indriasari, E., Prabowo, H., Gaol, F. L., & Purwandari, B. (2022). Intelligent Digital Banking Technology and Architecture: A Systematic Literature Review. *International Journal of Interactive Mobile Technologies*, *16*(19), 98–117. https://doi.org/10.3991/ijim.v16i19.30993

[32] Shema, A. (2022). Effects of increasing credit limit in digital microlending: A study of airtime lending in East Africa. *Electronic Journal of Information Systems in Developing Countries*, *88*(3). https://doi.org/10.1002/isd2.12199

[33] Gao, M., He, X., Chen, L., Liu, T., Zhang, J., & Zhou, A. (2022). Learning Vertex Representations

for Bipartite Networks. *IEEE Transactions on Knowledge and Data Engineering*, *34*(1), 379–393. https://doi.org/10.1109/TKDE.2020.2979980

[34] Thaipisutikul, T. (2022). An Adaptive Temporal-Concept Drift Model for Sequential Recommendation. *ECTI Transactions on Computer and Information Technology*, *16*(2), 221–235. https://doi.org/10.37936/ecticit.2022162.248019

[35] Ahmad, J., Rehman, A., Rauf, H. T., Javed, K., Alkhayyal, M. A., & Alnuaim, A. A. (2022). Service Recommendations Using a Hybrid Approach in Knowledge Graph with Keyword Acceptance Criteria. *Applied Sciences (Switzerland)*, *12*(7). https://doi.org/10.3390/app12073544

[36] Gao, S., & Meng, W. (2022). Development of a Personalized Recommendation System for E-Commerce Products for Distributed Storage Systems. *Computational Intelligence and Neuroscience*, *2022*. https://doi.org/10.1155/2022/4752981

[37] Yuliawati, A., Tohari, H., Mahendra, R., & Budi, I. (2022). On the Long Tail Products Recommendation using Tripartite Graph. *International Journal of Advanced Computer Science and Applications*, *13*(1), 816–822. https://doi.org/10.14569/IJACSA.2022.0130195

[38] Liu, L. (2022). E-Commerce Personalized Recommendation Based on Machine Learning Technology. *Mobile Information Systems*, *2022*. https://doi.org/10.1155/2022/1761579

[39] Shen, R. (2022). Prediction Method of User Behavior Label Based on the BP Neural Network. *Scientific Programming*, *2022*. https://doi.org/10.1155/2022/7241956

[40] Wei, Y. (2022). Advertising Image Design Skills of E-Commerce Products in the Context of the Internet of Things. *Mobile Information Systems*, *2022*. https://doi.org/10.1155/2022/1022825

[41] Jankeeparsad, R. W., & Tewari, D. (2022). Bitcoin: an Exploratory Study Investigating Adoption in South Africa. *Interdisciplinary Journal of Information, Knowledge, and Management*, *17*, 191–214. https://doi.org/10.28945/4947

[42] Hou, X. (2022). Core Technology Optimization of Intelligent Financial Technology Based on Collaborative Filtering Algorithm in Big Data Environment. *Wireless Communications and Mobile Computing*, *2022*. https://doi.org/10.1155/2022/1693066

[43] Li, L., Fu, L., & Zhang, W. (2022). Impact of Text Diversity on Review Helpfulness: A Topic Modeling Approach. *Interdisciplinary Journal of Information, Knowledge, and Management*, *17*, 87–100. https://doi.org/10.28945/4922

[44] Blagu, D., Szabo, D., Dragomir, D., Neamțu, C., & Popescu, D. (2022). Offering Carbon Smart Options through Product Development to Meet Customer Expectations. *Sustainability (Switzerland)*, *14*(16). https://doi.org/10.3390/su14169913

[45] Al-Hazmi, N. M. (2022). E-marketing by Mobile Apps for Tourism Products and Its Impact on the Performance of Travel and Tourism Organizations. *International Journal of Interactive Mobile Technologies*, *16*(12), 145–153. https://doi.org/10.3991/ijim.v16i12.30515

[46] Beyari, H., & Garamoun, H. (2022). The Effect of Artificial Intelligence on End-User Online Purchasing Decisions: Toward an Integrated Conceptual Framework. *Sustainability (Switzerland)*, *14*(15). https://doi.org/10.3390/su14159637

[47] Stitini, O., Kaloun, S., & Bencharef, O. (2022). An Improved Recommender System Solution to Mitigate the Over-Specialization Problem Using Genetic Algorithms. *Electronics (Switzerland)*, *11*(2). https://doi.org/10.3390/electronics11020242

[48] Anggraeni, E. W., Handayati, Y., & Novani, S. (2022). Improving Local Food Systems through the Coordination of Agriculture Supply Chain Actors. *Sustainability (Switzerland)*, *14*(6). https://doi.org/10.3390/su14063281

[49] An, Y., Meng, S., & Wu, H. (2022). Discover Customers' Gender From Online Shopping Behavior. *IEEE Access*, *10*, 13954–13965. https://doi.org/10.1109/ACCESS.2022.3147447

[50] Bagwari, A., Sinha, A., Singh, N. K., Garg, N., & Kanti, J. (2022). CBIR-DSS: Business Decision Oriented Content-Based Recommendation Model for E-Commerce. *Information (Switzerland)*, *13*(10). https://doi.org/10.3390/info13100479

[51] Sabitha, R., Vaishnavi, S., Karthik, S., & Bhavadharini, R. M. (2022). User interaction based recommender system using machine learning. *Intelligent Automation and Soft Computing*, *31*(2), 1037–1049. https://doi.org/10.32604/iasc.2022.018985

[52] Chopra, A. B., & Dixit, V. S. (2022). An adaptive RNN algorithm to detect shilling attacks for online products in hybrid recommender system. *Journal of Intelligent Systems*, *31*(1), 1133–1149. https://doi.org/10.1515/jisys-2022-1023

[53] Ali, N. M., Alshahrani, A., Alghamdi, A. M., & Novikov, B. (2022). SmartTips: Online Products Recommendations System Based on Analyzing Customers Reviews. *Applied Sciences (Switzerland)*, *12*(17). https://doi.org/10.3390/app12178823

[54] Liu, W., & Ji, L. (2022). Multi-Feature Extraction Method of Power Customer's Portrait based on Knowledge Map and Label Extraction. *International Journal of Advanced Computer Science and Applications*, *13*(11), 129–138. https://doi.org/10.14569/IJACSA.2022.0131114

[55] Chowdhury, M. N., Haque, H. M. Z., Tahmid, K. T., Salma, F. T. Z., & Ahmed, N. (2022). A Novel Approach for Product Recommendation Using Smartphone Sensor Data. *International Journal of Interactive Mobile Technologies*, *16*(16), 190–204. https://doi.org/10.3991/ijim.v16i16.31617

[56] Shajalal, M., Boden, A., & Stevens, G. (2022). Explainable product backorder prediction exploiting CNN: Introducing explainable models in businesses. *Electronic Markets*, *32*(4), 2107–2122. https://doi.org/10.1007/s12525-022-00599-z

[57] Almajali, D. A. (2022). Determinants of Online Behavior Among Jordanian Consumers: an Empirical Study of Opensooq. *Interdisciplinary Journal of Information, Knowledge, and Management*, *17*, 339–359. https://doi.org/10.28945/4994

[58] Jarman, D., Berry, J., Smith, R., Thung, F., & Lo, D. (2022). Legion: Massively Composing Rankers for Improved Bug Localization at Adobe. *IEEE Transactions on Software Engineering*, *48*(8), 3010–3024. https://doi.org/10.1109/TSE.2021.3075215

[59] Mohamed, S., Sethom, K., Namoun, A., Tufail, A., Kim, K. H., & Almoamari, H. (2022). Customer Profiling Using Internet of Things Based Recommendations. *Sustainability (Switzerland)*, *14*(18). https://doi.org/10.3390/su141811200

[60] Somya, R., Winarko, E., & Priyanta, S. (2022). A hybrid recommender system based on customer behavior and transaction data using generalized sequential pattern algorithm. *Bulletin of Electrical Engineering and Informatics*, *11*(6), 3422–3432. https://doi.org/10.11591/eei.v11i6.4021

[61] Bonney, S. O., Song, J., Jingwei, Z., & Peng, Y. (2022). Consumer preference for cement brands used in concrete production: the Ghanaian perspective. *Cogent Engineering*, *9*(1). https://doi.org/10.1080/23311916.2022.2062876

[62] Xiao, M., Zhou, Q., Lu, L., Tao, X., He, W., & Zhou, Y. (2022). Applying Deep Learning-Based Personalized Item Recommendation for Mobile Service in Retailor Industry. *Mobile Information Systems*, *2022*. https://doi.org/10.1155/2022/2364154

[63] Gunawan, A. A., Bloemer, J., van Riel, A. C. R., & Essers, C. (2022). Institutional Barriers and Facilitators of Sustainability for Indonesian Batik SMEs: A Policy Agenda. *Sustainability (Switzerland)*, *14*(14). https://doi.org/10.3390/su14148772

[64] Wu, M. Y., Ke, C. K., & Lai, S. C. (2022). Optimizing the Routing of Urban Logistics by Context-Based Social Network and Multi-Criteria Decision Analysis. *Symmetry*, *14*(9). https://doi.org/10.3390/sym14091811

[65] Yu, C. L., Shu, M. H., Ho, P. T., & Huang, J. C. (2022). Consumer Behavior Based on Big Data and Cloud Computing and Construction of Customer Perception Mobile Terminal System. *Security and Communication Networks*, *2022*. https://doi.org/10.1155/2022/7531530

[66] Mahmoud, M. A., Tsetse, E. K. K., Tulasi, E. E., & Muddey, D. K. (2022). Green Packaging, Environmental Awareness, Willingness to Pay and Consumers' Purchase Decisions. *Sustainability (Switzerland)*, *14*(23). https://doi.org/10.3390/su142316091

[67] Dogan, O., Kem, F. C., & Oztaysi, B. (2022). Fuzzy association rule mining approach to identify e-commerce product association considering sales amount. *Complex and Intelligent Systems*, *8*(2), 1551–1560. https://doi.org/10.1007/s40747-021-00607-3

[68] Jeong, J., Kim, D., Li, X., Li, Q., Choi, I., & Kim, J. (2022). An Empirical Investigation of Personalized Recommendation and Reward Effect on Customer Behavior: A Stimulus–Organism–Response (SOR) Model Perspective. *Sustainability (Switzerland)*, *14*(22). https://doi.org/10.3390/su142215369

[69] Esheiba, L., Helal, I. M. A., Elgammal, A., & El-Sharkawi, M. E. (2022). A Data Warehouse-Based

System for Service Customization Recommendations in Product-Service Systems. *Sensors*, *22*(6). https://doi.org/10.3390/s22062118

[70] Ahmad, A., Leifler, O., & Sandahl, K. (2022). Data visualisation in continuous integration and delivery: Information needs, challenges, and recommendations. *IET Software*, *16*(3), 331–349. https://doi.org/10.1049/sfw2.12030

[71] Sulikowski, P., Kucznerowicz, M., Bąk, I., Romanowski, A., & Zdziebko, T. (2022). Online Store Aesthetics Impact Efficacy of Product Recommendations and Highlighting. *Sensors*, *22*(23). https://doi.org/10.3390/s22239186

[72] Li, S., Zhu, B., Zhu, H., Liu, F., Zhang, Y., Wang, R., & Lu, H. (2022). Heterogeneous Attention Concentration Link Prediction Algorithm for Attracting Customer Flow in Online Brand Community. *IEEE Access*, *10*, 20898–20912. https://doi.org/10.1109/ACCESS.2022.3151112

[73] Kafkas, K., Perdahçı, Z. N., & Aydın, M. N. (2021). Discovering customer purchase patterns in product communities: An empirical study on co-purchase behavior in an online marketplace. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(7), 2965–2980. https://doi.org/10.3390/jtaer16070162

[74] Pazhaniraja, N., Sountharrajan, S., Suganya, E., & Karthiga, M. (2021). Top 'N' Variant Random Forest Model for High Utility Itemsets Recommendation. *EAI Endorsed Transactions on Energy Web*, *8*(35), 1–7. https://doi.org/10.4108/eai.25-1-2021.168225

[75] Vahidi Farashah, M., Etebarian, A., Azmi, R., & Ebrahimzadeh Dastjerdi, R. (2021). A hybrid recommender system based-on link prediction for movie baskets analysis. *Journal of Big Data*, *8*(1). https://doi.org/10.1186/s40537-021-00422-0

[76] Yin, H., Hu, Z., Peng, Y., Wang, Z., Xu, G., & Xu, Y. (2021). Deep semi-supervised learning with weight map for review helpfulness prediction. *Computer Science and Information Systems*, *18*(4), 1159–1174. https://doi.org/10.2298/CSIS201228044Y

[77] Pasquier, N., & Chatterjee, S. (2021). Customer choice modelling: A multilevel consensus clustering approach. *Annals of Emerging Technologies in Computing*, *5*(2), 103–120. https://doi.org/10.33166/AETiC.2021.02.009

[78] Chen, G., & Li, Z. (2021). A new method combining pattern prediction and preference prediction for next basket recommendation. *Entropy*, *23*(11). https://doi.org/10.3390/e23111430

[79] Al-Safi, J., & Kaleli, C. (2021). Item genre-based users similarity measure for recommender systems. *Applied Sciences (Switzerland)*, *11*(13). https://doi.org/10.3390/app11136108

[80] Fu, L., & Ma, X. (2021). An Improved Recommendation Method Based on Content Filtering and Collaborative Filtering. *Complexity*, *2021*. https://doi.org/10.1155/2021/5589285

[81] Cassaniti, J., Kumoji, K., Rariewa, F., Ohkubo, S., & Oyenubi, O. (2021). Influence networks relating to health knowledge among nairobi⇔s micro-retailers and their clients. *Electronic Journal of Knowledge Management*, *18*(3), 302–324. https://doi.org/10.34190/EJKM.18.3.2068

[82] Kazmi, S. H. A., Ahmed, R. R., Soomro, K. A., Hashem E, A. R., Akhtar, H., & Parmar, V. (2021). Role of augmented reality in changing consumer behavior and decision making: Case of Pakistan. *Sustainability (Switzerland)*, *13*(24). https://doi.org/10.3390/su132414064

[83] Le, N. B. Van, & Huh, J. H. (2021). Applying sentiment product reviews and visualization for bi systems in vietnamese e-commerce website: Focusing on vietnamese context. *Electronics (Switzerland)*, *10*(20). https://doi.org/10.3390/electronics10202481

[84] Uz Zaman, M. W., Hafeez, Y., Hussain, S., Anwaar, H., Yang, S., Ali, S., Abbasi, A. A., & Song, O. Y. (2021). Recommender System for Configuration Management Process of Entrepreneurial Software Designing Firms. *Computers, Materials and Continua*, *67*(2), 2373–2391. https://doi.org/10.32604/cmc.2021.015112

[85] Alaa, R., Gawish, M., & Fernández-Veiga, M. (2021). Improving recommendations for online retail markets based on ontology evolution. *Electronics (Switzerland)*, *10*(14). https://doi.org/10.3390/electronics10141650

[86] Fang, B., Hu, E., Shen, J., Zhang, J., & Chen, Y. (2021). Implicit Feedback Recommendation Method Based on User-Generated Content. *Scientific Programming*, *2021*. https://doi.org/10.1155/2021/3982270

[87] Schröter, I., Grillo, N. R., Limpak, M. K., Mestiri, B., Osthold, B., Sebti, F., & Mergenthaler, M. (2021). Webcam eye tracking for monitoring visual attention in hypothetical online shopping tasks. *Applied Sciences (Switzerland)*, *11*(19). https://doi.org/10.3390/app11199281

[88] Chindyana, M., & Wulandhari, L. A. (2021). Segmentation of tourist interest on tourism object categories by comparing PSO K-means and DBSCAN method. *Revue d'Intelligence Artificielle*, *35*(1), 23–37. https://doi.org/10.18280/ria.350103

[89] Kuang, D., Li, X. F., & Bi, W. W. (2021). How to effectively design referral rewards to increase the referral likelihood for green products. *Sustainability (Switzerland)*, *13*(13). https://doi.org/10.3390/su13137177

[90] Esheiba, L., Elgammal, A., Helal, I. M. A., & El-Sharkawi, M. E. (2021). A hybrid knowledge-based recommender for product-service systems mass customization. *Information (Switzerland)*, *12*(8). https://doi.org/10.3390/info12080296

[91] Giat, Y., & Bouhnik, D. (2021). A decision support system and warehouse operations design for pricing products and minimizing product returns in a food plant. *Interdisciplinary Journal of Information, Knowledge, and Management*, *16*, 39–54. https://doi.org/10.28945/4692

[92] Simeone, A., Zeng, Y., & Caggiano, A. (2021). Intelligent decision-making support system for manufacturing solution recommendation in a cloud framework. *International Journal of Advanced Manufacturing Technology*, *112*(3–4), 1035–1050. https://doi.org/10.1007/s00170-020-06389-1

[93] Naous, D., & Legner, C. (2021). Leveraging market research techniques in is: A review and framework of conjoint analysis studies in the is discipline. *Communications of the Association for Information Systems*, *49*, 126–155. https://doi.org/10.17705/1CAIS.04906

[94] Sharma, S., Koehl, L., Bruniaux, P., Zeng, X., & Wang, Z. (2021). Development of an intelligent data-driven system to recommend personalized fashion design solutions. *Sensors*, *21*(12). https://doi.org/10.3390/s21124239

[95] Wu, Y., Huo, Z., Xing, W., Ma, Z., & Ahmed Aldeeb, H. M. (2021). Application of experience economy and recommendation algorithm in tourism reuse of industrial wasteland. *Applied Mathematics and Nonlinear Sciences*, *6*(2), 227–238. https://doi.org/10.2478/amns.2021.2.00039

[96] Suresh, A., & Carmel Mary Belinda, M. J. (2021). Accelerated - Generic gradient descent for e-commerce recommender systems. *Indian Journal of Computer Science and Engineering*, *12*(1), 135–147. https://doi.org/10.21817/indjcse/2021/v12i1/211201157

[97] Wu, C. H., Wang, Y., & Ma, J. (2021). Maximal Marginal Relevance-Based Recommendation for Product Customisation. *Enterprise Information Systems*. https://doi.org/10.1080/17517575.2021.1992018

[98] Yoon, Y., Fu, Y., & Joo, J. (2021). Unintended CSR violation caused by online recommendation. *Sustainability (Switzerland)*, *13*(7). https://doi.org/10.3390/su13074053

[99] Ye, X., & Chen, M. (2021). Personalized Recommendation for Mobile Internet Wealth Management Based on User Behavior Data Analysis. *Scientific Programming*, *2021*. https://doi.org/10.1155/2021/9326932

[100] Ohashi, F. K., Gaspar, M. A., Costa, I., Martins, F. S., & de Magalhães, F. L. F. (2021). Recommender System Architecture to support salesperson using Sales Force Automation Systems In large product portfolio companies. *RISTI - Revista Iberica de Sistemas e Tecnologias de Informacao*, *42*, 46–61. https://doi.org/10.17013/RISTI.42.46-61

[101] Kit, T. C., & Azmi, N. F. M. (2021). Customer Profiling for Malaysia Online Retail Industry using K-Means Clustering and RM Model. *International Journal of Advanced Computer Science and Applications*, *12*(1), 106–113. https://doi.org/10.14569/IJACSA.2021.0120114

[102] Werder, K., Richter, J., Hennel, P., Dreesen, T., Fischer, M., & Weingarth, J. (2021). A Three-Pronged View on Organizational Agility. *IT Professional*, *23*(2), 89–95. https://doi.org/10.1109/MITP.2020.3016488

[103] Korösi, G., & Vinkó, T. (2021). A Practical Framework for Real Life Webshop Sales Promotion Targeting. *Informatica (Slovenia)*, *45*(4), 625–632. https://doi.org/10.31449/inf.v45i4.3066

[104] Olsson, T., Wnuk, K., & Jansen, S. (2021). A validated model for the scoping process of quality requirements: a multi-case study. *Empirical Software Engineering*, *26*(2). https://doi.org/10.1007/s10664-020-09896-7

[105] Islam, M. M., & Baek, J. H. (2021). Deep learning based real age and gender estimation from unconstrained face image towards smart store customer relationship management. *Applied Sciences (Switzerland)*, *11*(10). https://doi.org/10.3390/app11104549

[106] Feng, D., Fu, X., Jiang, S., & Jing, L. (2021). Conceptual solution decision based on rough sets and shapley value for product-service system: Customer value-economic objective trade-off perspective. *Applied Sciences (Switzerland)*, *11*(22). https://doi.org/10.3390/app112211001

[107] Hasnul Hadi, M. H., Ker, P. J., Thiviyanathan, V. A., Tang, S. G. H., Leong, Y. S., Lee, H. J., Hannan, M. A., Jamaludin, M. Z., & Mahdi, M. A. (2021). The amber-colored liquid: A review on the color standards, methods of detection, issues and recommendations. *Sensors*, *21*(20). https://doi.org/10.3390/s21206866

[108] Stöckli, D. R., & Khobzi, H. (2021). Recommendation systems and convergence of online reviews: The type of product network matters! *Decision Support Systems*, *142*. https://doi.org/10.1016/j.dss.2020.113475

[109] Hanafi, & Mohd Aboobaider, B. (2021). Word Sequential Using Deep LSTM and Matrix Factorization to Handle Rating Sparse Data for E-Commerce Recommender System. *Computational Intelligence and Neuroscience*, *2021*. https://doi.org/10.1155/2021/8751173

[110] Sadreddini, Z., Donmez, I., & Yanikomeroglu, H. (2021). Cancel-for-Any-Reason Insurance Recommendation Using Customer Transaction-Based Clustering. *IEEE Access*, *9*, 39363–39374. https://doi.org/10.1109/ACCESS.2021.3064929

[111] Kobayashi, M., & Takeda, T. (2020). Product recommendation based on analysis of aesthetic elements used to customer's favorite products. *Computer-Aided Design and Applications*, *18*(4), 682–691. https://doi.org/10.14733/cadaps.2021.682-691

[112] Goyani, M., & Chaurasiya, N. (2020). A Review of Movie Recommendation System: Limitations, Survey and Challenges. *Electronic Letters on Computer Vision and Image Analysis*, *19*(3), 18–37. https://doi.org/10.5565/rev/elcvia.1232

[113] Lee, D., Gopal, A., & Park, S. H. (2020). Different but equal? a field experiment on the impact of recommendation systems on mobile and personal computer channels in retail. *Information Systems Research*, *31*(3), 892–912. https://doi.org/10.1287/ISRE.2020.0922

[114] Wu, Z., Li, L., & Liu, H. (2020). Process Knowledge Recommendation System for Mechanical Product Design. *IEEE Access*, *8*, 112795–112804. https://doi.org/10.1109/ACCESS.2020.3002922

[115] Hu, S., Kumar, A., Al-Turjman, F., Gupta, S., Seth, S., & Shubham. (2020). Reviewer Credibility and Sentiment Analysis Based User Profile Modelling for Online Product Recommendation. *IEEE Access*, *8*, 26172–26189. https://doi.org/10.1109/ACCESS.2020.2971087

[116] Abbas, K., Afaq, M., Khan, T. A., & Song, W. C. (2020). A blockchain and machine learning-based drug supply chain management and recommendation system for smart pharmaceutical industry. *Electronics (Switzerland)*, *9*(5). https://doi.org/10.3390/electronics9050852

[117] Liu, R., Liu, R., Pugliese, A., & Subrahmanian, V. S. (2020). STARS: Defending against Sockpuppet-Based Targeted Attacks on Reviewing Systems. *ACM Transactions on Intelligent Systems and Technology*, *11*(5). https://doi.org/10.1145/3397463

[118] Wang, G., & Wu, N. (2020). A Comparative Study on Contract Recommendation Model: Using Macao Mobile Phone Datasets. *IEEE Access*, *8*, 39747–39757. https://doi.org/10.1109/ACCESS.2020.2975029

[119] Diao, W., Saxena, S., & Pecht, M. G. (2020). Analysis of Specified Capacity in Power Banks. *IEEE Access*, *8*, 21326–21332. https://doi.org/10.1109/ACCESS.2020.2969410

[120] Li, Z., Wang, H., Ding, D., Hu, S., Zhang, Z., Liu, W., Gao, J., Zhang, Z., & Zhang, J. (2020). Deep Interest-Shifting Network with Meta-Embeddings for Fresh Item Recommendation. *Complexity*, *2020*. https://doi.org/10.1155/2020/8828087

[121] Abugabah, A., Cheng, X., & Wang, J. (2020). Learning context-aware outfit recommendation. *Symmetry*, *12*(6). https://doi.org/10.3390/SYM12060873

[122] Lamberz, J., Litfin, T., Teckert, Ö., & Meeh-Bunse, G. (2020). Is there a Link between Sustainability, Perception and Buying Decision at the Point of Sale? *Business Systems Research*, *11*(3), 1–13. https://doi.org/10.2478/bsrj-2020-0023

[123] Fabra, J., Álvarez, P., & Ezpeleta, J. (2020). Log-based session profiling and online behavioral prediction in e-commerce websites. *IEEE Access*, *8*, 171834–171850. https://doi.org/10.1109/ACCESS.2020.3024649

[124] Ullah, F., Zhang, B., & Khan, R. U. (2020). Image-Based Service Recommendation System: A JPEG-Coefficient RFs Approach. *IEEE Access*, *8*,

3308–3318. https://doi.org/10.1109/ACCESS.2019.2962315

[125] Cao, R., Zhang, X., & Wang, H. (2020). A Review Semantics Based Model for Rating Prediction. *IEEE Access*, *8*, 4714–4723. https://doi.org/10.1109/ACCESS.2019.2962075

[126] Chodak, G. (2020). The problem of shelf-warmers in electronic commerce: a proposed solution. *Information Systems and E-Business Management*, *18*(2), 259–280. https://doi.org/10.1007/s10257-020-00473-5

[127] Gunjal, S. N., Yadav, S. K., & Kshirsagar, D. B. (2020). A distributed item based similarity approach for collaborative filtering on hadoop framework. *Advances in Parallel Computing*, *37*, 407–415. https://doi.org/10.3233/APC200176

[128] Kala, K. U., & Nandhini, M. (2020). Gated recurrent unit architecture for context-aware recommendations with improved similarity measures. *KSII Transactions on Internet and Information Systems*, *14*(2), 538–561. https://doi.org/10.3837/tiis.2020.02.004

[129] Lee, H. I., Choi, I. Y., Moon, H. S., & Kim, J. K. (2020). A multi-period product recommender system in online food market based on recurrent neural networks. *Sustainability (Switzerland)*, *12*(3). https://doi.org/10.3390/su12030969

[130] Jintana, J., Sopadang, A., & Ramingwong, S. (2020). Matching consignees/shippers recommendation system in courier service using data analytics. *Applied Sciences (Switzerland)*, *10*(16). https://doi.org/10.3390/app10165585

[131] Chu, P. M., Mao, Y. S., Lee, S. J., & Hou, C. L. (2020). Leveraging user comments for recommendation in E-commerce. *Applied Sciences (Switzerland)*, *10*(7). https://doi.org/10.3390/app10072540

[132] Babeetha, S., Muruganantham, B., Ganesh Kumar, S., & Murugan, A. (2020). An enhanced kernel weighted collaborative recommended system to alleviate sparsity. *International Journal of Electrical and Computer Engineering*, *10*(1), 447–454. https://doi.org/10.11591/ijece.v10i1.pp447-454

[133] Khalid, J., Abbas, A., Mahmood, M. Q., Tariq, A., Khatoon, M., Azhar, S., Akbar, R., Rafia, Akbar, A., Meer, A., & Ud Din, M. J. (2020). Significance of electronic word of mouth (e-WOM) in opinion formation. *International Journal of Advanced Computer Science and Applications*, *2*, 537–544. https://doi.org/10.14569/ijacsa.2020.0110268

[134] Al-Hadi, I. A. A. Q., Sharef, N. M., Sulaiman, M. N., Mustapha, N., & Nilashi, M. (2020). Latent Based Temporal Optimization Approach for Improving the Performance of Collaborative Filtering. *PeerJ Computer Science*, *6*. https://doi.org/10.7717/PEERJ-CS.331

[135] Pradeep, I. K., Bhaskar, M. J., & Satyanarayana, B. (2020). Data science and deep learning applications in the e-commerce industry: A survey. *Indian Journal of Computer Science and Engineering*, *11*(5), 497–509. https://doi.org/10.21817/indjcse/2020/v11i5/201105135

[136] Shafqat, W., & Byun, Y. C. (2020). Enabling 'untact' culture via online product recommendations: An optimized graph-CNN based approach. *Applied Sciences (Switzerland)*, *10*(16). https://doi.org/10.3390/APP10165445

[137] Anoop, V. S., & Asharaf, S. (2020). Aspect-oriented sentiment analysis: A topic modeling-powered approach. *Journal of Intelligent Systems*, *29*(1), 1166–1178. https://doi.org/10.1515/jisys-2018-0299

[138] Ehikioya, S. A., & Lu, S. (2020). A traffic tracking analysis model for the effective management of e-commerce transactions. *International Journal of Networked and Distributed Computing*, *8*(3), 171–193. https://doi.org/10.2991/ijndc.k.200515.006

[139] Li, W., & Xu, B. (2020). Aspect-Based Fashion Recommendation with Attention Mechanism. *IEEE Access*, *8*, 141814–141823. https://doi.org/10.1109/ACCESS.2020.3013639

[140] Wang, D., & Chen, Y. (2020). A novel many-objective recommendation algorithm for multistakeholders. *IEEE Access*, *8*, 196482–196499. https://doi.org/10.1109/ACCESS.2020.3034716

[141] Pan, H. (2020). Consumer engagement in online brand communities: Community values, brand symbolism and social strategies. *Interdisciplinary Journal of Information, Knowledge, and Management*, *15*, 65–90. https://doi.org/10.28945/4536

[142] Beheshti, A., Yakhchi, S., Mousaeirad, S., Ghafari, S. M., Goluguri, S. R., & Edrisi, M. A. (2020). Towards cognitive recommender systems. *Algorithms*, *13*(8). https://doi.org/10.3390/A13080176

[143] Shahbazi, Z., Hazra, D., Park, S., & Byun, Y. C. (2020). Toward improving the prediction accuracy of product recommendation system using extreme gradient boosting and encoding approaches. *Symmetry*, *12*(9). https://doi.org/10.3390/SYM12091566

[144] Pratama, B. Y., Budi, I., & Yuliawati, A. (2020). Product recommendation in offline retail industry by using collaborative filtering. *International Journal of Advanced Computer Science and Applications*, *11*(9), 635–643. https://doi.org/10.14569/IJACSA.2020.0110975

[145] Bai, Y., Jia, S., Wang, S., & Tan, B. (2020). Customer loyalty improves the effectiveness of recommender systems based on complex network. *Information (Switzerland)*, *11*(3). https://doi.org/10.3390/INFO11030171

[146] Khrais, L. T. (2020). Role of artificial intelligence in shaping consumer demand in e-commerce. *Future Internet*, *12*(12), 1–14. https://doi.org/10.3390/fi12120226

[147] Sundar, A. P., Li, F., Zou, X., Gao, T., & Russomanno, E. D. (2020). Understanding shilling attacks and their detection traits: A comprehensive survey. *IEEE Access*, *8*, 171703–171715. https://doi.org/10.1109/ACCESS.2020.3022962

[148] Naicker, N., & Maharaj, M. S. (2020). Investigating agile requirements engineering practices in the South African software development market. *Journal of Computing and Information Technology*, *28*(1), 33–58. https://doi.org/10.20532/cit.2020.1004868

[149] Aspeling, J. M., & Mason, R. B. (2020). Towards an e-learning support strategy for the retail sector in South Africa. *International Journal of Web-Based Learning and Teaching Technologies*, *15*(3), 1–18. https://doi.org/10.4018/IJWLTT.2020070101

[150] Jaffali, S., Jamoussi, S., Smaili, K., & Ben Hamadou, A. (2020). Like-tasted user groups to predict ratings in recommender systems. *Social Network Analysis and Mining*, *10*(1). https://doi.org/10.1007/s13278-020-00643-w

[151] Holder, C. J., Ricketts, S., & Obara, B. (2020). Convolutional networks for appearance-based recommendation and visualisation of mascara products. *Machine Vision and Applications*, *31*(1). https://doi.org/10.1007/s00138-019-01053-5

[152] Hu, H., Tang, Y., Xie, Y., Dai, Y., & Dai, W. (2020). Cognitive computation on consumer's decision making of internet financial products based on neural activity data. *Computer Science and Information Systems*, *17*(2), 689–704. https://doi.org/10.2298/CSIS200229013H

[153] Chaudhary, N., & Chowdhury, D. R. (2019). Data preprocessing for evaluation of recommendation models in E-commerce. *Data*, *4*(1). https://doi.org/10.3390/data4010023

[154] Shoja, B. M., & Tabrizi, N. (2019). Customer Reviews Analysis with Deep Neural Networks for E-Commerce Recommender Systems. *IEEE Access*, *7*, 119121–119130. https://doi.org/10.1109/ACCESS.2019.2937518

[155] Yeh, H., & Kuo, F. (2019). Effects of online advocacy banners on customers after abandoning products in online shopping carts. *Interdisciplinary Journal of Information, Knowledge, and Management*, *14*, 165–181. https://doi.org/10.28945/4310

[156] Górajski, M., & Machowska, D. (2019). How do loyalty programs affect goodwill? An optimal control approach. *4or*, *17*(3), 297–316. https://doi.org/10.1007/s10288-018-0386-2

[157] Long, H. V., Son, L. H., Khari, M., Arora, K., Chopra, S., Kumar, R., Le, T., & Baik, S. W. (2019). A new approach for construction of geodemographic segmentation model and prediction analysis. *Computational Intelligence and Neuroscience*, *2019*. https://doi.org/10.1155/2019/9252837

[158] Sariki, T. P., & Bharadwaja Kumar, G. (2019). Exploiting visual content of book front cover to aggrandize the content based book recommendation system. *International Journal of Innovative Technology and Exploring Engineering*, *8*(12), 1631–1634. https://doi.org/10.35940/ijitee.L3158.1081219

[159] Rahman, M. M., & Hasan, M. K. (2019). A framework for predicting personalized product packages. *International Journal of Advanced Trends in Computer Science and Engineering*, *8*(4), 1069–1075. https://doi.org/10.30534/ijatcse/2019/13842019

[160] Poirson, E., & Cunha, C. Da. (2019). A recommender approach based on customer emotions. *Expert Systems with Applications*, *122*, 281–288. https://doi.org/10.1016/j.eswa.2018.12.035

[161] Guo, B., Liu, Y., Ouyang, Y., Zheng, V. W., Zhang, D., & Yu, Z. (2019). Harnessing the Power of the General Public for Crowdsourced

Business Intelligence: A Survey. *IEEE Access*, *7*, 26606–26630. https://doi.org/10.1109/ACCESS.2019.2901027

[162] Nelaturi, N., & Devi, G. L. (2019). A product recommendation model based on recurrent neural network. *Journal Europeen Des Systemes Automatises*, *52*(5), 501–507. https://doi.org/10.18280/jesa.520509

[163] Díez, J., Martínez-Rego, D., Alonso-Betanzos, A., Luaces, O., & Bahamonde, A. (2019). Optimizing novelty and diversity in recommendations. *Progress in Artificial Intelligence*, *8*(1), 101–109. https://doi.org/10.1007/s13748-018-0158-4

[164] Lee, D., & Hosanagar, K. (2019). How do recommender systems affect sales diversity? A cross-category investigation via randomized field experiment. *Information Systems Research*, *30*(1), 239–259. https://doi.org/10.1287/isre.2018.0800

[165] Lytvyn, V., Vysotska, V., Demchuk, A., Demkiv, I., Ukhanska, O., Hladun, V., Kovalchuk, R., Petruchenko, O., Dzyubyk, L., & Sokulska, N. (2019). Design of the architecture of an intelligent system for distributing commercial content in the internet space based on seo-technologies, neural networks, and machine learning. *Eastern-European Journal of Enterprise Technologies*, *2*(2–98), 15–34. https://doi.org/10.15587/1729-4061.2019.164441

[166] Ziemba, E., Eisenbardt, M., Mullins, R., & Dettmer, S. (2019). Prosumers' engagement in business process innovation – the case of Poland and the UK. *Interdisciplinary Journal of Information, Knowledge, and Management*, *14*, 119–143. https://doi.org/10.28945/4320

[167] Penumetsa, H. K., & Mogalla, S. (2019). Ml based naive bayes methodology for rate prediction using textual rating and find actual or movie rating based on mbnbr optimization. *International Journal of Innovative Technology and Exploring Engineering*, *8*(10), 314–321. https://doi.org/10.35940/ijitee.I8232.0881019

[168] Bag, S., Ghadge, A., & Tiwari, M. K. (2019). An integrated recommender system for improved accuracy and aggregate diversity. *Computers and Industrial Engineering*, *130*, 187–197. https://doi.org/10.1016/j.cie.2019.02.028

[169] Sahoo, K., Samal, A. K., Pramanik, J., & Pani, S. K. (2019). Exploratory data analysis using python. *International Journal of Innovative Technology and Exploring Engineering*, *8*(12), 4727–4735. https://doi.org/10.35940/ijitee.L3591.1081219

[170] Saravana Kumar, S., & Murali, S. (2019). Brand awareness and preference towards qualcomm snapdragon in mobile among consumers. *International Journal of Management*, *10*(4), 9–18. https://doi.org/10.34218/IJM.10.4.2019.002

[171] Gallagher, C., Furey, E., & Curran, K. (2019). The application of sentiment analysis and text analytics to customer experience reviews to understand what customers are really saying. *International Journal of Data Warehousing and Mining*, *15*(4), 21–47. https://doi.org/10.4018/IJDWM.2019100102

[172] Lammatha, K., Chinnusamy, K., & Malgireddy, N. R. (2019). Swift five force LRP data process algorithm machine learning Ai data process. *International Journal of Engineering and Advanced Technology*, *8*(6 Special Issue), 443–451. https://doi.org/10.35940/ijeat.F1095.0886S19

[173] Shafqat, W., & Byun, Y. C. (2019). Topic predictions and optimized recommendation mechanism based on integrated topic modeling and deep neural networks in crowdfunding platforms. *Applied Sciences (Switzerland)*, *9*(24). https://doi.org/10.3390/app9245496

[174] Serrano, W. (2019). Intelligent recommender system for big data applications based on the random neural network. *Big Data and Cognitive Computing*, *3*(1), 1–29. https://doi.org/10.3390/bdcc3010015

[175] Ramzan, B., Bajwa, I. S., Jamil, N., Amin, R. U., Ramzan, S., Mirza, F., & Sarwar, N. (2019). An Intelligent Data Analysis for Recommendation Systems Using Machine Learning. *Scientific Programming*, *2019*. https://doi.org/10.1155/2019/5941096

[176] Chen, K. S., & Yang, C. M. (2019). Quality Capability Assessment for Thin-Film Chip Resistor. *IEEE Access*, *7*, 92511–92516. https://doi.org/10.1109/ACCESS.2019.2927657

[177] Chen, J., & Abdul, A. (2019). A Session-Based Customer Preference Learning Method by Using the Gated Recurrent Units with Attention Function. *IEEE Access*, *7*, 17750–17759. https://doi.org/10.1109/ACCESS.2019.2895647

[178] Sangeetha, J., & Sinthu Janita Prakash, V. (2019). Opinion based memory access algorithms using collaborative filtering in recommender systems. *International Journal of Innovative Technology*

and Exploring Engineering, *8*(12), 606–612. https://doi.org/10.35940/ijitee.L3274.1081219

[179] Hwangbo, H., & Kim, Y. (2019). Session-Based Recommender system for sustainable digital marketing. *Sustainability (Switzerland)*, *11*(12). https://doi.org/10.3390/SU11123336

[180] Zhang, J. (2019). Personalised product recommendation model based on user interest. *Computer Systems Science and Engineering*, *34*(4), 231–236. https://doi.org/10.32604/CSSE.2019.34.231

[181] Bawiskar, M., & Injamuri, V. (2019). Aspect based mobile recommendation system. *International Journal of Innovative Technology and Exploring Engineering*, *8*(10), 3840–3846. https://doi.org/10.35940/ijitee.J9996.0881019

[182] Jain, A. M., & Carandang, C. B. (2018). Development of an Online Laguna Agricultural Trading Center. *International Journal of Computing*, *2*(4), 131–150. https://doi.org/10.25147/ijcsr.2017.001.1.29

[183] Ram Mohan Rao, P., Murali Krishna, S., & Siva Kumar, A. P. (2018). Privacy preservation techniques in big data analytics: a survey. *Journal of Big Data*, *5*(1). https://doi.org/10.1186/s40537-018-0141-8

[184] Erum, M., Waqas, M., Arshad, S., & Nawaz, T. (2018). Features Analysis of Online Shopping System Using WCM. *EAI Endorsed Transactions on Scalable Information Systems*, *5*(16), 1–8. https://doi.org/10.4108/eai.13-4-2018.154471

[185] Zhang, L., Zhang, H., & Hao, S. M. (2018). An equity fund recommendation system by combing transfer learning and the utility function of the prospect theory. *Journal of Finance and Data Science*, *4*(4), 223–233. https://doi.org/10.1016/j.jfds.2018.02.003

[186] Naveen, N., & Ganesh Kumar, S. (2018). Efficient mining and recommendation of extensive data through collaborative filtering in E-commerce: A survey. *International Journal of Engineering and Technology(UAE)*, *7*(2), 331–335. https://doi.org/10.14419/ijet.v7i2.24.12077

[187] Lakshmanaprabu, S. K., Shankar, K., Gupta, D., Khanna, A., Rodrigues, J. J. P. C., Pinheiro, P. R., & de Albuquerque, V. H. C. (2018). Ranking analysis for online customer reviews of products using opinion mining with clustering. *Complexity*, *2018*. https://doi.org/10.1155/2018/3569351

[188] Venugopal, S., & Nagraj, G. (2018). A proficient web recommender system using hybrid possiblistic fuzzy clustering and Bayesian model approach. *International Journal of Intelligent Engineering and Systems*, *11*(6), 190–198. https://doi.org/10.22266/IJIES2018.1231.19

[189] Nasip, I., & Sudarmaji, E. (2018). Managing tax dispute due to IFRS-16 on the retrofits implementation in Indonesia. *International Journal of Engineering and Technology(UAE)*, *7*(3), 200–208. https://doi.org/10.14419/ijet.v7i3.21.17160

[190] Girish, S., Ramamurthy, B., & Senthilnathan, T. (2018). Mining the web data for classifying and predicting users' requests. *International Journal of Electrical and Computer Engineering*, *8*(4), 2390–2398. https://doi.org/10.11591/ijece.v8i4.pp2390-2398

[191] Sfenrianto, S., Saragih, M. H., & Nugraha, B. (2018). E-commerce recommender for usage bandwidth hotel. *Indonesian Journal of Electrical Engineering and Computer Science*, *9*(1), 227–233. https://doi.org/10.11591/ijeecs.v9.i1.pp227-233

[192] Al-Enezi, K. A., Al Shaikhli, I. F. T., & Aldabbagh, S. S. M. (2018). The influence of internet and social media on purchasing decisions in Kuwait. *Indonesian Journal of Electrical Engineering and Computer Science*, *10*(2), 792–797. https://doi.org/10.11591/ijeecs.v10.i2.pp792-797

[193] Ziemba, E., & Eisenbardt, M. (2018). The ways of prosumers' knowledge sharing with organizations. *Interdisciplinary Journal of Information, Knowledge, and Management*, *13*, 95–115. https://doi.org/10.28945/4067

[194] Guidotti, R., Gabrielli, L., Monreale, A., Pedreschi, D., & Giannotti, F. (2018). Discovering temporal regularities in retail customers' shopping behavior. *EPJ Data Science*, *7*(1). https://doi.org/10.1140/epjds/s13688-018-0133-0

[195] Kanavos, A., Iakovou, S. A., Sioutas, S., & Tampakas, V. (2018). Large scale product recommendation of supermarket ware based on customer behaviour analysis. *Big Data and Cognitive Computing*, *2*(2), 1–19. https://doi.org/10.3390/bdcc2020011

[196] Magboul, I. H. M., & Abbad, M. (2018). Antecedents and adoption of e-banking in bank performance: The perspective of private bank

employees. *Interdisciplinary Journal of Information, Knowledge, and Management*, *13*, 361–381. https://doi.org/10.28945/4132

[197] Zhang, J., Chen, D., & Lu, M. (2018). Combining sentiment analysis with a fuzzy kano model for product aspect preference recommendation. *IEEE Access*, *6*, 59163–59172. https://doi.org/10.1109/ACCESS.2018.2875026

[198] Koolen, D., Sadat-Razavi, N., & Ketter, W. (2017). Machine learning for identifying demand patterns of home energy management systems with dynamic electricity pricing. *Applied Sciences (Switzerland)*, *7*(11). https://doi.org/10.3390/app7111160

[199] Aldayel, M., & Ykhlef, M. (2017). A new sentiment case-based recommender. *IEICE Transactions on Information and Systems*, *E100D*(7), 1484–1493. https://doi.org/10.1587/transinf.2016EDP7441

[200] Bilici, E., & Saygın, Y. (2017). Why do people (not) like me?: Mining opinion influencing factors from reviews. *Expert Systems with Applications*, *68*, 185–195. https://doi.org/10.1016/j.eswa.2016.10.001

[201] Tewari, A. S., & Barman, A. G. (2017). Collaborative recommendation system using dynamic content based filtering, association rule mining and opinion mining. *International Journal of Intelligent Engineering and Systems*, *10*(5), 57–66. https://doi.org/10.22266/ijies2017.1031.07

[202] Gimenes, G., Cordeiro, R. L. F., & Rodrigues-Jr, J. F. (2017). ORFEL: Efficient detection of defamation or illegitimate promotion in online recommendation. *Information Sciences*, *379*, 274–287. https://doi.org/10.1016/j.ins.2016.09.006

[203] Morawski, J., Stepan, T., Dick, S., & Miller, J. (2017). A Fuzzy Recommender System for Public Library Catalogs. *International Journal of Intelligent Systems*, *32*(10), 1062–1084. https://doi.org/10.1002/int.21884

[204] Allauddin Mulla, R. ., Eknath Pawar, M. ., S. Banait, S. ., N. Ajani, S. ., Pravin Borawake, M. ., & Hundekari, S. . (2023). Design and Implementation of Deep Learning Method for Disease Identification in Plant Leaf. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 278–285. https://doi.org/10.17762/ijritcc.v11i2s.6147

[205] Guo, Y., Wang, M., & Li, X. (2017). An interactive personalized recommendation system using the hybrid algorithm model. *Symmetry*, *9*(10). https://doi.org/10.3390/sym9100216

[206] Yang, M., Ma, Y., & Nie, J. (2017). Research on a personalized recommendation algorithm. *International Journal of Grid and Distributed Computing*, *10*(1), 123–136. https://doi.org/10.14257/ijgdc.2017.10.1.12

[207] Zhang, Q., Wu, D., Lu, J., Liu, F., & Zhang, G. (2017). A cross-domain recommender system with consistent information transfer. *Decision Support Systems*, *104*, 49–63. https://doi.org/10.1016/j.dss.2017.10.002

[208] Ho, C. T., Yang, J. M., & Chen, W. T. (2017). Factors affecting re-usage intentions of virtual communities supporting cosmetic products. *Interdisciplinary Journal of Information, Knowledge, and Management*, *12*, 17–36. https://doi.org/10.28945/3644

[209] Yuen, K. K. F. (2017). The fuzzy cognitive pairwise comparisons for ranking and grade clustering to build a recommender system: An application of smartphone recommendation. *Engineering Applications of Artificial Intelligence*, *61*, 136–151. https://doi.org/10.1016/j.engappai.2017.02.001

[210] Sung, H., Kim, W. J., & Shin, J. I. (2016). The antecedent and consequence of trust in social shopping. *International Journal of Security and Its Applications*, *10*(11), 143–152. https://doi.org/10.14257/ijsia.2016.10.11.13

[211] Choi, K., Suh, Y., & Yoo, D. (2016). Extended collaborative filtering technique for mitigating the sparsity problem. *International Journal of Computers, Communications and Control*, *11*(5), 631–644. https://doi.org/10.15837/ijccc.2016.5.2152

[212] Nam, K., Lee, Z., & Lee, B. G. (2016). How internet has reshaped the user experience of banking service? *KSII Transactions on Internet and Information Systems*, *10*(2), 684–702. https://doi.org/10.3837/tiis.2016.02.014

[213] Molina-Castillo, F. J., Rodriguez-Guirao, A., Lopez-Nicolas, C., & Bouwman, H. (2016). Analysis of mobile pre-payment (pay in advance) and post-payment (pay later) services. *International Journal of Mobile Communications*, *14*(5), 499–517. https://doi.org/10.1504/IJMC.2016.078725

[214] Lei, X., Qian, X., & Zhao, G. (2016). Rating Prediction Based on Social Sentiment from Textual Reviews. *IEEE Transactions on*

Multimedia, *18*(9), 1910–1921. https://doi.org/10.1109/TMM.2016.2575738

[215] Preibusch, S., Peetz, T., Acar, G., & Berendt, B. (2016). Shopping for privacy: Purchase details leaked to PayPal. *Electronic Commerce Research and Applications*, *15*, 52–64. https://doi.org/10.1016/j.elerap.2015.11.004

[216] Mr. Ather Parvez Abdul Khalil. (2012). Healthcare System through Wireless Body Area Networks (WBAN) using Telosb Motes. International Journal of New Practices in Management and Engineering, 1(02), 01 - 07. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/4

[217] Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: A survey. *Decision Support Systems*, *74*, 12–32. https://doi.org/10.1016/j.dss.2015.03.008

[218] Zhou, D., & Yao, Z. (2015). Optimal referral reward considering customer's budget constraint. *Future Internet*, *7*(4), 516–529. https://doi.org/10.3390/fi7040516

[219] Sneha, Y. S., & Mahadevan, G. (2015). A novel approach to personalized recommender systems based on multi criteria ratings. *Research Journal of Applied Sciences, Engineering and Technology*, *9*(10), 841–849. https://doi.org/10.19026/rjaset.9.2633

[220] Oyza, I., & Edwin, A. M. (2015). Effectiveness of social media networks as a strategic tool for organizational marketing management. *Journal of Internet Banking and Commerce*, *1*. https://doi.org/10.4172/1204-5357.S2-006

[221] Wu, D., Zhang, G., & Lu, J. (2015). A fuzzy preference tree-based recommender system for personalized business-to-business e-services. *IEEE Transactions on Fuzzy Systems*, *23*(1), 29–43. https://doi.org/10.1109/TFUZZ.2014.2315655

[222] Honda, K., Nakano, T., Oh, C. H., Ubukata, S., & Notsu, A. (2015). Partially exclusive item partition in MMMs-induced fuzzy co-clustering and its effects in collaborative filtering. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, *19*(6), 810–817. https://doi.org/10.20965/jaciii.2015.p0810

[223] Jatain, R. ., & Jailia, M. . (2023). Automatic Human Face Detection and Recognition Based On Facial Features Using Deep Learning Approach. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 268–277. https://doi.org/10.17762/ijritcc.v11i2s.6146

[224] Hsieh, H. C., Chen, Y. C., & Lin, H. C. (2014). More precise: Stores recommendation under O2O commerce. *International Journal of Computing and Digital Systems*, *3*(2), 91–99. https://doi.org/10.12785/IJCDS/030203

[225] Zhong, H., Zhang, S., Wang, Y., & Shu, Y. (2014). Study on directed trust graph based recommendation for e-commerce system. *International Journal of Computers, Communications and Control*, *9*(4), 510–523. https://doi.org/10.15837/ijccc.2014.4.228

[226] Kalaivani, P., & Shunmuganathan, K. L. (2014). An agent based framework for sentiment classification of online reviews using ontology. *Journal of Computer Science*, *10*(5), 809–820. https://doi.org/10.3844/jcssp.2014.809.820

[227] Brooks, A. L. (2014). Disruptive innovation in healthcare and rehabilitation. *Studies in Computational Intelligence*, *536*, 323–351. https://doi.org/10.1007/978-3-642-45432-5_16

[228] Casarejos, F., Frota, M. N., Penha-Lopes, G., Silva, V. V., & Particelli, F. (2014). Commitment to emissions restrictions of major consumers of electricity in Brazil. *Sustainability (Switzerland)*, *6*(9), 6377–6399. https://doi.org/10.3390/su6096377

[229] Mesquida, A. L., Mas, A., Feliu, T. S., & Arcilla, M. (2014). Integración de Estándares de Gestión de TI mediante MIN-ITs. *RISTI - Revista Iberica de Sistemas e Tecnologias de Informacao*, *E1*, 31–45. https://doi.org/10.4304/risti.e1.31-45

[230] Wang, T., & Wang, D. (2014). Why Amazon's ratings might mislead you: The story of herding effects. *Big Data*, *2*(4), 196–204. https://doi.org/10.1089/big.2014.0063

[231] Vera-Del-Campo, J., Pegueroles, J., Hernández-Serrano, J., & Soriano, M. (2014). DocCloud: A document recommender system on cloud computing with plausible deniability. *Information Sciences*, *258*, 387–402. https://doi.org/10.1016/j.ins.2013.04.007

[232] Apeh, E., Gabrys, B., & Schierz, A. (2014). Customer profile classification: To adapt classifiers or to relabel customer profiles? *Neurocomputing*, *132*, 3–13. https://doi.org/10.1016/j.neucom.2013.07.048

[233] Jeong, W. H., Kim, S. J., Park, D. S., & Kwak, J. (2013). Performance improvement of a movie recommendation system based on personal propensity and secure collaborative filtering. *Journal of Information Processing Systems*, *9*(1), 157–172. https://doi.org/10.3745/JIPS.2013.9.1.157

[234] Jing, Y., & Liu, H. (2013). A model for collaborative filtering recommendation in E-commerce environment. *International Journal of Computers, Communications and Control*, *8*(4), 560–570. https://doi.org/10.15837/ijccc.2013.4.577

[235] Zhang, Z., Lin, H., Liu, K., Wu, D., Zhang, G., & Lu, J. (2013). A hybrid fuzzy-based personalized recommender system for telecom products/services. *Information Sciences*, *235*, 117–129. https://doi.org/10.1016/j.ins.2013.01.025

[236] Haruyama, S., Kim, S. K., Beiter, K. A., Dijkema, G. P. J., & De Weck, O. L. (2013). A new project-based curriculum of design thinking with systems engineering techniques. *International Journal of System of Systems Engineering*, *4*(2), 162–173. https://doi.org/10.1504/IJSSE.2013.056296

[237] Lu, H., Chen, Y., & Du, J. (2013). An interactive system based on Kansei Engineering to support clothing design process. *Research Journal of Applied Sciences, Engineering and Technology*, *6*(24), 4531–4535. https://doi.org/10.19026/rjaset.6.3462

[238] Yoon, V. Y., Hostler, R. E., Guo, Z., & Guimaraes, T. (2013). Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty. *Decision Support Systems*, *55*(4), 883–893. https://doi.org/10.1016/j.dss.2012.12.024

[239] Gómez-Barroso, J. L., Bacigalupo, M., Nikolov, S. G., Compañó, R., & Feijóo, C. (2012). Factors required for mobile search going mainstream. *Online Information Review*, *36*(6), 846–857. https://doi.org/10.1108/14684521211287918

[240] Kujala, S., Roto, V., Väänänen-Vainio-Mattila, K., Karapanos, E., & Sinnelä, A. (2011). UX Curve: A method for evaluating long-term user experience. *Interacting with Computers*, *23*(5), 473–483. https://doi.org/10.1016/j.intcom.2011.06.005

[241] Sepulveda, J., Gonzalez, J., Alfaro, M., & Camargo, M. (2010). A metrics-based diagnosis tool for enhancing innovation capabilities in SMEs. *International Journal of Computers, Communications and Control*, *5*(5), 919–928. https://doi.org/10.15837/ijccc.2010.5.2255

[242] Rodriguez, R. R., Ortiz, A., & Alfaro, J. J. (2009). Fostering collaborative meta-value chain practices. *International Journal of Computer Integrated Manufacturing*, *22*(5), 385–394. https://doi.org/10.1080/09511920802389546

[243] Dholakia, U. M., Blazevic, V., Wiertz, C., & Algesheimer, R. (2009). Communal service delivery: How customers benefit from ParticiPation in Firm-hosted virtual P3 communities. *Journal of Service Research*, *12*(2), 208–226. https://doi.org/10.1177/1094670509338618

[244] Martínez, L., Pérez, L. G., & Barranco, M. (2007). A multigranular linguistic content-based recommendation model. *International Journal of Intelligent Systems*, *22*(5), 419–434. https://doi.org/10.1002/int.20207

[245] Farsani, H. K., & Nematbakhsh, M. A. (2007). Designing a catalog management system - An ontology approach. *Malaysian Journal of Computer Science*, *20*(1), 35–50. https://doi.org/10.22452/mjcs.vol20no1.4

[246] Zhang, X., Edwards, J., & Harding, J. (2007). Personalised online sales using web usage data mining. *Computers in Industry*, *58*(8–9), 772–782. https://doi.org/10.1016/j.compind.2007.02.004

[247] Kim, J. W., Lee, K. M., Shaw, M. J., Chang, H. L., Nelson, M., & Easley, R. F. (2006). A preference scoring technique for personalized advertisements on Internet storefronts. *Mathematical and Computer Modelling*, *44*(1–2), 3–15. https://doi.org/10.1016/j.mcm.2004.12.011

[248] Guan, S. U., Chan, T. K., & Zhu, F. (2005). Evolutionary intelligent agents for e-commerce: Generic preference detection with feature analysis. *Electronic Commerce Research and Applications*, *4*(4), 377–394. https://doi.org/10.1016/j.elerap.2005.07.002

[249] Huang, Z., Chen, H., & Zeng, D. (2004). Applying associative retrieval techniques to alleviate the sparsity problem in collaborative filtering. *ACM Transactions on Information Systems*, *22*(1), 116–142. https://doi.org/10.1145/963770.963775

[250] Jannach, D., & Kreutler, G. (2004). A knowledge-based framework for the rapid development of

conversational recommenders. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *3306*, 390–402. https://doi.org/10.1007/978-3-540-30480-7_40

[251] Huang, Z., Chung, W., & Chen, H. (2004). A graph model for e-commerce recommender systems. *Journal of the American Society for Information Science and Technology*, *55*(3), 259–274. https://doi.org/10.1002/asi.10372

[252] Cheung, K. W., Tsui, K. C., & Liu, J. (2004). Extended Latent Class Models for Collaborative Recommendation. *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans.*, *34*(1), 143–148. https://doi.org/10.1109/TSMCA.2003.818877

[253] Weng, S. S., & Liu, M. J. (2004). Feature-based recommendations for one-to-one marketing. *Expert Systems with Applications*, *26*(4), 493–508. https://doi.org/10.1016/j.eswa.2003.10.008

[254] Coyle, L., & Cunningham, P. (2004). Improving recommendation ranking by learning personal feature weights. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *3155*, 560–572. https://doi.org/10.1007/978-3-540-28631-8_41