JUNE 17, 2024

RESEARCH REPORT

BIG DATA CHALLENGES IN SMALL AND MEDIUM-SIZED ENTERPRISES IN EMERGING MARKETS.

DLMCSP01 PROJECT: COMPUTER SCIENCE PROJECT

JULIUS WANYAMA MATRICULATION # 92114720
Tutor: Cetin, Oezdemir, Dr.

Table of Contents

1 Abstract

The widespread use of information and communication technologies has empowered customers to express their thoughts and desires online, presenting a valuable opportunity for product designers. Despite this, many small and medium-sized enterprises in emerging markets have yet to tap into these online customer insights for innovative design, even though they play a crucial role in national economic growth. Extracting meaningful business value from the internet's vast and diverse data poses challenges, including dealing with different data types, immense volume, and real-time flow. Research indicates that factors such as complexity, uncertainty, and top-level managerial support, among others, significantly influence the adoption of Big data analytics among these firms. Leadership, technology, and organizational culture also impact the capacity to make informed decisions based on Big data. In today's dynamic business landscape, Big data, predictive analytics, and visual tools are essential in aiding complex business decisions. Unlike traditional data methods and platforms, these techniques offer more accurate, faster, and scalable results in Big data analytics. However, small and medium-sized enterprises in emerging markets face financial constraints to innovate and must adopt low-cost innovations. This study introduces specialized natural language processing techniques tailored for small and medium-sized enterprises in emerging markets to harness online customer insights, aiming to develop an algorithm that extracts product-related online customer reviews and sentiments to enhance the process of product design refinement.

2 Introduction

Big data analytics implies the implementation and procedures applied to large and complex datasets to derive actionable insights (Mikalef et al., 2021). They can enable small and medium-sized enterprises to make accurate decisions and enhance business performance, but their uptake is still low, and it's unclear why it is (Maroufkhani, Tseng, et al., 2020). They can enable businesses to remain competitive in an ever-changing market (Ciampi et al., 2021). They can empower small and medium-sized enterprises to transition from old business models (Rialti et al., 2019). They can enhance innovation in small and medium-sized enterprises (Mikalef et al., 2019). Firms could leverage Big data analytics to understand customer behavior, sentiments, and opinions (Perdana et al., 2022). They could leverage Big data analytics to in integrate customer requirements into product design (Shaik Vadla et al., 2024). The Technology- Organization-Environment framework provides three factors that may influence the adoption of information technologies in firms: technological, organizational, and environmental (Na et al., 2022). Human resources, information technology readiness, and others influence digital innovations in small and medium enterprises (Taganoviq et al., 2023). Furthermore, digital business transformation heavily influences low-cost innovations and the resilience of small and medium-sized enterprises in emerging markets (Al Omoush et al., 2023). Frugal innovations are affordable, simple, sustainable, and concentrate on core functionality (Velananda et al., 2023).

3 Related Work

3.1 Tools and Techniques

Kaur and Sharma propose a deep learning-based model using feature extraction to obtain customer insights for business innovation (Kaur & Sharma, 2023). Bharadiya and Bharadiya combine Artificial Intelligence, Machine Learning, and Business Intelligence to foster business competitiveness (Bharadiya & Bharadiya, 2023). Daradkeh suggests that Knowledge Orientation and Business Analytics capabilities significantly influence business innovation (Daradkeh, 2023). There is a low level of digitization in small and medium-sized enterprises in emerging markets, subsequently affecting the adoption of Big data analytics (Mishrif & Khan, 2023). Data quality significantly influences the adoption of Big data analytics in small and medium-sized enterprises in emerging markets (M. Sharma et al., 2023). Iranmanesh and others found that efficiency and cost influence Big data analytics uptake in small and medium-sized enterprises (Iranmanesh et al., 2023).

3.2 Theories and Frameworks

Lufti and others present the drivers for Big data analytics in small and medium-sized enterprises anchored on the Technology-Organization-Environment framework and the resource-based view theory (Lutfi et al., 2023). Technology adoption models and theories like the technology acceptance model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of

Reasoned Action (TRA), the Theory of Planned Behavior (TPB), and the Innovations Diffusion Theory (IDT) explain factors influencing the uptake of technological innovations in different settings (FakhrHosseini et al., 2024). Each of these theories has its strengths and limitations, and some scholars integrate at least two theories or extend a given model to enhance the outcomes of their studies (Al-Rahmi et al., 2021). The Technology Acceptance Model is not applicable in intelligent environments (Sagnier et al., 2020). The Technology Acceptance Model handles individual adoption of technology and not organizational-level adoption (C. Wang et al., 2023). The Technology-Organization-Environment framework enhances innovations and management of internal and external drivers (Alraja et al., 2022). It is superior to previous frameworks because it integrates human and non-human factors into a single framework (QALATI et al., 2020). It includes all essential aspects of creativity (Ghaleb et al., 2021). The Technology-Organization-Environment framework and the Resource-based View theory provide the best understanding of factors influencing the adoption of Big data analytics in small and medium-sized enterprises in emerging markets (Rakshit et al., 2024).

4 Technical Background

The Technology-Organization-Environment framework groups the challenges to innovations in firms (Mohammad et al., 2019). It identifies the factors influencing innovation in firms (Badi et al., 2021). Based on this framework and the Resource-based View theory, the study seeks to understand the challenges of adopting Big data analytics in small and medium enterprises in emerging markets. In the resource-based view, firms are collections of resources that provide leverage for competitiveness (Ozdemir et al., 2023). It shows relationships between resources and capabilities (Kosiol et al., 2023). It shows how firms can exploit those resources (Varadarajan, 2023). Technological and organizational factors influence the adoption of Big data analytics in small and medium-sized enterprises the most (Maroufkhani, Wan Ismail, et al., 2020). Technology and organization characteristics impact the adoption of Big data analytics the most (Salisu et al., 2021). Technology and organization aspects significantly influence the adoption of Big data analytics in small and medium-sized enterprises in emerging markets (Jere et al., 2020). Technological and organizational contexts are the biggest drivers for the adoption of Big data analytics in small and medium-sized enterprises (Mehedi et al., 2023). However, small and medium-sized enterprises in emerging markets face unique challenges like resource constraints that significantly influence innovation decisions (Chandni et al., 2021). The costs associated with setting up Big data analytics infrastructure are the main barrier to adopting Big data analytics for firms in emerging markets (Chaudhry & Chaudhry, 2023). These firms must formulate and adopt a frugal innovation strategy (Santos et al., 2020).

4.1 Technological Factors

The technological factors affecting the adoption of new technologies in firms are perceived benefits, compatibility, information transparency, and direct customer-to-business interactions (Malik et al., 2021). They are internal and external technologies to the organization and their relative usefulness, compatibility, and usage (Chittipaka et al., 2022). They enhance firm productivity (Črešnar et al., 2023). Small and medium-sized enterprises in emerging markets face limited resources and infrastructure, which limits the adoption of Big data analytics (Nasrollahi et al., 2021). Open science can alleviate Big data challenges (Brennan et al., 2023). Information and product delivery significantly influence the adoption of Big data analytics in small and medium-sized enterprises (Narwane et al., 2021). Data quality and technological competence significantly influence the adoption of Big data analytics in small and medium-sized enterprises (Park & Kim, 2021). Financial and technological uncertainties hinder the adoption of Big data analytics in small and medium-sized enterprises (Tamvada et al., 2022). Internal programming and data analytics skills significantly influence a firm's adoption of Big data analytics (Bag et al., 2021). The knowledge management practices of small and medium-sized enterprises influence the adoption of Big data analytics (Shabbir & Gardezi, 2020). Technical skills influence the adoption of Big data analytics in small and medium-sized enterprises (AlSharji et al., 2018). Employee digital skills positively influence the adoption of Big data analytics in small and medium-sized enterprises (Gonzalez-Tamayo et al., 2023). Specialized IT skills enable the adoption of Big data analytics (Silvestri et al., 2023). Enterprise architecture could be a significant driver for the adoption of Big data analytics in small and medium-sized enterprises (Gong & Janssen, 2020). Data management influences the adoption of Big data analytics in small and medium-sized enterprises (Bandara et al., 2024). Internal digital systems influence the adoption of Big data analytics in small and medium-sized enterprises (Al-Taie & AL-Khafaji, 2024). Their digital readiness influences Big data analytics adoption (Pingali et al., 2023). Firms with digital tools effortlessly adopt Big data analytics (KUSUMA et al., 2020).

4.2 Organizational Factors

The organizational factors that could impact the adoption of Big data analytics in small to medium-sized enterprises are leadership, culture, innovation, and skills (Chowdhury et al., 2022). Staff technical skills can affect the adoption of big data analytics in small and medium-sized enterprises (Bhalerao & Kumar, 2022). Small and medium-sized enterprises have limited resources and lack the necessary skills to handle Big data analytics (Willetts et al., 2020). Most small and medium-sized enterprises do not have the resources and infrastructure for Big data analytics (Chernova et al., 2023). They have limited resources for Big data analytics (Clemente-Almendros et al., 2024). Small and medium-sized enterprises in emerging markets lack skilled human resources and the capital to adopt Big data analytics (Ta et al., 2023). The individual characteristics of owners of small and medium-sized enterprises in emerging markets could also contribute to the adoption of Big data analytics (Nazir et al., 2021). When managers understand the benefits of Big data analytics, small and medium-sized enterprises effortlessly adopt the technologies (Al-Azzam et al., 2023). Some firms may not have a technology acceptance strategy, which hinders the adoption of new technologies (Jayawardena et al., 2023). Firms without a Big data strategy and skills face challenges in adopting Big data analytics (Justy et al., 2023). Digital marketing strategy influences the adoption of Big data analytics in small and medium-sized enterprises (C. W. Wu et al., 2024). Inadequate employee training could limit the adoption of big data analytics in small and medium-sized enterprises (Qalati et al., 2022). Firms should implement frequent online reviews to understand and prioritize common customer complaints for their market segment and adopt big data analytics to understand customer sentiments, further strengthening their market position (J. Wu & Zhao, 2023). Short-form video advertising could encourage direct customer engagement and subsequently spur the adoption of big data analytics in understanding customer sentiments (Xiao et al., 2023). Firms seeking a sustainable consumer experience should adopt big data analytics to gain insights into customer behavior and predict buying patterns (Chandra & Verma, 2021).

Swiftly changing data environments within firms could limit the adoption of Big data analytics (Sekli & De La Vega, 2021). Firms should have a clear map of big data applications for successful adoption (Acciarini et al., 2023). Firms with Big data analytics capabilities have a competitive advantage (Alkhatib & Valeri, 2024). Small and medium-sized enterprises can benefit from Big data analytics when they focus on knowledge management instead of complex IT solutions and vast amounts of data (S. Wang & Wang, 2020). Organizational culture can influence the adoption of Big data analytics in small and medium-sized enterprises (Behl, 2022).

4.3 Environmental Factors

Government regulations are the most prominent environmental factor affecting the adoption of information technologies in small and medium-sized enterprises (Zide & Jokonya, 2022). African nations have laws to protect personal data (Daigle, 2021). They require strict data security and protection, a challenge to collect and use large datasets (Brauneck et al., 2023). However, they should promote Big data exploitation to drive economic growth and development (Joubert et al., 2023). The secure-federated learning framework can enable knowledge sharing between different entities without compromising user privacy (Q. Yang et al., 2019). There are some concerns with federated learning to fully comply with data protection regulations (Chalamala et al., 2022). The turbulent business environment in emerging markets affects the adoption of Big data analytics in small and medium enterprises (Asad et al., 2021). Emerging markets experience poor IT infrastructure and a lack of government initiatives limiting the adoption of Big data analytics by small and medium-sized enterprises (Skafi et al., 2020). Poor national infrastructure hinders the adoption of Big data analytics in small and medium-sized firms in emerging markets (Obokoh & Goldman, 2016). Synchronized government IT policy can encourage small and medium-sized enterprises to adopt Big data analytics (Vu & Nguyen, 2022). Supportive government policy positively influences the adoption of Big data analytics in small and medium-sized enterprises in emerging markets (Zayed et al., 2022). Regulatory barriers can hinder the adoption of Big data analytics in small and medium-sized enterprises in emerging markets (Rahman et al., 2020). Competitive pressure influences the adoption of Big data analytics in small and medium-sized enterprises (Shahzad et al., 2023).

5 Methodology

The methodology for this study consists of developing research questions, writing a literature review, collecting data from an e-commerce website, analyzing the collected data, and testing the proposed solution.

5.1 Research questions

RQ1: What technological, organizational, and environmental factors influence the adoption of Big Data analytics within small and medium-sized enterprises operating in emerging markets?

RQ2: What open-source techniques are commonly used in Big Data analytics to extract insights from online customer behavior?

RQ3: What are the primary Big Data analytics tools for analyzing online customer product reviews?

RQ4: Which sentiment analysis technique is predominantly employed to evaluate customer perceptions and opinions regarding products and services?

RQ5: What are the various techniques for implementing aspect-based sentiment analysis?

5.2 Literature Review

5.2.1 Tools and Techniques

Infrastructure capability is essential for digital innovation in small and medium-sized enterprises in emerging markets (Isichei et al., 2020). Systems, tools, and technologies are some of the factors that influence the adoption of Big data analytics in firms (Surbakti et al., 2020). Python is one of the tools that can help firms overcome Big data challenges (Saeed & Ebrahim, 2024). Some scholars utilize supervised clustering and unsupervised learning to analyze customer product reviews (Alsayat, 2023). Techniques for analyzing customer reviews should consider the multidimensional nature of the information contained therein (F. Wang et al., 2023). Some scholars utilize machine learning algorithms to analyze online product reviews (Z. Liu et al., 2023). They can extract and summarise information from Big data (Rodriguez-Garcia et al., 2023). They optimize customer feedback on product features (Rosário & Dias, 2023). It contains information on products, features, and services (Kauffmann et al., 2020).

Web scraping enables businesses to extract online customer opinions about their products and services (Barbera et al., 2023). It extracts large amounts of unstructured data from Websites for further analysis (Sirisuriya, 2023). It enables scholars to extract valuable data from the Internet (Yuan, 2023). Some websites prohibit Web scraping, and one has to be careful with the implementation (Dogra et al., 2023). It is an automated process involving open-source tools (Kumar & Roy, 2023). Python is the regular tool for web scraping (Xie, 2023). Python libraries for Web scraping are the most efficient at data extraction (Ruchitaa Raj et al., 2023). BeautifulSoup is a Python library for extracting data from the internet (Srinivasan et al., 2023). Other Python libraries are Scrapy and Selenium, but BeautifulSoup is appropriate for a low-level data extraction requirement (K. Sharma & Borkar, 2023). One could further apply sentiment analysis techniques to derive further meaning. While sentiment analysis can detect the overall sentiment of a given text, aspect-based sentiment analysis determines the various features therein and the sentiment associated with each (AL-Smadi et al., 2023).

5.2.2 Aspect-Based Sentiment Analysis

Aspect-based sentiment analysis (ABSA) comprises data pre-processing, extracting features, and classifying sentiment aspects (Mubarok et al., 2017). It is a part of sentiment analysis that seeks to derive sentiments for different aspects of a given text (Fu et al., 2019). It is best for product reviews because it can associate sentiment with product price, quality, and customer service(Abubakar & Shahzad, 2024). It involves extracting aspects, expressing sentiments, and aggregating aspects (Kasum Yusuf et al., 2024). It splits data into aspects and then extracts the sentiment polarities (Horsa & Tune, 2023). It derives entities like products, services, and topics from customer reviews (Alqaryouti et al., 2024a). Aspects are implicit and explicit (Chatterjee et al., 2023). Implicit elements do not have an explicit keyword and require domain knowledge to extract the terms (Rani & Jain, 2024). Some studies leverage neural networks to derive aspect terms from customer reviews (Mei et al., 2023). Most recent studies leverage graph neural networks for aspect extraction (H. Wu et al., 2023). Graph neural networks in aspect extraction could compromise information preservation (C. Li et al., 2024). While most studies consider aspect extraction and sentiment classification independent tasks, unifying them could improve model performance (Chen et al., 2023). Aspect extraction and sentiment classification should interact to improve aspect-based sentiment analysis outcomes (Zou et al., 2024). Integrating external knowledge could enhance aspect extraction outcomes (Jin, Zhao, Zhang, et al., 2023). Some studies successfully utilize pre-trained BERT models for aspect extraction (X. Zhu, Zhu, et al., 2023). Pre-trained BERT models perform better than other models at aspect extraction (He et al., 2023a). They utilize encoders to extract aspects from text (Agathangelou et al., 2024). They improve aspect-based sentiment analysis outcomes (Huang et al., 2023). They make practical aspect-based sentiment analysis systems possible (Zhang et al., 2023).

Because most product reviews contain more than one aspect, it is necessary to identify the sentiment polarity of each term (Jiang et al., 2023a). Where aspects overlap between sentences in a review, it could lead to an inaccurate sentiment polarity (Jiang et al., 2023b). It is machine learning-based, pattern-based, and deep learning-based (Truşcǎ & Frasincar, 2022). Its approaches are machine learning-based, lexicon-based, and hybrid methods (Birjali et al., 2021). The several ways of implementing aspect-based sentiment analysis are the neural network model (Gu et al., 2023), graph-based method (Zhong et al., 2023), and knowledge-based method (Alqaryouti et al., 2024b).

Machine learning-based aspect-based sentiment analysis involves supervised and unsupervised techniques (Hajek et al., 2023). It utilizes machine-learning algorithms to obtain aspect categories for each input sentence (Priya & Rao, 2023). Support Vector Machines (SVM) and Naïve Bayes are familiar classification algorithms for supervised machine learning-based aspect-based sentiment analysis (Singh et al., 2023). They are regular aspect-based sentiment analysis classifiers (Hammi et al., 2023).

Deep learning-based aspect-based sentiment analysis utilizes neural network models to build neural representations for input sentences and their labels to train classifiers for automatic feature extraction (Zheng et al., 2023). It utilizes neural networks, pre-trained, and generative models (Z. Li et al., 2024). Some studies utilize graph neural networks to extract aspects and provide sentiment polarity classification (G. Zhao et al., 2023). Deep learning techniques include Bidirectional Encoder Representations from Transformers (Rizwan Rashid Rana et al., 2023). Neural network models are transformer models, adversarial networks, and generative models (Bandi et al., 2023). The highest-performing are the Bidirectional Encoder Representations from Transformers (BERT) models (Lengkeek et al., 2023). Most neural network models do not offer bidirectional feature extraction from text (He et al., 2023b).

Pattern-based aspect-based sentiment analysis identifies similarities between documents to extract sentence topics and keywords (George & Srividhya, 2023). It utilizes similarity-based lexicons to extract aspects (Ayub et al., 2022). Some studies leverage dependency-based rules to extract nouns, verbs, and aspects from customer reviews (Mishra & Panda, 2023). Pattern-based and machine-learning approaches cannot cope with the volume of data generated on the Internet (H. Liu et al., 2020).

5.2.3 Pre-Trained Models

Transformer models are the prevalent pre-trained models in aspect-based sentiment analysis (Du et al., 2023). They are efficient in aspect-based sentiment analysis tasks (Hu et al., 2023). They perform best in aspect-based sentiment analysis tasks (Al-Jarrah et al., 2023). They have been essential in aspect-based sentiment analysis (Mughal et al., 2024a). It is still difficult to reproduce (H. Yang et al., 2023). They are domain-specific (Mughal et al., 2024b). They are susceptible to backdoor and adversarial attacks (H. Wang et al., 2023). They also require vast training datasets (C. Zhao et al., 2024). They require substantial computational resources and cannot be easily deployed on edge devices (Ur Rahman et al., 2023). Transfer Learning could help overcome some limitations of pre-trained models (Shinde et al., 2021).

5.3 Data Collection

Data is collected from an e-commerce website utilizing the web scraping technique with Python BeautifulSoup Library (Chaib et al., 2020). Web scraping and Web APIs are the prevalent methods of collecting data from the Internet (Boegershausen et al., 2022). Web scraping is forbidden on some websites and could fail, but utilizing proxy servers can help circumvent the limitations. It is more flexible and faster than web APIs in extracting information from websites but is affected by changes in website structure (Dongo et al., 2020). It collects data adequately (Gallagher & Beveridge, 2021). It converts unstructured data into structured data (Khder, 2021). It doesn't require extensive programming knowledge like Web APIs (Alrashed et al., 2020). In some cases, Web scraping is the only available means of collecting data from a Website (Dogucu & Çetinkaya-Rundel, 2021).

BeautifulSoup and Scrapy are some of the prevalent Web scraping tools (Dikilitaş et al., 2024). This study utilizes BeautifulSoup and Requests for data collection (Vijaya et al., 2024).

5.4 Data Analysis

The data collected undergoes aspect-based sentiment analysis to derive actionable insights for stakeholders. Aspect-based sentiment analysis extracts attitudes mentioned about each feature in the given text (Kandhro et al., 2024). It predicts the sentiment polarity for each feature in the given text (H. Liu et al., 2024). Pre-trained BERT models have demonstrated effectiveness in aspect-based sentiment analysis tasks (Jin, Zhao, Liu, et al., 2023). Some aspect-based sentiment analysis subtasks depend on others for their success (Uday et al., 2023).

5.5 Solution Testing

Solution testing has the aim of determining whether the proposed solution is sufficient. We utilize metrics for testing machine learning models. The prevalent evaluation metrics are accuracy, recall, specificity, and precision (Rainio et al., 2024). The F1 - score is another metric for evaluating the performance of a classifier (Shrivastava et al., 2023). It is the harmonic mean of recall and precision (Kuppusamy & Selvaraj, 2023). This study utilizes the scikit-Learn metrics to evaluate model performance (Shawkat, 2023). A comprehensive evaluation of ABSA models includes Precision, Accuracy, Recall, and F1-score (Goud & Garg, 2023).

$$\text{Accuracy} = (TN + TP) / (TP + TN + FN + FP)$$

$$\text{Precision} = TP / (TP + FP)$$

$$\text{Sensitivity} = \text{Recall} = TP / (TP + FN)$$

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

6 Implementation

The proposed solution utilizes aspect-based sentiment analysis of online customer product reviews to inform business decisions and product design. It comprises Web scraping, pre-processing, and aspect-based sentiment analysis. The aspect-based sentiment analysis involves three sub-tasks: aspect extraction, sentiment classification, and aggregation (Waheeb, 2023).

6.1 Product Choice

Product design translates ideas into reality to meet customer needs (Chitale & Gupta, 2023). Firms can improve performance by considering customer feedback in decision-making (Ismail, 2023). Online reviews are the best source for customer feedback (Joung & Kim, 2023). Product quality is a vital metric in customer feedback (Rane et al., 2023). The price and quality of a product influence customer satisfaction (Zuliawaty Rajasa et al., 2023).

Bottled drinking water is an end product for consumers in the food industry driven by a lack of alternative safe drinking water sources (Dijkstra & de Roda Husman, 2023). Its quality influences the purchasing decisions of consumers (Saldanha Barreto et al., 2023).

6.2 Web Scraping

This stage involves scraping data from an e-commerce website in Kenya utilizing the Python BeautifulSoup Library on the URL below.

https://www.jumia.co.ke/catalog/productratingsreviews/sku/AQ014DR0PDU7GNAFAMZ/?page=2

Web scraping requests flow through a proxy server, which then forwards them to the target website to circumvent limitations on scraping. The study obtained 50 reviews of bottled drinking water.

6.3 Manual Content Analysis

Content analysis derives patterns, similarities, and differences in textual data (Kleinheksel et al., 2020). Data from the scraped reviews was subjected to manual content analysis to find the keywords and aspects within the reviews. The study placed the reviews into similar aspect categories and recorded the frequency of occurrence of each aspect. The table below shows the aspects derived from the analysis and the examples of keywords associated with each.

Review	Aspect 1	Keywords	Aspect 2	keywords
Tasted filtered so it was good	Taste	good taste		
I like the water taste	Taste	good taste		
So wet, so clear. Water as it should be.	Quality	wet, clear		
Great taste	Taste	Great taste		
ORIGINAL BOTTLES WERE COMING WITH BLUE CAP WHICH WAS VERY GOOD QUALITY. THE NEW CAP BLACK IN COLOR IS VERY HARD AND BREAKS THE WATER DISPENSER. UNLESS THEY DON'T CHANGE TO THE ORIGINAL I WOULD NOT BUY BECAUSE TO REPAIR THE DISPENSER IS VERY COSTLY. IT IS STUPID AND POUND FOOLISH TO SAVE A FEW COINS THEY USE SUNSTANDARD MATERIAL.	Quality	very hard	price	costly
Very nice	Quality	nice		
I ordered 7 pc 18. 5 litres of aquamist water. For each bottle I was charged 100 shillings per bottle for delivery total 700. Yet the delivery was done once for 7 pc of bottles. I don't understand how this works.	Price	charged		
Tasted filtered so it was good	Taste	good taste		
I like the water taste	Taste	good taste		
So wet, so clear. Water as it should be.	Quality	wet, clear		
Great taste	Taste	great taste		
The water is very nice. The problem is delivery. They don't package it well most of the time and it arrives with seal broken or dusty/ muddy bottle. I think they let it keep rolling in the dusty back of their vans. I stopped ordering but if you package better I will definitely order again.	Quality	very nice water,	safety	muddy bottle
Clean and cool water	Quality	clean, cool		
Good price offer on Jumia	Price	good Price		
Perfect	Quality	perfect		
Good water	Quality	good		
It tastes good not salty	Taste	good taste		
Good deal	Price	good deal		
Try hardening the container like glacier dispenser water	Aesthetics	weak container		
I like it	Quality	like		
Bought this only to find it has a salty taste like borehole water. I feel conned.	Taste	salty taste		
Genuine	Quality	Genuine		
To be delivered with caution....my bottle looks like someone strangled it...it gat depressions and bruises	Aesthetics	bruises, depressions		
Good quality, nice taste- not full of chloride taste.	Taste	nice taste	quality	
I appreciate the cost, unbeatable price to other shops	price	low cost, unbeatable price		
Clean and safe water	Quality	clean	safety	safe
Way cheaper than offline stores.	price	cheap		
As described	quality	expectation		
Good water	quality	good		
Try it's the best water	quality	best		
Pocket friendly prices	price	pockect friendly		
well bottled and refreshing to drink!	quality	well bottled	Taste	refreshing
Purchased 4 of them then I got a free dispenser. So good so far, one and year after	price	free dispenser	quality	good

Table of product reviews

# Code	Aspect	Example of Keywords
1	Aesthetics	Bruised, Beautiful, Wrinkled
2	Quality	Clean, Clear, Genuine, Good,
3	Taste	Taste, Salty, Chloride,
4	Safety	Safe, Seal, Muddy
5	Price	Expensive, Cheap, Cost, Deal

Table of aspects and keywords.

# Code	Aspect	Frequency	% reviews	Normalized %
1	Aesthetics	2	4.76190476	5
2	Quality	20	47.6190476	47
3	Taste	10	23.8095238	24
4	Safety	2	4.76190476	5
5	Price	8	19.047619	19

Table of frequency of aspects

6.4 Artificial Data Generation

From the manual content analysis, the study produces categories of the reviews and their distribution in each category. Professional Web scraping is expensive and cannot avail sufficient labeled data to fine-tune a model. The study utilizes GPT3.5 to generate artificial data mimicking real-world reviews of bottled drinking water according to the aspects, keywords, and distributions derived from the manual content analysis. The study generates data from GPT3.5 utilizing prompts.

The first prompt is: Kindly create customer reviews for bottled drinking water with a focus on the following aspects: aesthetics, quality, taste, safety, and price.

The second prompt is: Kindly provide reviews with the following keywords for each aspect; Aesthetics: bruised, beautiful, wrinkled. Quality: clean, clear, genuine, good, nice. Taste: taste, salty, chloride, refreshing, cool. Safety: safe, seal, muddy. Price: expensive, cheap, cost, deal.

The third prompt is: Kindly provide reviews with the following distribution:
5% covering the aesthetics, 47% the quality, 24% the taste, 5% safety, 19% price".
The three prompts 270 synthetic reviews of bottled drinking water.

6.5 Pre-processing

Pre-processing involves cleaning and formatting data (AlMasaud & Al-Baity, 2023). This stage removes unnecessary data and converts each unique word to its vector representation (Tesfa et al., 2024). With the pre-trained BERT models, the pre-processing is automated (Bimaputra & Sutoyo, 2023). This stage removes stop words and punctuations from the text (Ramasamy & Elangovan, 2024). It prepares data for the feature extraction stage (Prabhu & Nashappa, 2024). It labels data in preparation for the supervised learning during the fine-tuning of the BERT model. It adds a label to each review manually. It removes duplicate reviews and splits the data into 80% training and 20% testing datasets.

6.6 Model training

The training data facilitates the fine-tuning of the pre-trained BERT model. This model enables the aspect extraction stage. The study selected a pre-trained BERT model with fewer parameters for fine-tuning to minimize the computational cost and storage requirements during fine-tuning (Ding et al., 2023). The prevalent pre-trained transformer models for text classification tasks include bert-base-cased and bert-base-uncased (Pilicita & Barra, 2023). These models have fewer layers and hidden neurons per layer when compared to the larger BERT models (Agbesi et al., 2023).

6.7 Aspect Extraction Model

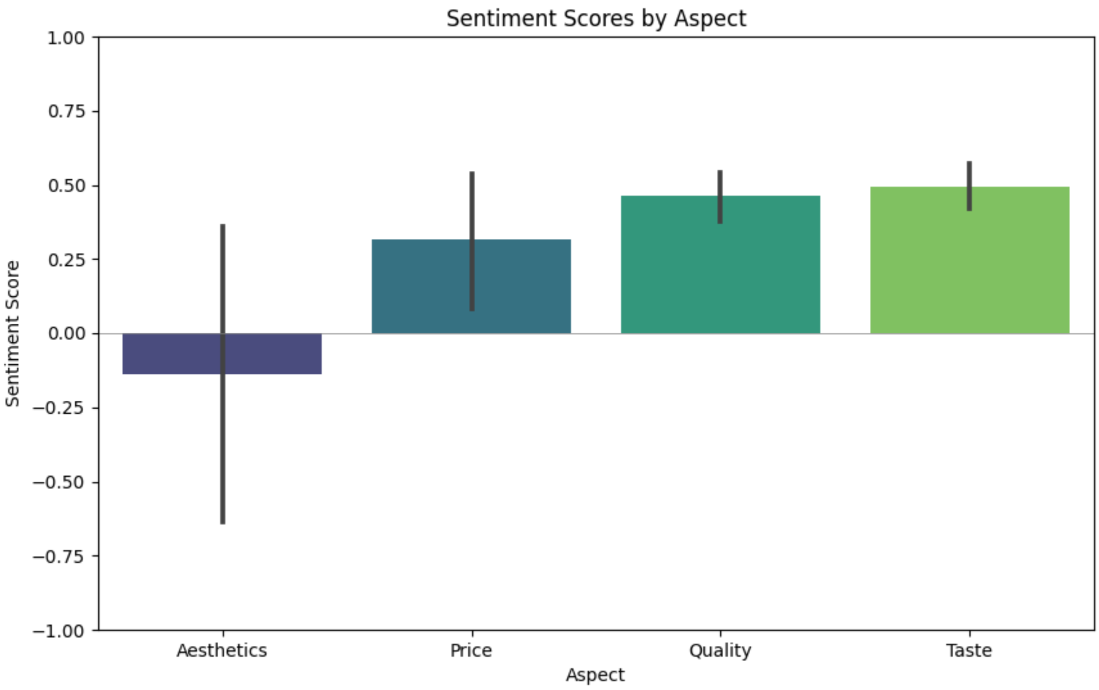
The study combines the synthetic data and the data from web scraping to form a combined dataset. The fine-tuned BERT model predicts the aspects of the combined testing dataset. The sci-kit-learn metrics evaluate the model performance. The small dataset utilized in the fine-tuning impacts the performance of the aspect extraction model.

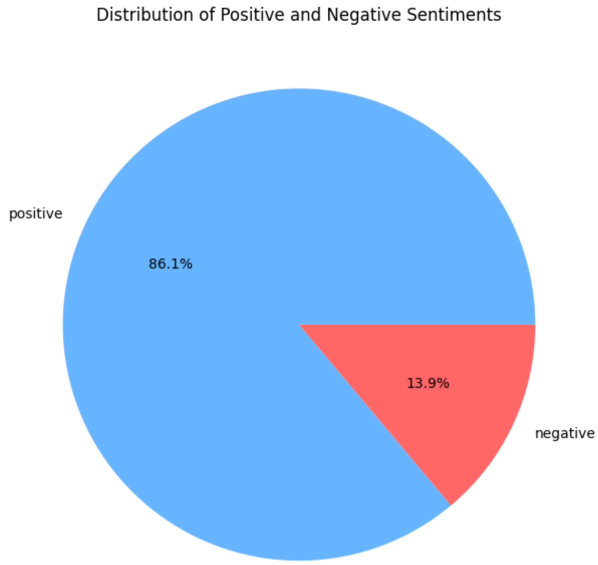
6.8 Sentiment Classification

Sentiment Classification identifies the sentiment polarity for each aspect term (Ping et al., 2024). They are positive, negative, or neutral (Aziz et al., 2024). Recent studies leverage graph neural networks to derive the sentiment polarity for each aspect term (L. Zhu, Zhu, et al., 2023). Conventional machine learning methods utilize machine learning algorithms to derive the sentiment polarity for each aspect term but are still less accurate than the neural network methods (Hridoy et al., 2021). They are time-consuming and require manual crafting of features (N. Liu et al., 2023). Pre-trained BERT models are effective at sentiment classification (Talaat, 2023). They perform well on positive and negative sentiments but poorly on neutral sentiments (X. Zhu, Kuang, et al., 2023). They could exhibit contextual bias in deriving sentiment polarities towards certain aspects (An et al., 2024). The Valence Aware Dictionary and sEntiment Reasoner (VADER) sentiment analysis tool is an alternative pre-trained model that identifies the sentiment polarity associated with the aspects in the user reviews utilizing rules and lexicons (Samaras et al., 2023). It is a robust sentiment analysis tool (Chatzimina et al., 2023).

6.9 Results Presentation

This stage shares the final results of the aspect-based sentiment analysis with the decision-makers and stakeholders. This stage presents the data in visualizations like word clouds, bar charts, and pie charts. The figures below are a summary of the results presentation to stakeholders.


Sentiment Scores by Aspect
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Sentiment Score
Aesthetics
Price
Quality
Taste
Aspect


Distribution of Positive and Negative Sentiments
positive
86.1%
13.9%
negative

7 Testing

The Confusion matrix is the basis for model performance testing (Chukwura & Chukwura Obi, 2023). The testing criteria are accuracy, precision, and F1 Score (Jazuli et al., 2023). Accuracy is a regular measurement of classifier performance (Y. Zhu, Li, et al., 2023). It is the percentage of the correct classifications as a fraction of the total classifications (Busst et al., 2024). Because model training is expensive and often utilizes private datasets (Y. Liu et al., 2019), this study leverages an open-source pre-trained BERT-base model and the VADER sentiment analysis tool for aspect-based sentiment analysis. The figure below shows the ABSA implementation in this study. One can find the source code for the solution in the following repository:

https://github.com/BarasaWanyama/ABSA-with-BERT

The solution achieves an accuracy score of 92.86%, precision of 94.07%, Recall of 92.86%, and F1 score of 92.86%.

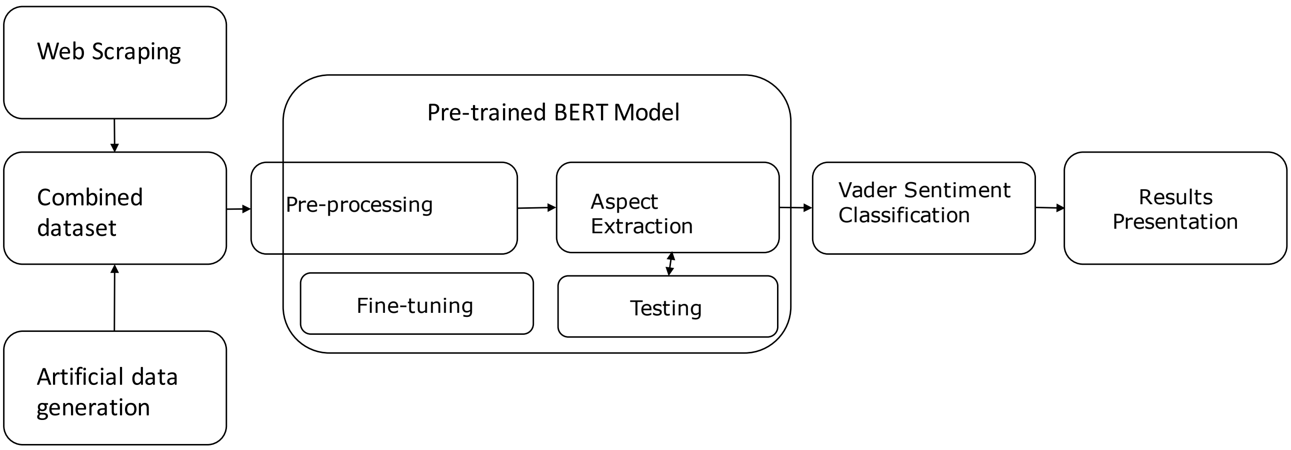


Fig 1. Implementation Summary

8 Conclusion

The proposed solution meets the requirements for frugal innovation in small and medium-sized enterprises in emerging markets by utilizing open-source tools while offering a high-accuracy aspect-based sentiment analysis algorithm that can provide comprehensive customer feedback on any product from an e-commerce website to inform product design and business strategy. It also addresses the organizational factors influencing the adoption of Big data analytics in Small and medium-sized enterprises in emerging markets by addressing employee coding skills. Given more time, the study could have provided an overview of the IT infrastructure required for Big data analytics in a typical small and medium-sized enterprise in emerging markets.

9 References

Abubakar, M., & Shahzad, A. (2024). Aspect-Based Sentiment Analysis on Product Reviews. *ASEAN Journal of Economic and Economic Education*, *3*(1), 29–34. https://ejournal.bumipublikasinusantara.id/index.php/ajeee/article/view/292

Acciarini, C., Cappa, F., Boccardelli, P., & Oriani, R. (2023). How can organizations leverage big data to innovate their business models? A systematic literature review. *Technovation*, *123*, 102713. https://doi.org/10.1016/J.TECHNOVATION.2023.102713

Agathangelou, P., Katakis, I., & Kasnesis, P. (2024). Word- and Sentence-Level Representations for Implicit Aspect Extraction. *IEEE Transactions on Computational Social Systems*. https://doi.org/10.1109/TCSS.2024.3391833

Agbesi, V. K., Chen, W., Yussif, S. B., Hossin, M. A., Ukwuoma, C. C., Kuadey, N. A., Agbesi, C. C., Abdel Samee, N., Jamjoom, M. M., & Al-antari, M. A. (2023). Pre-Trained Transformer-Based Models for Text Classification Using Low-Resourced Ewe Language. *Systems 2024, Vol. 12, Page 1*, *12*(1), 1. https://doi.org/10.3390/SYSTEMS12010001

Al Omoush, K., Lassala, C., & Ribeiro-Navarrete, S. (2023). The role of digital business transformation in frugal innovation and SMEs' resilience in emerging markets. *International Journal of Emerging Markets*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/IJOEM-12-2022-1937/FULL/XML

Al-Azzam, M. K. A., Al-Alwan, M. A. M., Alqahtani, M. M., Al-Hawary, S. I. S., & Alserhan, A. F. (2023). Determinants of behavioral intention to use big data analytics (BDA) on the information and communication technologies (ICT) SMEs in Jordan. *Decision Science Letters*, *12*(3), 605–616. https://doi.org/10.5267/J.DSL.2023.4.004

Al-Jarrah, I., Mustafa, A. M., & Najadat, H. (2023). Aspect-Based Sentiment Analysis for Arabic Food Delivery Reviews. *ACM Transactions on Asian and Low-Resource Language Information Processing*, *22*(7). https://doi.org/10.1145/3605146

Alkhatib, A. W., & Valeri, M. (2024). Can intellectual capital promote the competitive advantage? Service innovation and big data analytics capabilities in a moderated mediation model. *European Journal of Innovation Management*, *27*(1), 263–289. https://doi.org/10.1108/EJIM-04-2022-0186/FULL/XML

AlMasaud, A., & Al-Baity, H. H. (2023). AraMAMS: Arabic Multi-Aspect, Multi-Sentiment Restaurants Reviews Corpus for Aspect-Based Sentiment Analysis. *Sustainability (Switzerland)*, *15*(16), 12268. https://doi.org/10.3390/SU151612268/S1

Alqaryouti, O., Siyam, N., Abdel Monem, A., & Shaalan, K. (2024a). Aspect-based sentiment analysis using smart government review data. *Applied Computing and Informatics*, *20*(1–2), 142–161. https://doi.org/10.1016/J.ACI.2019.11.003/FULL/PDF

Alqaryouti, O., Siyam, N., Abdel Monem, A., & Shaalan, K. (2024b). Aspect-based sentiment analysis using smart government review data. *Applied Computing and Informatics*, *20*(1–2), 142–161. https://doi.org/10.1016/J.ACI.2019.11.003/FULL/PDF

Al-Rahmi, W. M., Yahaya, N., Alamri, M. M., Alyoussef, I. Y., Al-Rahmi, A. M., & Kamin, Y. Bin. (2021). Integrating innovation diffusion theory with technology acceptance model: supporting students' attitude towards using a massive open online courses (MOOCs) systems. *Interactive Learning Environments*, *29*(8), 1380–1392. https://doi.org/10.1080/10494820.2019.1629599

Alraja, M. N., Imran, R., Khashab, B. M., & Shah, M. (2022). Technological Innovation, Sustainable Green Practices and SMEs Sustainable Performance in Times of Crisis (COVID-19 pandemic). *Information Systems Frontiers 2022 24:4*, *24*(4), 1081–1105. https://doi.org/10.1007/S10796-022-10250-Z

Alrashed, T., Almahmoud, J., Zhang, A. X., & Karger, D. R. (2020). ScrAPIr: Making Web Data APIs Accessible to End Users. *Conference on Human Factors in Computing Systems - Proceedings*. https://doi.org/10.1145/3313831.3376691

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/FIGURES/5

AlSharji, A., Ahmad, S. Z., & Abu Bakar, A. R. (2018). Understanding social media adoption in SMEs: Empirical evidence from the United Arab Emirates. *Journal of Entrepreneurship in Emerging Economies*, *10*(2), 302–328. https://doi.org/10.1108/JEEE-08-2017-0058

AL-Smadi, M., Hammad, M. M., Al-Zboon, S. A., AL-Tawalbeh, S., & Cambria, E. (2023). Gated recurrent unit with multilingual universal sentence encoder for Arabic aspect-based sentiment analysis. *Knowledge-Based Systems*, *261*, 107540. https://doi.org/10.1016/J.KNOSYS.2021.107540

Al-Taie, Y., & AL-Khafaji, J. (2024). The effect of the digital business ecosystem on enhance big data analytics capabilities: An analytical study of the employees opinions in tourism companies in Al-Najaf Al-Ashraf. *2ND INTERNATIONAL CONFERENCE ON ENGINEERING AND SCIENCE TO ACHIEVE THE SUSTAINABLE DEVELOPMENT GOALS*, *3092*(1), 040010. https://doi.org/10.1063/5.0200558/3270014

An, R., Zhang, C., & Song, D. (2024). Eliminating Contextual Bias in Aspect-Based Sentiment Analysis. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *14608 LNCS*, 90–107. https://doi.org/10.1007/978-3-031-56027-9_6

Asad, M., Asif, M. U., Bakar, L. J. A., & Altaf, N. (2021). Entrepreneurial Orientation, Big Data Analytics, and SMEs Performance under the Effects of Environmental Turbulence. *2021 International Conference on Data Analytics for Business and Industry, ICDABI 2021*, 144–148. https://doi.org/10.1109/ICDABI53623.2021.9655870

Ayub, N., Ramzan Talib, M., Kashif Hanif, M., & Awais, M. (2022). *Aspect Extraction Approach for Sentiment Analysis Using Keywords*. https://doi.org/10.32604/cmc.2023.034214

Aziz, M. M., Bakar, A. A., & Yaakub, M. R. (2024). CoreNLP dependency parsing and pattern identification for enhanced opinion mining in aspect-based sentiment analysis. *Journal of King Saud University - Computer and Information Sciences*, 102035. https://doi.org/10.1016/J.JKSUCI.2024.102035

Badi, S., Ochieng, E., Nasaj, M., & Papadaki, M. (2021). Technological, organisational and environmental determinants of smart contracts adoption: UK construction sector viewpoint. *Construction Management and Economics*, *39*(1), 36–54. https://doi.org/10.1080/01446193.2020.1819549

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, *163*, 120420. https://doi.org/10.1016/J.TECHFORE.2020.120420

Bandara, F., Jayawickrama, U., Subasinghage, M., Olan, F., Alamoudi, H., & Alharthi, M. (2024). Enhancing ERP Responsiveness Through Big Data Technologies: An Empirical Investigation. *Information Systems Frontiers*, *26*(1), 251–275. https://doi.org/10.1007/S10796-023-10374-W/FIGURES/8

Bandi, A., Adapa, P. V. S. R., & Kuchi, Y. E. V. P. K. (2023). The Power of Generative AI: A Review of Requirements, Models, Input–Output Formats, Evaluation Metrics, and Challenges. *Future Internet 2023, Vol. 15, Page 260*, *15*(8), 260. https://doi.org/10.3390/FI15080260

Barbera, G., Araujo, L., & Fernandes, S. (2023). The Value of Web Data Scraping: An Application to TripAdvisor. *Big Data and Cognitive Computing 2023, Vol. 7, Page 121*, *7*(3), 121. https://doi.org/10.3390/BDCC7030121

Behl, A. (2022). Antecedents to firm performance and competitiveness using the lens of big data analytics: a cross-cultural study. *Management Decision*, *60*(2), 368–398. https://doi.org/10.1108/MD-01-2020-0121/FULL/XML

Bhalerao, K., & Kumar, A. (2022). *A STUDY OF BARRIERS AND BENEFITS OF ARTIFICIAL INTELLIGENCE ADOPTION IN SMALL AND MEDIUM ENTERPRISE*. https://www.researchgate.net/publication/360912025

Bharadiya, J., & Bharadiya, J. P. (2023). Machine Learning and AI in Business Intelligence: Trends and Opportunities. *International Journal of Computer (IJC) International Journal of Computer*, *48*(1), 123–134. https://www.researchgate.net/publication/371902170

Bimaputra, D. S., & Sutoyo, E. (2023). Aspect-Based Sentiment Analysis of Hotels in Bali on Tripadvisor Using BERT Algorithm. *International Journal of Advances in Data and Information Systems*, *4*(1), 29–40. https://doi.org/10.25008/IJADIS.V4I2.1284

Birjali, M., Kasri, M., & Beni-Hssane, A. (2021). A comprehensive survey on sentiment analysis: Approaches, challenges and trends. *Knowledge-Based Systems*, *226*, 107134. https://doi.org/10.1016/J.KNOSYS.2021.107134

Boegershausen, J., Datta, H., Borah, A., & Stephen, A. T. (2022). Fields of Gold: Scraping Web Data for Marketing Insights. *Journal of Marketing*, *86*(5), 1–20. https://doi.org/10.1177/00222429221100750/ASSET/IMAGES/LARGE/10.1177_00222429221100750-FIG2.JPEG

Brauneck, A., Schmalhorst, L., Majdabadi, M. M. K., Bakhtiari, M., Völker, U., Baumbach, J., Baumbach, L., & Buchholtz, G. (2023). Federated Machine Learning, Privacy-Enhancing Technologies, and Data Protection Laws in Medical Research: Scoping Review. *J Med Internet Res 2023;25:E41588 Https://Www.Jmir.Org/2023/1/E41588*, *25*(1), e41588. https://doi.org/10.2196/41588

Brennan, J. R., Menendez, H. M., Ehlert, K., & Tedeschi, L. O. (2023). ASAS-NANP symposium: mathematical modeling in animal nutrition—Making sense of big data and machine learning: how open-source code can advance training of animal scientists. *Journal of Animal Science*, *101*. https://doi.org/10.1093/JAS/SKAD317

Busst, M. M. A., Anbananthen, K. S. M., Kannan, S., Krishnan, J., & Subbiah, S. (2024). Ensemble BiLSTM: A Novel Approach for Aspect Extraction From Online Text. *IEEE Access*, *12*, 3528–3539. https://doi.org/10.1109/ACCESS.2023.3349203

Chaib, H., Asikri[1], M. El, Krit, S., & Chaib, H. (2020). Using Web Scraping In A Knowledge Environment To Build Ontologies Using Python And Scrapy Article in. *European Journal of Translational and Clinical Medicine*. https://www.researchgate.net/publication/346215371

Chalamala, S. R., Kummari, N. K., Singh, A. K., Saibewar, A., & Chalavadi, K. M. (2022). Federated learning to comply with data protection regulations. *CSI Transactions on ICT 2022 10:1*, *10*(1), 47–60. https://doi.org/10.1007/S40012-022-00351-0

Chandni, N. H., Antonacci, G., Barlow, J., & Harris, M. (2021). Defining frugal innovation: A critical review. *BMJ Innovations*, *7*(4), 647–656. https://doi.org/10.1136/BMJINNOV-2021-000830

Chandra, S., & Verma, S. (2021). Big Data and Sustainable Consumption: A Review and Research Agenda. *Https://Doi.Org/10.1177/09722629211022520*, *27*(1), 11–23. https://doi.org/10.1177/09722629211022520

Chatterjee, S., Prakash, S., & Nürnberger, A. (2023). *Flavours of Convolution for Unsupervised Aspect Extraction and Aspect-based Sentiment Analysis*. http://ceur-ws.org

Chatzimina, M. E., Oikonomou, N., Papadaki, H., Tsiknakis, M., & Pontikoglou, C. (2023). Sentiment Analysis in Greek Clinical Conversations: A Comparative Study of BERT, VADER, and Lexicon Approaches. *Proceedings - 2023 2023 IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2023*, 4800–4806. https://doi.org/10.1109/BIBM58861.2023.10385833

Chaudhry, U. B., & Chaudhry, M. A. (2023). Harnessing Big Data for Business Innovation and Effective Business Decision Making. *Advanced Sciences and Technologies for Security Applications*, 47–60. https://doi.org/10.1007/978-3-031-20160-8_4/COVER

Chen, L., Ge, L., & Zhou, W. (2023). IIM: an information interaction mechanism for aspect-based sentiment analysis. *Connection Science*, *35*(1), 2283390. https://doi.org/10.1080/09540091.2023.2283390

Chernova, O. A., Mitrofanova, I. V., Pleshakova, M. V., & Batmanova, V. V. (2023). Use of big data analytics for small and medium sized businesses. *Serbian Journal of Management*, *18*(1), 93–109. https://doi.org/10.5937/SJM18-41822

Chitale, A. K., & Gupta, R. C. (2023). *Product Design and Manufacturing, Seventh Edition - Chitale, Avinash K., Gupta, R. C. - Google Books*. https://books.google.co.ug/books?hl=en&lr=&id=J8fAEAAAQBAJ&oi=fnd&pg=PP1&dq=what+are+the+customer++the+considerations+in+product+design%3F&ots=xKnvZYcWpe&sig=u0kKndiDFPq_tcwmpRto-IM3lyQ&redir_esc=y#v=onepage&q=what%20are%20the%20customer%20%20the%20considerations%20in%20product%20design%3F&f=false

Chittipaka, V., Kumar, S., Sivarajah, U., Bowden, J. L. H., & Baral, M. M. (2022). Blockchain Technology for Supply Chains operating in emerging markets: an empirical examination of technology-organization-environment (TOE) framework. *Annals of Operations Research 2022 327:1*, *327*(1), 465–492. https://doi.org/10.1007/S10479-022-04801-5

Chowdhury, S., Dey, P. K., Rodríguez-Espíndola, O., Parkes, G., Tuyet, N. T. A., Long, D. D., & Ha, T. P. (2022). Impact of Organisational Factors on the Circular Economy Practices and Sustainable Performance of Small and Medium-sized Enterprises in Vietnam. *Journal of Business Research*, *147*, 362–378. https://doi.org/10.1016/J.JBUSRES.2022.03.077

Chukwura, J., & Chukwura Obi, J. (2023). A Comparative Study of Several Classification Metrics and Their Performances on Data. *World Journal of Advanced Engineering Technology and Sciences*, *2023*(01), 308–314. https://doi.org/10.30574/wjaets.2023.8.1.0054

Ciampi, F., Demi, S., Magrini, A., Marzi, G., & Papa, A. (2021). Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *Journal of Business Research*, *123*, 1–13. https://doi.org/10.1016/J.JBUSRES.2020.09.023

Clemente-Almendros, J. A., Popescu-Nicoara, D., & Pastor-Sanz, I. (2024). Digital transformation in SMEs: Understanding its determinants and size heterogeneity. *Technology in Society*, *77*, 102483. https://doi.org/10.1016/J.TECHSOC.2024.102483

Črešnar, R., Dabić, M., Stojčić, N., & Nedelko, Z. (2023). It takes two to tango: technological and non-technological factors of Industry 4.0 implementation in manufacturing firms. *Review of Managerial Science*, *17*(3), 827–853. https://doi.org/10.1007/S11846-022-00543-7/TABLES/5
Daigle, B. (2021). Data Protection Laws in Africa: A Pan-African Survey and Noted Trends. *Journal of International Commerce & Economics*, *2021*. https://heinonline.org/HOL/Page?handle=hein.journals/jice2021&id=1&div=&collection=
Daradkeh, M. (2023). The Nexus between Business Analytics Capabilities and Knowledge Orientation in Driving Business Model Innovation: The Moderating Role of Industry Type. *Informatics 2023, Vol. 10, Page 19*, *10*(1), 19. https://doi.org/10.3390/INFORMATICS10010019
Dijkstra, A. F., & de Roda Husman, A. M. (2023). Bottled and Drinking Water. *Food Safety Management: A Practical Guide for the Food Industry, Second Edition*, 339–362. https://doi.org/10.1016/B978-0-12-820013-1.00042-5
Dikilitaş, Y., Çakal, Ç., Okumuş, A. C., Yalçın, H. N., Yıldırım, E., Ulusoy, Ö. F., Macit, B., Kırkaya, A. E., Yalçın, Ö., Erdoğmuş, E., & Sayar, A. (2024). *Performance Analysis for Web Scraping Tools: Case Studies on Beautifulsoup, Scrapy, Htmlunit and Jsoup*. 471–480. https://doi.org/10.1007/978-3-031-56728-5_39
Ding, N., Qin, Y., Yang, G., Wei, F., Yang, Z., Su, Y., Hu, S., Chen, Y., Chan, C. M., Chen, W., Yi, J., Zhao, W., Wang, X., Liu, Z., Zheng, H. T., Chen, J., Liu, Y., Tang, J., Li, J., & Sun, M. (2023). Parameter-efficient fine-tuning of large-scale pre-trained language models. *Nature Machine Intelligence 2023 5:3*, *5*(3), 220–235. https://doi.org/10.1038/s42256-023-00626-4
Dogra, K. S., Nirwan, N., & Chauhan, R. (2023). Unlocking the Market Insight Potential of Data Extraction Using Python-Based Web Scraping on Flipkart. *2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology, ICSEIET 2023*, 453–457. https://doi.org/10.1109/ICSEIET58677.2023.10303328
Dogucu, M., & Çetinkaya-Rundel, M. (2021). Web Scraping in the Statistics and Data Science Curriculum: Challenges and Opportunities. *Journal of Statistics and Data Science Education*, *29*(S1), S112–S122. https://doi.org/10.1080/10691898.2020.1787116
Dongo, I., Cadinale, Y., Aguilera, A., Martínez, F., Quintero, Y., & Barrios, S. (2020). Web Scraping versus Twitter API: A Comparison for a Credibility Analysis. *ACM International Conference Proceeding Series*, 263–273. https://doi.org/10.1145/3428757.3429104
Du, K., Xing, F., & Cambria, E. (2023). Incorporating Multiple Knowledge Sources for Targeted Aspect-based Financial Sentiment Analysis. *ACM Transactions on Management Information Systems*, *14*(3). https://doi.org/10.1145/3580480
FakhrHosseini, S., Chan, K., Lee, C., Jeon, M., Son, H., Rudnik, J., & Coughlin, J. (2024). User Adoption of Intelligent Environments: A Review of Technology Adoption Models, Challenges, and Prospects. *International Journal of Human–Computer Interaction*. https://doi.org/10.1080/10447318.2022.2118851
Fu, X., Wei, Y., Xu, F., Wang, T., Lu, Y., Li, J., & Huang, J. Z. (2019). Semi-supervised Aspect-level Sentiment Classification Model based on Variational Autoencoder. *Knowledge-Based Systems*, *171*, 81–92. https://doi.org/10.1016/J.KNOSYS.2019.02.008
Gallagher, J. R., & Beveridge, A. (2021). Project-Oriented Web Scraping in Technical Communication Research. *Https://Doi.Org/10.1177/10506519211064619*, *36*(2), 231–250. https://doi.org/10.1177/10506519211064619
George, S., & Srividhya, V. (2023). Implicit aspect based sentiment analysis for restaurant review using LDA topic modeling and ensemble approach. *International Journal of Advanced Technology and Engineering Exploration*, *10*, 2394–7454. https://doi.org/10.19101/IJATEE.2022.10100099

Ghaleb, E. A. A., Dominic, P. D. D., Fati, S. M., Muneer, A., & Ali, R. F. (2021). The Assessment of Big Data Adoption Readiness with a Technology–Organization–Environment Framework: A Perspective towards Healthcare Employees. *Sustainability 2021, Vol. 13, Page 8379*, *13*(15), 8379. https://doi.org/10.3390/SU13158379

Gong, Y., & Janssen, M. (2020). Roles and Capabilities of Enterprise Architecture in Big Data Analytics Technology Adoption and Implementation. *Journal of Theoretical and Applied Electronic Commerce Research 2021, Vol. 16, Pages 37-51*, *16*(1), 37–51. https://doi.org/10.4067/S0718-18762021000100104

Gonzalez-Tamayo, L. A., Maheshwari, G., Bonomo-Odizzio, A., Herrera-Avilés, M., & Krauss-Delorme, C. (2023). Factors influencing small and medium size enterprises development and digital maturity in Latin America. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(2), 100069. https://doi.org/10.1016/J.JOITMC.2023.100069

Goud, A., & Garg, B. (2023). A novel framework for aspect based sentiment analysis using a hybrid BERT (HybBERT) model. *Multimedia Tools and Applications*, 1–33. https://doi.org/10.1007/S11042-023-17647-1/METRICS

Gu, T., Zhao, H., He, Z., Li, M., & Ying, D. (2023). Integrating external knowledge into aspect-based sentiment analysis using graph neural network. *Knowledge-Based Systems*, *259*, 110025. https://doi.org/10.1016/J.KNOSYS.2022.110025

Hajek, P., Hikkerova, L., & Sahut, J. M. (2023). Fake review detection in e-Commerce platforms using aspect-based sentiment analysis. *Journal of Business Research*, *167*, 114143. https://doi.org/10.1016/J.JBUSRES.2023.114143

Hammi, S., Hammami, S. M., & Belguith, L. H. (2023). Advancing aspect-based sentiment analysis with a novel architecture combining deep learning models CNN and bi-RNN with the machine learning model SVM. *Social Network Analysis and Mining*, *13*(1), 1–17. https://doi.org/10.1007/S13278-023-01126-4/METRICS

He, Z., Wang, H., & Zhang, X. (2023a). Multi-Task Learning Model Based on BERT and Knowledge Graph for Aspect-Based Sentiment Analysis. *Electronics 2023, Vol. 12, Page 737*, *12*(3), 737. https://doi.org/10.3390/ELECTRONICS12030737

He, Z., Wang, H., & Zhang, X. (2023b). *Multi-Task Learning Model Based on BERT and Knowledge Graph for Aspect-Based Sentiment Analysis*. https://doi.org/10.3390/electronics12030737

Horsa, O. G., & Tune, K. K. (2023). Aspect-Based Sentiment Analysis for Afaan Oromoo Movie Reviews Using Machine Learning Techniques. *Applied Computational Intelligence and Soft Computing*, *2023*. https://doi.org/10.1155/2023/3462691

Hridoy, M. N. H., Islam, M. M., & Khatun, A. (2021). Aspect Based Sentiment Analysis for Bangla Newspaper Headlines. *2021 3rd International Conference on Sustainable Technologies for Industry 4.0, STI 2021*. https://doi.org/10.1109/STI53101.2021.9732611

Hu, Z., Wang, Z., Wang, Y., & Tan, A. H. (2023). MSRL-Net: A multi-level semantic relation-enhanced learning network for aspect-based sentiment analysis. *Expert Systems with Applications*, *217*, 119492. https://doi.org/10.1016/J.ESWA.2022.119492

Huang, J., Cui, Y., & Wang, S. (2023). Adaptive Local Context and Syntactic Feature Modeling for Aspect-Based Sentiment Analysis. *Applied Sciences 2023, Vol. 13, Page 603*, *13*(1), 603. https://doi.org/10.3390/APP13010603

Iranmanesh, M., Lim, K. H., Foroughi, B., Hong, M. C., & Ghobakhloo, M. (2023). Determinants of intention to adopt big data and outsourcing among SMEs: organisational and technological factors as moderators. *Management Decision*, *61*(1), 201–222. https://doi.org/10.1108/MD-08-2021-1059/FULL/XML

Isichei, E. E., Emmanuel Agbaeze, K., & Odiba, M. O. (2020). Entrepreneurial orientation and performance in SMEs: The mediating role of structural infrastructure capability. *International*

Journal of Emerging Markets, *15*(6), 1219–1241. https://doi.org/10.1108/IJOEM-08-2019-0671/FULL/XML

Ismail, I. J. (2023). Speaking to the hearts of the customers! The mediating effect of customer loyalty on customer orientation, technology orientation and business performance. *Technological Sustainability*, *2*(1), 44–66. https://doi.org/10.1108/TECHS-03-2022-0016/FULL/XML

Jayawardena, C., Ahmad, A., Valeri, M., & Jaharadak, A. A. (2023). Technology acceptance antecedents in digital transformation in hospitality industry. *International Journal of Hospitality Management*, *108*, 103350. https://doi.org/10.1016/J.IJHM.2022.103350

Jazuli, A., Widowati, & Kusumaningrum, R. (2023). Aspect-based sentiment analysis on student reviews using the Indo-Bert base model. *E3S Web of Conferences*, *448*, 02004. https://doi.org/10.1051/E3SCONF/202344802004

Jere, J. N., Ngidi, N., & Jere, J. (2020). A technology, organisation and environment framework analysis of information and communication technology adoption by small and medium enterprises in Pietermaritzburg. *South African Journal of Information Management*, *22*(1), 1–9. https://doi.org/10.4102/SAJIM.V22I1.1166

Jiang, L., Li, Y., Liao, J., Zou, Z., & Jiang, C. (2023a). Research on non-dependent aspect-level sentiment analysis. *Knowledge-Based Systems*, *266*, 110419. https://doi.org/10.1016/J.KNOSYS.2023.110419

Jiang, L., Li, Y., Liao, J., Zou, Z., & Jiang, C. (2023b). Research on non-dependent aspect-level sentiment analysis. *Knowledge-Based Systems*, *266*, 110419. https://doi.org/10.1016/J.KNOSYS.2023.110419

Jin, W., Zhao, B., Liu, C., Zhang, H., & Jiang, M. (2023). Using Masked Language Modeling to Enhance BERT-Based Aspect-Based Sentiment Analysis for Affective Token Prediction. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *14263 LNCS*, 530–542. https://doi.org/10.1007/978-3-031-44204-9_44

Jin, W., Zhao, B., Zhang, L., Liu, C., & Yu, H. (2023). Back to common sense: Oxford dictionary descriptive knowledge augmentation for aspect-based sentiment analysis. *Information Processing & Management*, *60*(3), 103260. https://doi.org/10.1016/J.IPM.2022.103260

Joubert, A., Murawski, M., & Bick, M. (2023). Measuring the Big Data Readiness of Developing Countries – Index Development and its Application to Africa. *Information Systems Frontiers*, *25*(1), 327–350. https://doi.org/10.1007/S10796-021-10109-9/METRICS

Joung, J., & Kim, H. (2023). Interpretable machine learning-based approach for customer segmentation for new product development from online product reviews. *International Journal of Information Management*, *70*, 102641. https://doi.org/10.1016/J.IJINFOMGT.2023.102641

Justy, T., Pellegrin-Boucher, E., Lescop, D., Granata, J., & Gupta, S. (2023). On the edge of Big Data: Drivers and barriers to data analytics adoption in SMEs. *Technovation*, *127*, 102850. https://doi.org/10.1016/J.TECHNOVATION.2023.102850

Kandhro, I. A., Ali, F., Uddin, M., Kehar, A., & Manickam, S. (2024). Exploring aspect-based sentiment analysis: an in-depth review of current methods and prospects for advancement. *Knowledge and Information Systems*, 1–31. https://doi.org/10.1007/S10115-024-02104-8/METRICS

Kasum Yusuf, K., Ogbuju, E., Abiodun, T., Oladipo, F., & Author, C. (2024). A Technical Review of the State-of-the-Art Methods in Aspect-Based Sentiment Analysis. *Journal of Computing Theories and Applications*, *2*(1), 67–78. https://doi.org/10.62411/JCTA.9999

Kauffmann, E., Peral, J., Gil, D., Ferrández, A., Sellers, R., & Mora, H. (2020). A framework for big data analytics in commercial social networks: A case study on sentiment analysis and fake review detection for marketing decision-making. *Industrial Marketing Management*, *90*, 523–537. https://doi.org/10.1016/J.INDMARMAN.2019.08.003

Kaur, G., & Sharma, A. (2023). A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis. *Journal of Big Data*, *10*(1), 1–23. https://doi.org/10.1186/S40537-022-00680-6/TABLES/5

Khder, M. A. (2021). Web Scraping or Web Crawling: State of Art, Techniques, Approaches and Application. *Int. J. Advance Soft Compu. Appl*, *13*(3). https://doi.org/10.15849/IJASCA.211128.11

Kleinheksel, A. J., Rockich-Winston, N., Tawfik, H., & Wyatt, T. R. (2020). Demystifying Content Analysis. *American Journal of Pharmaceutical Education*, *84*(1), 7113. https://doi.org/10.5688/AJPE7113

Kosiol, J., Fraser, L., Fitzgerald, A., & Radford, K. (2023). *Resource-based view: A new strategic perspective for public health service managers | Asia Pacific Journal of Health Management*. https://search.informit.org/doi/abs/10.3316/informit.007870393088402

Kumar, S., & Roy, U. B. (2023). A technique of data collection: web scraping with python. *Statistical Modeling in Machine Learning: Concepts and Applications*, 23–36. https://doi.org/10.1016/B978-0-323-91776-6.00011-7

Kuppusamy, M., & Selvaraj, A. (2023). A novel hybrid deep learning model for aspect based sentiment analysis. *Concurrency and Computation: Practice and Experience*, *35*(4), e7538. https://doi.org/10.1002/CPE.7538

KUSUMA, H., MUAFI, M., AJI, H. M., & PAMUNGKAS, S. (2020). Information and Communication Technology Adoption in Small- and Medium-Sized Enterprises: Demographic Characteristics. *The Journal of Asian Finance, Economics and Business*, *7*(10), 969–980. https://doi.org/10.13106/JAFEB.2020.VOL7.NO10.969

Lengkeek, M., van der Knaap, F., & Frasincar, F. (2023). Leveraging hierarchical language models for aspect-based sentiment analysis on financial data. *Information Processing & Management*, *60*(5), 103435. https://doi.org/10.1016/J.IPM.2023.103435

Li, C., Zhang, J., Tang, H., Ju, P., Cheng, D., & Morimoto, Y. (2024). *Enhancing the Performance of Aspect-Based Sentiment Analysis Systems*. https://arxiv.org/abs/2404.03259v1

Li, Z., Song, Y., Lu, X., & Liu, M. (2024). Twin Towers End to End model for aspect-based sentiment analysis. *Expert Systems with Applications*, *249*, 123713. https://doi.org/10.1016/J.ESWA.2024.123713

Liu, H., Chatterjee, I., Zhou, M., Lu, X. S., & Abusorrah, A. (2020). Aspect-Based Sentiment Analysis: A Survey of Deep Learning Methods. *IEEE Transactions on Computational Social Systems*, *7*(6), 1358–1375. https://doi.org/10.1109/TCSS.2020.3033302

Liu, H., Li, X., Lu, W., Cheng, K., & Liu, X. (2024). Graph Augmentation Networks Based on Dynamic Sentiment Knowledge and Static External Knowledge Graphs for aspect-based sentiment analysis. *Expert Systems with Applications*, *251*, 123981. https://doi.org/10.1016/J.ESWA.2024.123981

Liu, N., Hu, J., & Liang, W. (2023). MIFINN: A novel multi-information fusion and interaction neural network for aspect-based sentiment analysis. *Knowledge-Based Systems*, *280*, 110983. https://doi.org/10.1016/J.KNOSYS.2023.110983

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., Stoyanov, V., & Allen, P. G. (2019). *RoBERTa: A Robustly Optimized BERT Pretraining Approach*. https://arxiv.org/abs/1907.11692v1

Liu, Z., Wu, J., Chen, Q., & Hu, T. (2023). An improved Kansei engineering method based on the mining of online product reviews. *Alexandria Engineering Journal*, *65*, 797–808. https://doi.org/10.1016/J.AEJ.2022.09.044

Lutfi, A., Alrawad, M., Alsyouf, A., Almaiah, M. A., Al-Khasawneh, A., Al-Khasawneh, A. L., Alshira'h, A. F., Alshirah, M. H., Saad, M., & Ibrahim, N. (2023). Drivers and impact of big data analytic adoption in the retail industry: A quantitative investigation applying structural equation modeling. *Journal of Retailing and Consumer Services*, *70*, 103129. https://doi.org/10.1016/J.JRETCONSER.2022.103129

Malik, S., Chadhar, M., Vatanasakdakul, S., & Chetty, M. (2021). Factors Affecting the Organizational Adoption of Blockchain Technology: Extending the Technology–Organization–Environment (TOE) Framework in the Australian Context. *Sustainability 2021, Vol. 13, Page 9404*, *13*(16), 9404. https://doi.org/10.3390/SU13169404

Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management*, *54*, 102190. https://doi.org/10.1016/J.IJINFOMGT.2020.102190

Maroufkhani, P., Wan Ismail, W. K., & Ghobakhloo, M. (2020). Big data analytics adoption model for small and medium enterprises. *Journal of Science and Technology Policy Management*, *11*(2), 171–201. https://doi.org/10.1108/JSTPM-02-2020-0018/FULL/XML

Mehedi, M., Emon, H., Nahid, M. H., & Hoque Nahid, M. (2023). Factors Affecting Sustainable E-Commerce Adoption: Empirical Evidence from Bangladeshi SMES. *Corporate Sustainable Management Journal*, *1*(1), 32–36. https://doi.org/10.26480/csmj.01.2023.32.36

Mei, X., Zhou, Y., Zhu, C., Wu, M., Li, M., & Pan, S. (2023). A disentangled linguistic graph model for explainable aspect-based sentiment analysis. *Knowledge-Based Systems*, *260*, 110150. https://doi.org/10.1016/J.KNOSYS.2022.110150

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. *British Journal of Management*, *30*(2), 272–298. https://doi.org/10.1111/1467-8551.12343

Mikalef, P., van de Wetering, R., & Krogstie, J. (2021). Building dynamic capabilities by leveraging big data analytics: The role of organizational inertia. *Information & Management*, *58*(6), 103412. https://doi.org/10.1016/J.IM.2020.103412

Mishra, P., & Panda, S. K. (2023). Dependency Structure-Based Rules Using Root Node Technique for Explicit Aspect Extraction From Online Reviews. *IEEE Access*, *11*, 65117–65137. https://doi.org/10.1109/ACCESS.2023.3287830

Mishrif, A., & Khan, A. (2023). Technology adoption as survival strategy for small and medium enterprises during COVID-19. *Journal of Innovation and Entrepreneurship*, *12*(1), 1–23. https://doi.org/10.1186/S13731-023-00317-9/TABLES/4

Mohammad, W. N. S. W., Abdullah, M. R., Ismail, S., & Takim, R. (2019). Technology-organisation-environment framework for Building Information Modelling (BIM) adoption challenges for contractor's organisations in Malaysia. *Journal of Computational and Theoretical Nanoscience*, *16*(5–6), 2282–2288. https://doi.org/10.1166/JCTN.2019.7885

Mubarok, M. S., Adiwijaya, A., & Aldhi, M. D. (2017). Aspect-based sentiment analysis to review products using Naïve Bayes. *AIP Conference Proceedings*, *1867*(1). https://doi.org/10.1063/1.4994463/972740

Mughal, N., Mujtaba, G., Kumar, A., & Daudpota, S. M. (2024a). Comparative Analysis of Deep Natural Networks and Large Language Models for Aspect-Based Sentiment Analysis. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3386969

Mughal, N., Mujtaba, G., Kumar, A., & Daudpota, S. M. (2024b). Comparative Analysis of Deep Natural Networks and Large Language Models for Aspect-Based Sentiment Analysis. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3386969

Na, S., Heo, S., Han, S., Shin, Y., & Roh, Y. (2022). Acceptance Model of Artificial Intelligence (AI)-Based Technologies in Construction Firms: Applying the Technology Acceptance Model (TAM) in Combination with the Technology–Organisation–Environment (TOE) Framework. *Buildings 2022, Vol. 12, Page 90*, *12*(2), 90. https://doi.org/10.3390/BUILDINGS12020090

Narwane, V. S., Raut, R. D., Yadav, V. S., Cheikhrouhou, N., Narkhede, B. E., & Priyadarshinee, P. (2021). The role of big data for Supply Chain 4.0 in manufacturing organisations of developing countries. *Journal of Enterprise Information Management*, *34*(5), 1452–1480. https://doi.org/10.1108/JEIM-11-2020-0463/FULL/XML

Nasrollahi, M., Ramezani, J., & Sadraei, M. (2021). The Impact of Big Data Adoption on SMEs' Performance. *Big Data and Cognitive Computing 2021, Vol. 5, Page 68*, *5*(4), 68. https://doi.org/10.3390/BDCC5040068

Nazir, M. A., Roomi, M. A., Arsalan, M., Muhammad, N., & Roomi, A. (2021). Barriers to Adopting Electronic Commerce for Small and Medium-sized Enterprises in Emerging Economies. *EMAJ: Emerging Markets Journal*, *10*(2), 43–55. https://doi.org/10.5195/emaj.2020.203

Obokoh, L. O., & Goldman, G. (2016). Infrastructure deficiency and the performance of small- and medium-sized enterprises in Nigeria's Liberalised Economy. *Acta Commercii*, *16*(1). https://doi.org/10.4102/AC.V16I1.339

Ozdemir, S., Carlos Fernandez de Arroyabe, J., Sena, V., & Gupta, S. (2023). Stakeholder diversity and collaborative innovation: Integrating the resource-based view with stakeholder theory. *Journal of Business Research*, *164*, 113955. https://doi.org/10.1016/J.JBUSRES.2023.113955

Park, J. H., & Kim, Y. B. (2021). Factors Activating Big Data Adoption by Korean Firms. *Journal of Computer Information Systems*, *61*(3), 285–293. https://doi.org/10.1080/08874417.2019.1631133

Perdana, A., Lee, H. H., Koh, S. K., & Arisandi, D. (2022). Data analytics in small and mid-size enterprises: Enablers and inhibitors for business value and firm performance. *International Journal of Accounting Information Systems*, *44*, 100547. https://doi.org/10.1016/J.ACCINF.2021.100547

Pilicita, A., & Barra, E. (2023). Using of Transformers Models for Text Classification to Mobile Educational Applications. *IEEE Latin America Transactions*, *21*(6), 730–736. https://doi.org/10.1109/TLA.2023.10172138

Ping, Z., Sang, G., Liu, Z., & Zhang, Y. (2024). Aspect category sentiment analysis based on prompt-based learning with attention mechanism. *Neurocomputing*, *565*, 126994. https://doi.org/10.1016/J.NEUCOM.2023.126994

Pingali, S. R., Singha, S., Arunachalam, S., & Pedada, K. (2023). Digital readiness of small and medium enterprises in emerging markets: The construct, propositions, measurement, and implications. *Journal of Business Research*, *164*, 113973. https://doi.org/10.1016/J.JBUSRES.2023.113973

Prabhu, R., & Nashappa, C. S. (2024). *INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY*. https://doi.org/10.17485/IJST/v17i2.2715

Priya, P. S., & Rao, N. N. M. (2023). An Aspect based Sentiment Analysis of Tour and Travel Recommendation Approach using Machine Learning. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(10s), 754–762. https://ijisae.org/index.php/IJISAE/article/view/3330

QALATI, S. A., LI, W., VELA, E. G., BUX, A., BARBOSA, B., & HERZALLAH, A. M. (2020). Effects of Technological, Organizational, and Environmental Factors on Social Media Adoption. *The Journal of Asian Finance, Economics and Business*, *7*(10), 989–998. https://doi.org/10.13106/JAFEB.2020.VOL7.NO10.989

Qalati, S. A., Ostic, D., Sulaiman, M. A. B. A., Gopang, A. A., & Khan, A. (2022). Social Media and SMEs' Performance in Developing Countries: Effects of Technological-Organizational-

Environmental Factors on the Adoption of Social Media. *SAGE Open*, *12*(2). https://doi.org/10.1177/21582440221094594/ASSET/IMAGES/LARGE/10.1177_21582440221094594-FIG1.JPEG
Rahman, M., Akter, M., & Radicic, D. (2020). Internationalization as a strategy for small and medium-sized enterprises and the impact of regulatory environment: An emerging country perspective. *Business Strategy & Development*, *3*(2), 213–225. https://doi.org/10.1002/BSD2.90
Rainio, O., Teuho, J., & Klén, R. (2024). Evaluation metrics and statistical tests for machine learning. *Scientific Reports 2024 14:1*, *14*(1), 1–14. https://doi.org/10.1038/s41598-024-56706-x
Rakshit, S., Jeyaraj, A., & Paul, T. (2024). SME Performance Through Blockchain Technologies. *Journal of Computer Information Systems*, *64*(2), 204–218. https://doi.org/10.1080/08874417.2023.2187482
Ramasamy, M., & Elangovan, M. (2024). Optimized neural attention mechanism for aspect-based sentiment analysis framework with optimal polarity-based weighted features. *Knowledge and Information Systems*, *66*(4), 2501–2535. https://doi.org/10.1007/S10115-023-01998-0/METRICS
Rane, N., Liladhar Rane, N., Achari, A., & Choudhary, S. P. (2023). Enhancing customer loyalty through quality of service: Effective strategies to improve customer satisfaction, experience, relationship, and engagement. *Www.Irjmets.Com @International Research Journal of Modernization in Engineering*, *427*. https://doi.org/10.56726/IRJMETS38104
Rani, S., & Jain, A. (2024). Aspect-based sentiment analysis of drug reviews using multi-task learning based dual BiLSTM model. *Multimedia Tools and Applications*, *83*(8), 22473–22501. https://doi.org/10.1007/S11042-023-16360-3/METRICS
Rialti, R., Zollo, L., Ferraris, A., & Alon, I. (2019). Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model. *Technological Forecasting and Social Change*, *149*, 119781. https://doi.org/10.1016/J.TECHFORE.2019.119781
Rizwan Rashid Rana, M., Ur Rehman, S., Nawaz, A., Ali, T., Imran, A., Alzahrani, A., Almuhaimeed, A., & Authors, C. (2023). *Aspect-Based Sentiment Analysis for Social Multimedia: A Hybrid Computational Framework*. https://doi.org/10.32604/csse.2023.035149
Rodriguez-Garcia, P., Li, Y., Lopez-Lopez, D., & Juan, A. A. (2023). Strategic decision making in smart home ecosystems: A review on the use of artificial intelligence and Internet of things. *Internet of Things*, *22*, 100772. https://doi.org/10.1016/J.IOT.2023.100772
Rosário, A. T., & Dias, J. C. (2023). How has data-driven marketing evolved: Challenges and opportunities with emerging technologies. *International Journal of Information Management Data Insights*, *3*(2), 100203. https://doi.org/10.1016/J.JJIMEI.2023.100203
Ruchitaa Raj, N. R., Nandhakumar Raj, S., & Vijayalakshmi, M. (2023). Web Scrapping Tools and Techniques: A Brief Survey. *2023 International Conference on Innovative Trends in Information Technology, ICITIIT 2023*. https://doi.org/10.1109/ICITIIT57246.2023.10068666
Saeed, A., & Ebrahim, H. (2024). The Intersection of Machine Learning, Artificial Intelligence, and Big Data. *Big Data Computing: Advances in Technologies, Methodologies, and Applications*, 111–131. https://doi.org/10.1201/9781032634050-6/INTERSECTION-MACHINE-LEARNING-ARTIFICIAL-INTELLIGENCE-BIG-DATA-ATIF-SAEED-HADIYA-EBRAHIM
Sagnier, C., Loup-Escande, E., Lourdeaux, D., Thouvenin, I., & Valléry, G. (2020). User Acceptance of Virtual Reality: An Extended Technology Acceptance Model. *International Journal of Human-Computer Interaction*, *36*(11), 993–1007. https://doi.org/10.1080/10447318.2019.1708612
Saldanha Barreto, J., Komang, L., Dewi, C., & Ximenes, ; Lucio. (2023). The Influence of Brand Image and Product Quality on Purchase Decisions of Packaged Drinking Water in Liquiça

District, DILi – Timor Leste. *International Journal of Multicultural and Multireligious Understanding*, *10*(1), 332–340. https://doi.org/10.18415/IJMMU.V10I1.4399

Salisu, I., Bin Mohd Sappri, M., & Bin Omar, M. F. (2021). The adoption of business intelligence systems in small and medium enterprises in the healthcare sector: A systematic literature review. *Cogent Business & Management*, *8*(1). https://doi.org/10.1080/23311975.2021.1935663

Samaras, L., García-Barriocanal, E., & Sicilia, M. A. (2023). Sentiment analysis of COVID-19 cases in Greece using Twitter data. *Expert Systems with Applications*, *230*, 120577. https://doi.org/10.1016/J.ESWA.2023.120577

Santos, L. L., Borini, F. M., & Oliveira Júnior, M. de M. (2020). In search of the frugal innovation strategy. *Review of International Business and Strategy*, *30*(2), 245–263. https://doi.org/10.1108/RIBS-10-2019-0142/FULL/XML

Sekli, G. F. M., & De La Vega, I. (2021). Adoption of Big Data Analytics and Its Impact on Organizational Performance in Higher Education Mediated by Knowledge Management. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(4), 221. https://doi.org/10.3390/JOITMC7040221

Shabbir, M. Q., & Gardezi, S. B. W. (2020). Application of big data analytics and organizational performance: the mediating role of knowledge management practices. *Journal of Big Data*, *7*(1), 1–17. https://doi.org/10.1186/S40537-020-00317-6/TABLES/5

Shahzad, A., bin Zakaria, M. S. A., Kotzab, H., Makki, M. A. M., Hussain, A., & Fischer, J. (2023). Adoption of fourth industrial revolution 4.0 among Malaysian small and medium enterprises (SMEs). *Humanities and Social Sciences Communications 2023 10:1*, *10*(1), 1–14. https://doi.org/10.1057/s41599-023-02076-0

Shaik Vadla, M. K., Suresh, M. A., & Viswanathan, V. K. (2024). Enhancing Product Design through AI-Driven Sentiment Analysis of Amazon Reviews Using BERT. *Algorithms 2024, Vol. 17, Page 59*, *17*(2), 59. https://doi.org/10.3390/A17020059

Sharma, K., & Borkar, G. M. (2023). *Computing and Intelligent Systems, SCRS, In-dia*. 241–252. https://doi.org/10.56155/978-81-955020-7-3-22

Sharma, M., Gupta, R., Sehrawat, R., Jain, K., & Dhir, A. (2023). The assessment of factors influencing Big data adoption and firm performance: Evidences from emerging economy. *Enterprise Information Systems*, *17*(12), 12. https://doi.org/10.1080/17517575.2023.2218160

Shawkat, N. (2023). Evaluation of Different Machine Learning, Deep Learning and Text Processing Techniques for Hate Speech Detection. *MSU Graduate Theses*. https://bearworks.missouristate.edu/theses/3913

Shinde, S., Kulkarni, U., Mane, D., & Sapkal, A. (2021). Deep Learning-Based Medical Image Analysis Using Transfer Learning. *Studies in Computational Intelligence*, *932*, 19–42. https://doi.org/10.1007/978-981-15-9735-0_2

Shrivastava, A., Chakkaravarthy, M., & Shah, M. A. (2023). A new machine learning method for predicting systolic and diastolic blood pressure using clinical characteristics. *Healthcare Analytics*, *4*, 100219. https://doi.org/10.1016/J.HEALTH.2023.100219

Silvestri, R., Adamashvili, N., Fiore, M., & Galati, A. (2023). How blockchain technology generates a trust-based competitive advantage in the wine industry: a resource based view perspective. *European Business Review*, *35*(5), 713–736. https://doi.org/10.1108/EBR-10-2022-0217/FULL/XML

Singh, S., Kaur, H., Kanozia, R., & Kaur, G. (2023). *Empirical Analysis of Supervised and Unsupervised Machine Learning Algorithms with Aspect-Based Sentiment Analysis*. *28*(1), 125–136. https://doi.org/10.2478/acss-2023-0012

Sirisuriya, S. C. M. D. S. (2023). Importance of Web Scraping as a Data Source for Machine Learning Algorithms - Review. *2023 IEEE 17th International Conference on Industrial and Information*

Systems, ICIIS 2023 - Proceedings, 134–139. https://doi.org/10.1109/ICIIS58898.2023.10253502

Skafi, M., Yunis, M. M., & Zekri, A. (2020). Factors influencing SMEs' adoption of cloud computing services in Lebanon: An empirical analysis using TOE and contextual theory. *IEEE Access*, *8*, 79169–79181. https://doi.org/10.1109/ACCESS.2020.2987331

Srinivasan, S., Ertz, M., & Latrous, I. (2023). *Web Scraping Techniques and Applications: A Literature Review*. https://doi.org/10.52458/978-93-91842-08-6-38

Surbakti, F. P. S., Wang, W., Indulska, M., & Sadiq, S. (2020). Factors influencing effective use of big data: A research framework. *Information & Management*, *57*(1), 103146. https://doi.org/10.1016/J.IM.2019.02.001

Ta, V. A., Lin, C.-Y., Program In Business, P. D., Management, O., & Jung, C. (2023). Exploring the Determinants of Digital Transformation Adoption for SMEs in an Emerging Economy. *Sustainability 2023, Vol. 15, Page 7093*, *15*(9), 7093. https://doi.org/10.3390/SU15097093

Taganoviq, B., Kurutkan, M. N., Bagis, M., Hoxha, A., Kryeziu, B., Hysenaj, A., Haxhijakupi, E., Bimbashi, A., Dalipi, A., Hyseni, B., & Harris, L. U. (2023). Psychometric assessment of organizational readiness scale for digital innovations and antecedents of organizational readiness. *Human Systems Management*, *Preprint*(Preprint), 1–18. https://doi.org/10.3233/HSM-220202

Talaat, A. S. (2023). Sentiment analysis classification system using hybrid BERT models. *Journal of Big Data*, *10*(1), 1–18. https://doi.org/10.1186/S40537-023-00781-W/TABLES/4

Tamvada, J. P., Narula, S., Audretsch, D., Puppala, H., & Kumar, A. (2022). Adopting new technology is a distant dream? The risks of implementing Industry 4.0 in emerging economy SMEs. *Technological Forecasting and Social Change*, *185*, 122088. https://doi.org/10.1016/J.TECHFORE.2022.122088

Tesfa, T., Belete, B., Abera, S., Mohapatra, S. K., & Das, T. K. (2024). Aspect-Based Sentiment Analysis on Amharic Text for Evaluating Ethio-Telecom Services. *2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE)*, 1–6. https://doi.org/10.1109/IC-ETITE58242.2024.10493748

Truşcǎ, M. M., & Frasincar, F. (2022). Survey on aspect detection for aspect-based sentiment analysis. *Artificial Intelligence Review 2022 56:5*, *56*(5), 3797–3846. https://doi.org/10.1007/S10462-022-10252-Y

Uday, S., Chebolu, S., Dernoncourt, F., Lipka, N., & Solorio, T. (2023). A Review of Datasets for Aspect-based Sentiment Analysis. *The Association for Computational Linguistics*, *1*, 611–628. https://github.com/RiTUAL-UH/

Ur Rahman, M. W., Abrar, M. M., Copening, H. G., Hariri, S., Shao, S., Satam, P., & Salehi, S. (2023). Quantized Transformer Language Model Implementations on Edge Devices. *Proceedings - 22nd IEEE International Conference on Machine Learning and Applications, ICMLA 2023*, *2023*, 709–716. https://doi.org/10.1109/ICMLA58977.2023.00104

Varadarajan, R. (2023). Resource advantage theory, resource based theory, and theory of multimarket competition: Does multimarket rivalry restrain firms from leveraging resource Advantages? *Journal of Business Research*, *160*, 113713. https://doi.org/10.1016/J.JBUSRES.2023.113713

Velananda, Y. L., Dissanayake, D. M. R., & Wickramasinghe, C. N. (2023). Frugal Innovation and Core Characteristics: A Systematic Literature Review. *Scope*, *13*, 75. http://repository.kln.ac.lk/handle/123456789/26498

Vijaya, J., Kulkarni, A., Ranjan, V. V., & Bajaj, V. (2024). An Enhanced Object-Oriented Programming-Based Web Page Linker. *2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation, IATMSI 2024*. https://doi.org/10.1109/IATMSI60426.2024.10503405

Vu, N. H., & Nguyen, N. M. (2022). Development of small-and medium-sized enterprises through information technology adoption persistence in Vietnam. *Information Technology for Development*, *28*(3), 585–616. https://doi.org/10.1080/02681102.2021.1935201

Waheeb, S. A. (2023). Multi-Task Aspect-Based Sentiment: A Hybrid Sampling and Stance Detection Approach. *Applied Sciences 2024, Vol. 14, Page 300*, *14*(1), 300. https://doi.org/10.3390/APP14010300

Wang, C., Fayaz Ahmad, S., Bani, A. Y. A., Ayassrah, A., Awwad, M., Irshad, M., Ali, Y. A., Al-Razgan, M., Khan, Y., & Han, H. (2023). An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce. *Heliyon*, *9*, e18349. https://doi.org/10.1016/j.heliyon.2023.e18349

Wang, F., Du, Z., & Wang, S. (2023). Information multidimensionality in online customer reviews. *Journal of Business Research*, *159*, 113727. https://doi.org/10.1016/J.JBUSRES.2023.113727

Wang, H., Li, J., Wu, H., Hovy, E., & Sun, Y. (2023). Pre-Trained Language Models and Their Applications. *Engineering*, *25*, 51–65. https://doi.org/10.1016/J.ENG.2022.04.024

Wang, S., & Wang, H. (2020). Big data for small and medium-sized enterprises (SME): a knowledge management model. *Journal of Knowledge Management*, *24*(4), 881–897. https://doi.org/10.1108/JKM-02-2020-0081/FULL/XML

Willetts, M., Atkins, A. S., & Stanier, C. (2020). Barriers to SMEs Adoption of Big Data Analytics for Competitive Advantage. *4th International Conference on Intelligent Computing in Data Sciences, ICDS 2020*. https://doi.org/10.1109/ICDS50568.2020.9268687

Wu, C. W., Botella-Carrubi, D., & Blanco-González-Tejero, C. (2024). The empirical study of digital marketing strategy and performance in small and medium-sized enterprises (SMEs). *Technological Forecasting and Social Change*, *200*, 123142. https://doi.org/10.1016/J.TECHFORE.2023.123142

Wu, H., Huang, C., & Deng, S. (2023). Improving aspect-based sentiment analysis with Knowledge-aware Dependency Graph Network. *Information Fusion*, *92*, 289–299. https://doi.org/10.1016/J.INFFUS.2022.12.004

Wu, J., & Zhao, N. (2023). What consumer complaints should hoteliers prioritize? Analysis of online reviews under different market segments. *Journal of Hospitality Marketing & Management*, *32*(1), 1–28. https://doi.org/10.1080/19368623.2022.2119187

Xiao, L., Li, X., & Zhang, Y. (2023). Exploring the factors influencing consumer engagement behavior regarding short-form video advertising: A big data perspective. *Journal of Retailing and Consumer Services*, *70*, 103170. https://doi.org/10.1016/J.JRETCONSER.2022.103170

Xie, Z. (2023). The Benefit and Risks for Scraping Based on Python. *Highlights in Science, Engineering and Technology*, *49*, 232–236. https://doi.org/10.54097/HSET.V49I.8511

Yang, H., Zhang, C., & Li, K. (2023). PyABSA: A Modularized Framework for Reproducible Aspect-based Sentiment Analysis. *International Conference on Information and Knowledge Management, Proceedings*, 5117–5122. https://doi.org/10.1145/3583780.3614752

Yang, Q., Liu, Y., Chen, T., & Tong, Y. (2019). Federated Machine Learning. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *10*(2). https://doi.org/10.1145/3298981

Yuan, S. (2023). Design and Visualization of Python Web Scraping Based on Third-Party Libraries and Selenium Tools. *Academic Journal of Computing & Information Science*, *6*, 25–31. https://doi.org/10.25236/AJCIS.2023.060904

Zayed, N. M., Mohamed, I. S., Islam, K. M. A., Perevozova, I., Nitsenko, V., & Morozova, O. (2022). Factors Influencing the Financial Situation and Management of Small and Medium Enterprises. *Journal of Risk and Financial Management 2022, Vol. 15, Page 554*, *15*(12), 554. https://doi.org/10.3390/JRFM15120554

Zhang, W., Li, X., Deng, Y., Bing, L., & Lam, W. (2023). A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges. *IEEE Transactions on Knowledge and Data Engineering*, *35*(11), 11019–11038. https://doi.org/10.1109/TKDE.2022.3230975

Zhao, C., Feng, R., Sun, X., Shen, L., Gao, J., & Wang, Y. (2024). Enhancing aspect-based sentiment analysis with BERT-driven context generation and quality filtering. *Natural Language Processing Journal*, *7*, 100077. https://doi.org/10.1016/J.NLP.2024.100077

Zhao, G., Luo, Y., Chen, Q., & Qian, X. (2023). Aspect-based sentiment analysis via multitask learning for online reviews. *Knowledge-Based Systems*, *264*, 110326. https://doi.org/10.1016/J.KNOSYS.2023.110326

Zheng, Y., Li, X., & Nie, J. Y. (2023). Store, share and transfer: Learning and updating sentiment knowledge for aspect-based sentiment analysis. *Information Sciences*, *635*, 151–168. https://doi.org/10.1016/J.INS.2023.03.102

Zhong, Q., Ding, L., Liu, J., Du, B., Jin, H., & Tao, D. (2023). Knowledge Graph Augmented Network Towards Multiview Representation Learning for Aspect-Based Sentiment Analysis. *IEEE Transactions on Knowledge and Data Engineering*, *35*(10), 10098–10111. https://doi.org/10.1109/TKDE.2023.3250499

Zhu, L., Zhu, X., Guo, J., & Dietze, S. (2023). Exploring rich structure information for aspect-based sentiment classification. *Journal of Intelligent Information Systems*, *60*(1), 97–117. https://doi.org/10.1007/S10844-022-00729-1/METRICS

Zhu, X., Kuang, Z., & Zhang, L. (2023). A prompt model with combined semantic refinement for aspect sentiment analysis. *Information Processing & Management*, *60*(5), 103462. https://doi.org/10.1016/J.IPM.2023.103462

Zhu, X., Zhu, Y., Zhang, L., & Chen, Y. (2023). A BERT-based multi-semantic learning model with aspect-aware enhancement for aspect polarity classification. *Applied Intelligence*, *53*(4), 4609–4623. https://doi.org/10.1007/S10489-022-03702-1/METRICS

Zhu, Y., Li, L., Li, C., & Zhang, W. (2023). *Opportunities and Challenges in Sustainability Challenges Confronting the Sustainability of Anti-Epidemic Policies Based on the BERT-Pair-ABSA Model*. https://doi.org/10.56578/ocs020105

Zide, O., & Jokonya, O. (2022). Factors affecting the adoption of Data Management as a Service (DMaaS) in Small and Medium Enterprises (SMEs). *Procedia Computer Science*, *196*, 340–347. https://doi.org/10.1016/J.PROCS.2021.12.022

Zou, W., Zhang, W., Tian, Z., & Wu, W. (2024). A syntactic features and interactive learning model for aspect-based sentiment analysis. *Complex and Intelligent Systems*, 1–19. https://doi.org/10.1007/S40747-024-01449-5/TABLES/8

Zuliawaty Rajasa, E., Manap, A., Doddy Heka Ardana, P., Yusuf, M., Pelita Bangsa, U., Jayabaya, U., Ngurah Rai, U., Bandung, S., & Negeri Medan, P. (2023). LITERATURE REVIEW: ANALYSIS OF FACTORS INFLUENCING PURCHASING DECISIONS, PRODUCT QUALITY AND COMPETITIVE PRICING. *Jurnal Ekonomi*, *12*(01), 451–455. https://ejournal.seaninstitute.or.id/index.php/Ekonomi/article/view/1202