IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 27 December 2023, accepted 2 March 2024, date of publication 11 March 2024, date of current version 2 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3376478

METHODS

WIPE: A Novel Web-Based Intelligent Packaging Evaluation via Machine Learning and Association Mining

MAHSA TAVASOLI[1], **EUIHARK LEE**[2], **YASHAR MOUSAVI**[3], **(Member, IEEE)**, **HANNANEH BARAHOUEI PASANDI**[4], **(Member, IEEE)**, **AND AFEF FEKIH**[5], **(Senior Member, IEEE)**

[1]School of Applied Science and Technology, North Carolina Agricultural and Technical University, Greensboro, 27411 NC, USA
[2]School of Packaging, Michigan State University, East Lansing, MI 48823, USA
[3]Department of Applied Science, School of Computing, Engineering and Built Environment, Glasgow Caledonian University, G4 0BA Glasgow, U.K.
[4]EECS Department, University of California, Berkeley, Berkeley, CA 94720, USA
[5]Department of Electrical and Computer Engineering, University of Louisiana at Lafayette, Lafayette, LA 70504, USA

Corresponding author: Euihark Lee (leeeuiha@msu.edu)

This work was supported by Michigan Translational Research and Commercialization Innovation Hub for AgBio Starter Grant (MTRACT AgBio Starter Grant).

ABSTRACT This paper introduces the Web-Based Intelligent Packaging Evaluation (WIPE) platform, a novel approach to assess the performance of product and packaging systems within the e-commerce distribution sector. Unlike traditional methods that primarily rely on laboratory evaluations under controlled conditions, WIPE addresses the unique challenges posed by e-commerce distribution, such as increased handling points and unforeseen hazards that standard physical tests may not capture. Leveraging advanced machine learning algorithms and association rule mining, WIPE extracts insights about packaging defects directly from customer reviews on e-commerce platforms. Analyzing both images and text from these reviews establishes connections between frequently used words and the predicted damages, causes, and effects. This innovative approach was exemplified in two case studies involving laundry detergent liquid bottles and pods sold on the Amazon. The findings from these studies demonstrate WIPE's capability to extract pertinent information from customer feedback and identify specific packaging defects and predict their potential causes. This integration of sentiment analysis and association rule mining into the packaging evaluation process marks a significant advancement in the field. The introduction of WIPE represents a transformative step in packaging evaluation, offering a more dynamic, real-world analysis that can significantly enhance product and packaging design, ultimately leading to improved customer satisfaction in the rapidly evolving e-commerce landscape.

INDEX TERMS Packaging evaluation, E-commerce distribution, machine learning algorithms, association rule mining, sentiment analysis, damage prediction, online purchasing platforms.

I. INTRODUCTION

The growth rate of e-commerce, as depicted in Figure 1, has significantly impacted the packaging industry [1]. The shift from traditional retail to e-commerce distribution has introduced new challenges and placed greater demands on protective packaging [2]. The e-commerce distribution network typically involves nearly three times as many touchpoints as traditional retail, elevating the risk of damage during transportation. In response to this, various packaging evaluation tests have been developed. These latter are classified into field, laboratory, and numerical evaluations and aim to assess and improve packaging performance under various conditions. These tests aim to assess and improve packaging performance under diverse conditions. However, while these methods collectively strive to ensure the safety of product-packaging systems during transportation, they exhibit similarities in their overarching goal of evaluating

The associate editor coordinating the review of this manuscript and approving it for publication was Francesco Mercaldo.

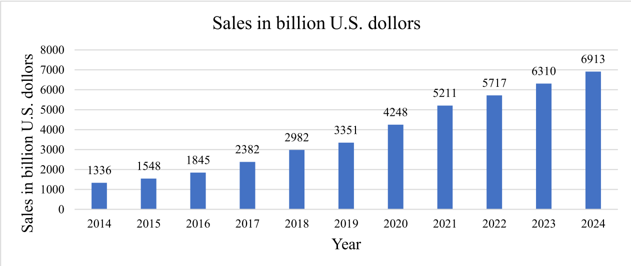


FIGURE 1. **Global retail e-commerce sales (in billion USD) worldwide over ten years [1].**

packaging performance. However, it is essential to acknowledge the drawbacks associated with these methods [3], which we detail in the subsequent subsections.

1) FIELD TESTING METHODS

Evaluating packaging performance in natural conditions facilitates the measurement and analysis of variables that laboratories struggle to mimic accurately. These methods involve real-world testing conditions, exem- plified by the van shipment test proposed by Böröcz and Molnár [4]. This approach provides direct insights into packaging performance under actual transportation conditions, capturing variables that laboratory tests may not fully replicate. Recent findings stress the necessity of field testing to assess packaging durability, as real-world conditions, notably during urban transport, present challenges not replicated in laboratory environments. This highlights the critical need for testing methods that accurately reflect the complexities of actual transport to ensure packaging integrity.

While field tests provide real-world data, they can be costly, time-consuming, and less controlled. The variability in transportation conditions makes it challenging to standardize these tests or replicate them precisely for comparative analysis.

2) LABORATORY TESTING METHODS

These methods are controlled experiments that simulate real-world conditions. Standardized tests like ASTM D1596 and ASTM 1185 are examples of this method. Laboratory testing is essential for ensuring consistency and accuracy in evaluating the performance of packaging materials against predefined standards and scenariosProper laboratory testing is critical to designing and selecting packaging materials for safe and reliable product transportation [4], [5], [6]. Despite their controlled environment, laboratory tests may not fully capture the complexity and unpredictability of real-world scenarios. There is also a risk of relying too heavily on standardized tests that may not encompass all potential damage scenarios or reflect the latest material innovations and transportation dynamics.

3) COMPUTATIONAL MODELING METHODS

Computational modeling methods such as finite element modeling (FEM) use computational tools to simulate and evaluate packaging performance. FEM is applied to various scenarios, such as drop testing and compression simulations. Its advantage lies in its ability to reduce the need for destructive physical tests, thereby saving time and resources [7], [8], [9], [10], [11], [12]. While FEM offers a time-saving and less resource-intensive approach, its accuracy heavily relies on the quality of the material models used. Simplified material models might suffer from accurately capturing the expected behaviors of packaging materials under different conditions. Additionally, FEM requires expertise in computational modeling and an understanding of packaging dynamics, which might limit its accessibility to all packaging engineers.

Given the aforementioned investigations, packaging evaluation methods have advantages and drawbacks, including field tests, laboratory tests, and numerical assessments. While field tests provide actual performance data, they are time-consuming, expensive, and non-repeatable. Laboratory tests are cost-effective and efficient but cannot replicate unexpected hazards encountered during distribution. Similarly, FEM analysis-based evaluations may not accurately predict packaging performance if the material model is complex or has geometrical imperfections. Researchers have turned to artificial intelligence (AI)-based techniques to address these limitations.

4) ARTIFICIAL INTELLIGENCE-BASED METHODS

Artificial intelligence (AI) has emerged as a versatile tool in a myriad of fields, ranging from supply chain, packaging, healthcare diagnostics, autonomous vehicles domain, wireless, and communication. AI has established itself as a verified approach to guide the industry's next evolution from manufacturing to packaging and distribution [13]. AI approaches have established themselves as verified approaches to guide the industry's next evolution from manufacturing to packaging and distribution. The concept of AI was first introduced in the 1950s, which involves simulating human cognitive abilities in machines [14]. AI has evolved from a theoretical concept to a practical application on a massive scale in the current era of rapid technological innovation and exponential increases in big data [15]. One of the most well-known subsets of AI is machine learning (ML), which focuses on using big data and algorithms to simulate human learning processes, progressively increasing the accuracy of those algorithms [16]. Deep learning on the other hand is a widely used subset of ML that uses a large-scale neural network (NN) of brain architecture to learn several levels of abstraction using multi-level learning. ML models offer highly accurate predictions through statistical approaches, which can be trained to discover patterns in training data [17]. General AI applications include a vast research area, such as speech recognition, data anomaly detection, product designs and evaluation, computer vision, and facility location optimization [18] General artificial intelligence applications are speech recognition [18], product designs [19], computer vision [20], recommendation engines [21], fraud detection [22] and facility location optimization [23]. However, the success of ML-based methods relies heavily on the quality and quantity of data used to train the models, and the models must be periodically updated to remain relevant [24]. The packaging industry's implementation of AI is driven by the demand for eco-friendly packaging, a circular economy, and reduced damage. AI is used for packaging planning, optimization of delivery, maintenance, design, chemical evaluation, and defect detection [25].

In this context, packaging planning methods include ML models for automated planning based on product features [26], KNN algorithms for categorizing biodegradable active packaging [27], and unsupervised ML-based optimal packaging selection [28]. Zhao et al. [29] utilized clustering algorithms for packaging optimization with the aim of minimizing size and cutting costs. Lepine et al. [30] showcased ML's superiority in shock detection over traditional methods. Archaviboonyobul et al. [31] proposed an Artificial Neural Networks (ANN) approach for predicting box strength and evaluating hand hole and ventilation designs. Wang et al. [2] and Chang and Lee [32] proposed machine learning-based approaches to optimize delivery routes for green logistics and truck/drone systems, respectively. Zhang [33] and Yang et al. [34] proposed machine learning-based methods for predicting the thermal degradation of PLA materials and classifying plastic waste, respectively. Moreover, packaging defect detection methods based on ML techniques such as support vector machine (SVM) and image processing have been proposed by several researchers [25], [35], [36]. Holland et al. [35] proposed an intelligent packaging evaluation system based on artificial neural networks that analyze images uploaded by customers to identify packaging failures. Wu and Lu [36] and Yang et al. [37] also developed packaging defect detection systems using SVM learning models. Taheri et al. [38] focused on preserving seal integrity in crucial sectors such as food and medical devices. they advocated nondestructive evaluation (NDTE) methods for inspection without damage while highlighting the real-time ML-based defect detection and automation in production lines. The research emphasized ML's potential in enhancing seal integrity assessment. In another study, Esfahanian and Lee [39] proposed a packaging evaluation method based on ML approaches and packaging review filtration. However, the method neglects informative uploaded images by customers and does not show the relationship between the damage and its location. Manual packaging evaluation could benefit from association rule mining of frequent problems and their causes. To provide a comprehensive understanding, a comparison of various packaging evaluation methods is illustrated in Table 1, highlighting their respective advantages and disadvantages.

In this paper, we introduce a Web-based Intelligent Packaging Evaluation Platform (WIPE) that addresses the limitations of traditional packaging evaluation methods in the context of e-commerce distribution. The proposed platform contributes to the literature as follows:

- Automating the data flow of packaging evaluation, which includes collecting and processing customer feedback and reviews.
- Better correlating images and text of online product reviews to understand the relationship between packaging failures and customer experiences.
- Determining the relationships between the most frequent words in customer reviews to predict damages and their causes and effects.

Hence, WIPE is not just a tool but a comprehensive end-to-end system solution designed to address the multifaceted challenges of packaging evaluation in the e-commerce sector by integrating multiple technologies, addressing e-commerce challenges, analyzing real-world data, predictive analysis, introducing novel data correlation, incorporating sentiment analysis, and enhancing customer satisfaction.

The remainder of the paper is structured as follows. Section II presents the methodology adopted for this study. Section III presents the results and discussion of the study. Finally, Section IV concludes the paper and outlines future directions for research.

II. METHODOLOGY

To achieve the above objectives, we propose a web-based automated intelligent approach for identifying packaging failures and their connections using sentiment analysis of customer evaluations. Our approach involves four main modules: Web scrapper, Sentiment analysis module, Association rule mining module, and data analysis dashboard. Each module presents this research's main contributions, including data process automation, automated embedded image downloading, and automatic association rule mining. By breaking down our model into these modules, we aim to provide a comprehensive and systematic approach to packaging evaluation that leverages advanced data analysis techniques and automation to improve the accuracy and efficiency of the evaluation process. The following sections will describe each module in detail, outlining its functionality and how it contributes to achieving the objectives of the WIPE platform.

A. WEB SCRAPPER

Amazon.com was chosen as the primary data source for this study due to its vast collection of products and millions of online reviews containing valuable information, such as reviewer name, credibility, rating, date and time, helpfulness, and the ability to edit reviews as shown in Figure 2 [40]. Numerous free online datasets related to Amazon reviews are available for research purposes. The Ref2Seq dataset, which was developed by Ni et al. [41], is the most recent dataset with high-quality, personalized, and relevant review justifications. Amazon [42] provides several review data collections, including "The Multilingual Amazon Reviews Corpus"

TABLE 1. Comparison of the most-implemented control approaches on WECS control.

Packaging Evaluation Method	Advantages	Disadvantages
Field evaluation	• Real-world data collection • Authentic results • Observes actual usage patterns • Identifies issues beyond lab settings	• Costly: Requires resources for field trials • Time-consuming: Field trials take time to execute • Limited resources: Might not cover all scenarios • Limited scalability: Hard to scale due to resource constraints
Laboratory evaluation	• Adheres to standardized procedures • Controlled environment for reproducibility • Effective compared to field tests	• Limited to simulating predefined scenarios • Cannot capture unforeseen hazards
Numerical evaluation	• Time and resource efficiency • Simulation of diverse scenarios • Allows for rapid testing and iterations	• Difficulty in obtaining accurate material properties • Complexity: Requires advanced modeling skills
WIPE	• Reduces the need for physical testing • Extracts insights from real-world distribution hazards via machine learning prediction • Discovers hidden patterns through association mining	• Only applicable to the product in the e-commerce market

FIGURE 2. Example of an Online Product Review on Amazon.com.

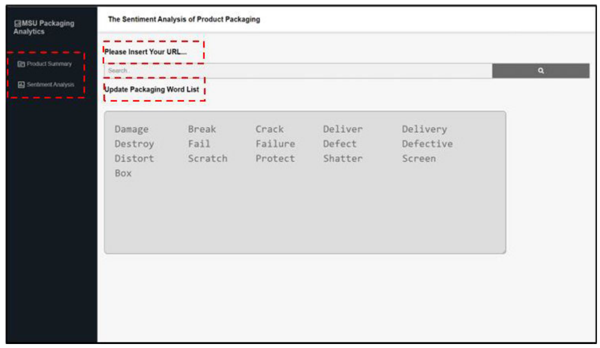


FIGURE 3. WIPE Platform Homepage Snapshot.

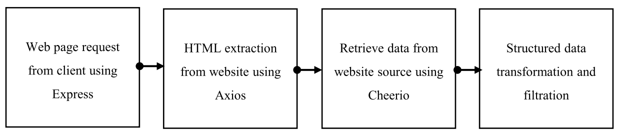


FIGURE 4. Embedded Web Scraping Flow Chart.

and "Helpful Sentences from Reviews," which feature the review's association with a verified purchase. However, these datasets lack essential information, such as reviewer names and ratings. Despite the wide range of products and categories included in these datasets, they are outdated and do not incorporate new review quality features established by Amazon, such as verified purchases [43]. A web scraper was implemented within the application to automate the data flow of packaging evaluation in our proposed Web-based Intelligent Packaging Evaluation Platform (WIPE). While manual data collection from webpages is possible, web scraping is an automated procedure embedded into the WIPE application. It allowed all modules to have a connected flow of data. Whenever an Amazon link for a specific product is received, the embedded web scraper returns all reviews' text and images associated with that product [40]. For web programming, several libraries were used. The main libraries of our program are Express, Cheerio, and Axios. A visual snapshot of the WIPE platform is shown in Figure 3.

Another main contribution of this study is to extend web scrapping capability by downloading customer-uploaded images and text. The HTTPS library was used for getting images and their attributes, like URLs. Figure 4 shows the embedded web scrapping flow.

The following section demonstrates how to extract computational features such as sentiment analysis score, frequent packaging word sets, and the relationship between each packaging word from structured data.

B. SENTIMENT ANALYSIS DESIGN

In the scope of this research, we employed sentiment analysis as our chosen methodology to explore the sentiments conveyed within Amazon product reviews centered on packaging damages. We evaluated three sentiment analysis approaches: neural network-based models like LSTM (Long Short-Term Memory), traditional ML models such as Naïve Bayes, and lexicon-based methods like AFINN. We employed the LSTM model, a type of artificial neural network, as a central component of our methodology. By using character and word-level embeddings, the LSTM model aims to categorize text into "positive," "neutral," or "negative" sentiments. This model underwent rigorous training for sentiment analysis within our study. What sets the LSTM-based model apart is its compact size and ability to work well on various platforms. Its adaptability for integration into web applications and portable platforms, like our web-based WIPE application, made it the most suitable choice for our analysis.

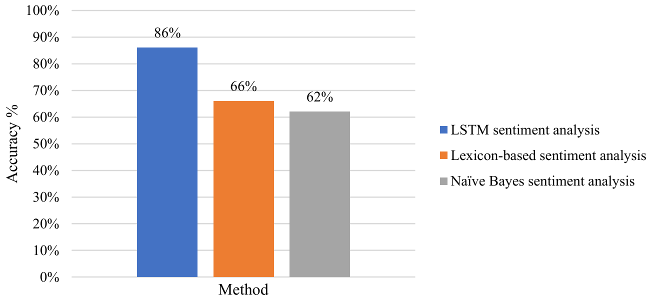


FIGURE 5. Comparisons of LSTM, Lexicon-based, and Naïve Bayes sentiment analysis methods accuracies.

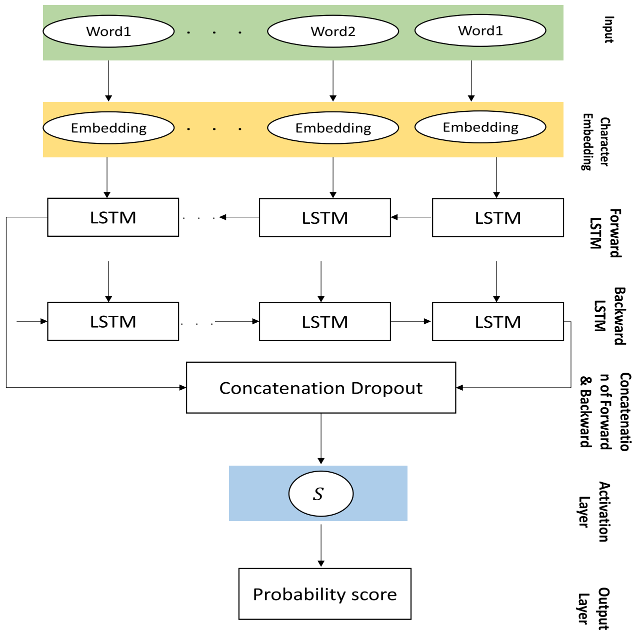


FIGURE 6. A General view of character-Level LSTM for sentiment analysis.

On the other hand, the Naïve Bayes model falls under traditional machine learning. It employs Bayes' theorem to estimate the likelihood of text expressing a "positive" or "negative" sentiment based on specific word occurrences. In contrast, the AFINN method employs a lexicon-based approach, assigning scores to words that indicate emotional nuances, either positive or negative. The aggregation of these scores determines the overall sentiment conveyed in the text.

Through our comparative analysis, as shown in Figure 5, a significant finding emerged: the LSTM model, particularly based on neural networks, showed exceptional proficiency in accurately predicting customer sentiments, surpassing the performance of both Naïve Bayes and lexicon-based methods. This superiority is rooted in several inherent attributes of the LSTM model. Operating as a neural network with memory, it effectively captures contextual nuances, enabling it to comprehend the sentiment of a sentence within a broader context. Additionally, it effectively addresses the challenge of vanishing gradients commonly encountered in traditional neural networks. The LSTM model adeptly handles sequences of varying lengths and recognizes complex long-term relationships, which is especially valuable when analyzing text rich in contextual information. Figure 6 depicts a sentiment analysis framework employing LSTM networks. It begins with converting input words into embeddings that reflect their semantic content. These character-level embeddings are processed by LSTM layers, known for their proficiency in managing sequences and capturing long-term contextual dependencies. The LSTM outputs then pass through a dropout layer to mitigate overfitting, followed by a softmax layer that categorizes sentiments into positive, negative, or neutral based on their probability scores. The model's automatic feature extraction minimizes the need for manual feature engineering, making it versatile for various textual analyses. Additionally, the integration of Large Language Models (LLM) promises to significantly refine the accuracy and precision of sentiment analysis, a development discussed in future research directions. This is elaborated as part of the future works of this research in the discussion section III.

The sentiment analysis process of the WIPE application consisted of four main steps, shown in Figure 7.

Step 1 involved selecting reviews with ratings lower than two stars, followed by generating packaging relevant word lists using the TF-IDF algorithm (that has been explained in section II-D).

Step 2 divided the review into separate sentences, and packaging relevant sentences were filtered and preprocessed.

Step 3 involved comparing three sentiment analyses: LSTM deep learning, Lexicon-based, and Naïve Bayes models. The LSTM model, which used character and word-level embeddings, was found to be the most accurate. Since the proposed WIPE application is a web-based application, using character and word-level embedding didn't reduce the speed of the application and also increased the sentiment accuracy of sentiment analysis from 66% to 86% by finding more negative reviews. The LSTM-based model initiates its analysis with character-based embeddings, processed through a bidirectional LSTM comprising 32 units, adept at uncovering complex character interactions. Following this, mean-pooling and statistical techniques refine the outputs, extracting crucial features. This preparatory work feeds into another bidirectional LSTM, this one equipped with 96 units, which delves into word-level semantic nuances, crafting a thorough bidirectional analysis across both character and word dimensions.

Step 4 involved converting sentiment scores into meaningful information and displaying the results using Word Cloud, bar charts, pie charts, and line charts. The most commonly repeated words in the reviews were leak, package, damage, and box, as shown in Figure 8.

To reveal the "reasons" and "causes" of damages stated in reviews, we used association rule mining, to extract the relationship between relevant concerns. This method is illustrated in the next section.

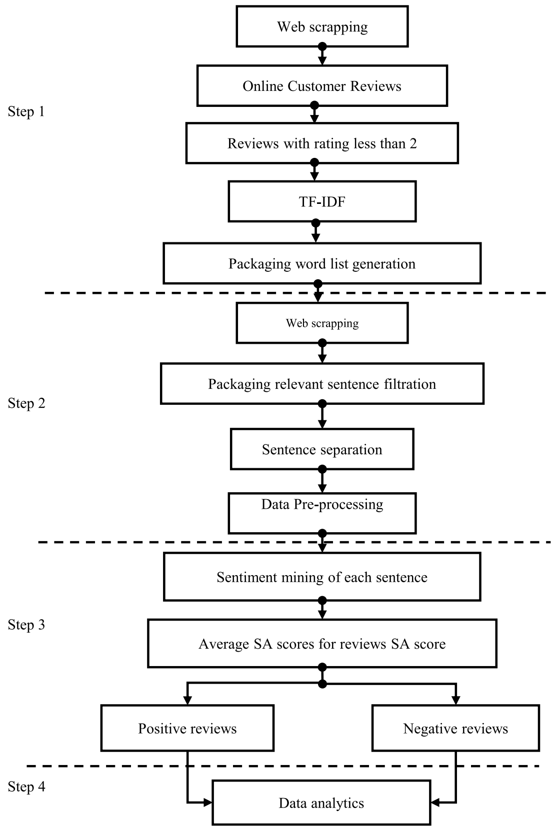


FIGURE 7. Sentiment analysis framework.

FIGURE 8. Frequent packaging words.

C. ASSOCIATION RULE MINING DESIGN

In the previous subsection, we explained how the sentiment analysis of a review is calculated and what problems are common in negative reviews. Sentiment analysis can show whether users are dissatisfied with a product, but it cannot explain why. Despite the simplicity of categorizing findings into binary categories, positive and negative, a sentiment's applicability to engineers is reduced when detached from its context [44]. Despite significant advances in sentiment analysis, sentiment does not offer engineers an entire context of what is causing the sentiment. For example, a review may express dissatisfaction with a "cap" feature but fail to specify what problem the cap causes. The discovery of "association rules" often describes the most frequently seen items in reviews and those items' relationship identification. We used association rule mining to identify where the most frequent damage happened or the relationships between frequent damages.

Association rule learning is an unsupervised automated learning approach that uses rules to extract meaningful relationships between variables in an extensive database [45]. These rules are represented by the form $X \rightarrow Y$, where X is an item or item set that indicates the antecedent, and Y is an item or itemset referred to as the consequent, and are used to extract hidden relationships between items that frequently co-occur in the database. Support and confidence parameters are commonly used to assess the validity of an association. Apriori [46] and Fp-growth [47] are two popular algorithms for obtaining association rule mining, with Fp-growth being faster due to its use of a compact data structure called a tree [2], [48].

In this research, Fp-growth was chosen to identify the relationship between frequent word sets of customer reviews, with a minimum value for support and confidence of rules defined through a pruning process. The resulting frequent word sets and their relationships were then used for data analytics. Apriori and Fp-growth are two popular algorithms for obtaining association rule mining, with Fp-growth being faster due to its use of a compact data structure called a tree. For this research study, Fp-growth was chosen to identify the relationship between frequent word sets of customer reviews, with a minimum value for support and confidence of rules defined through a pruning process. Finally, after setting association rule mining parameters, the framework is similar to Fig. 9. Association rule mining is applied to negative review results from the sentiment analysis step. As a result, most frequent words and their relationship are driven and used for data analytics.

D. DATA ANALYSIS

This section will discuss the various formulas and data analysis methods considered in our study. These include the calculation of Term Frequency-Inverse Document Frequency (TF-IDF) to find frequent packaging word lists, the computation of packaging failure and success rates, training and testing the sentiment analysis model, and determining parameters for association rule mining. These techniques extracted valuable insights from customer reviews and product images, providing a more comprehensive understanding of customer experiences and identifying packaging issues. We aimed to enhance customer satisfaction by improving packaging evaluation and utilizing these methods.

The TF-IDF machine learning technique is advantageous in assessing the relative value of words in the text. We used reviews with a rating lower than two stars, and then packaging relevant word lists were generated via the

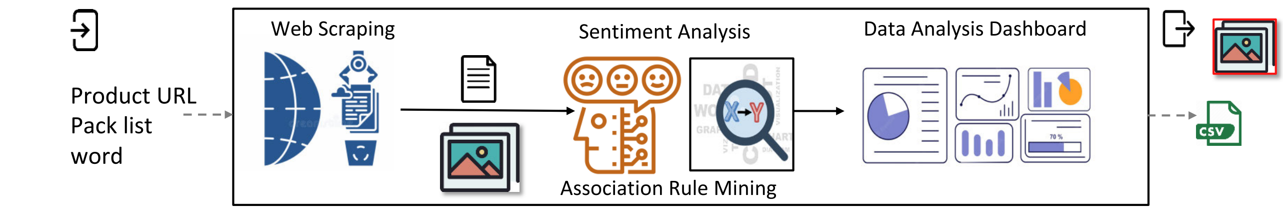


FIGURE 9. **Traditional packaging Evaluation vs Web-based Intelligent Packaging Evaluation (WIPE) platform architecture.**

Term Frequency-Inverse Document Frequency (TF-IDF) algorithm. It gives a term more weight when it appears more frequently in a single document and often occurs in many documents. In order to do this, two metrics must be multiplied: the number of times a word appears in a document, called "Term frequency (TF)," and the word's inverse document frequency across a group of documents, called "Inverse document frequency (IDF)" [49]. The simplest computation method of a word's frequency is the number of times it appears in a document. The frequency is then adjusted based on the document's length. By computing the logarithm of the total number of documents divided by the number of documents containing a keyword, the inverse frequency of a word is determined. So TF-IDF is calculated via (1):

$$TF - IDF = TF \times IDF, \tag{1}$$

where TF and IDF are calculated as follows,

$$TF = \frac{f_i}{f_r}, \tag{2}$$

$$IDF = \log\left(\frac{N}{N_i}\right), \tag{3}$$

where f_i is the number of times the term i appears in a review, f_r is the total number of terms in every review, N is the total number of reviews, and N_i is the number of reviews, including the term i.

This paper displays the sentiment analysis results on Word Cloud, bar charts, pie charts, and line charts. This project's data tool is the node JavaScript Chart library. For example, the word cloud is a way to show frequent words inside documents based on the TF-IDF parameter. To find the common problem, we can filter negative reviews and then apply the TF-IDF method to find the most frequent words in reviews. We could calculate packaging failure and positive rates (PFR and PPR) based on these sentiment analysis results. These parameters were calculated by (4) and (8) as follows,

$$PFR = \frac{No.\,of\ negative\ reviews}{Total\ no.\,of\ reviews} \times 100, \tag{4}$$

$$PPR = \frac{No.\,of\ positive\ reviews}{Total\ no.\,of\ reviews} \times 100. \tag{5}$$

The PFR helps designers rethink the packaging features, and if it is above their assurance level in manufacturing, they should redesign the package and address its problems. However, if the PFR is lower than the assurance level, it would be acceptable without significant design changes.

However, sentiment analysis alone cannot provide context to understand the root cause of customer dissatisfaction. To analyze customer feedback further, we employed association rule mining to determine the relationships between the most frequently used words in customer reviews. Using an FP-Growth algorithm, we identified the most frequent words in negative customer reviews and predicted packaging issues. This approach enables more accurate identification of packaging concerns and can assist designers in addressing them more effectively. Association rules are constructed by looking for common if-then patterns in the data and utilizing the support and confidence criterion (defined in the following section) to identify the most crucial associations. Support and Confidence are the two parameters commonly used to assess the validity of association rules. We will see how these measurements can be defined as following definitions [49]. Support is defined as the rule holds with support Sup in T (the transaction data set) if $Sup\%$ of transactions contain $X \rightarrow Y$. Support sup is calculated as follows,

$$Sup = Probability\,(X \rightarrow Y) \tag{6}$$

$$= \frac{No.\,of\ Transactions\ with\ X \cup Y}{Total\ no.\,of\ Transactions}. \tag{7}$$

Confidence is shown as $Conf\,(X \rightarrow Y)$. An association rule $X \rightarrow Y$ is a pattern that states when X occurs, Y occurs with a certain probability called Confidence. The rule holds in T with confidence $Conf$ if $Conf\,\%$ of transactions that contain X also contain Y. It is calculated by:

$$Conf\ (X \rightarrow Y) = Probability\,(X \cup Y) = \frac{Sup\,X \cup Y}{Sup\,X}. \tag{8}$$

Utilizing Confidence in association rule mining is an effective way to raise awareness of data relationships. Its main advantage is that it highlights the relationship between specific items within the set by comparing co-occurrences of items to the overall occurrence of the antecedent in the specified rule [13].

Additionally, the WIPE platform enables monitoring of packaging damages and customer satisfaction over time. By continuously analyzing customer feedback, the platform can identify trends and changes in customer sentiment towards packaging, allowing for proactive measures to be

FIGURE 10. Product photo and its features.

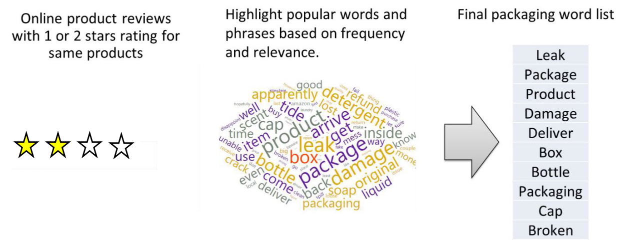


FIGURE 11. Generation process of a packaging word list.

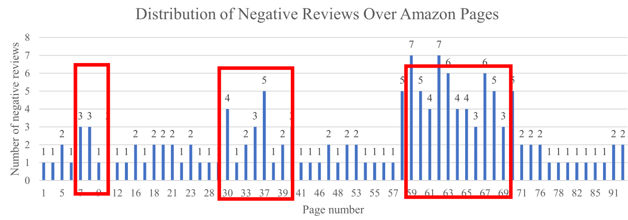


FIGURE 12. Distribution of negative reviews over the Amazon platform.

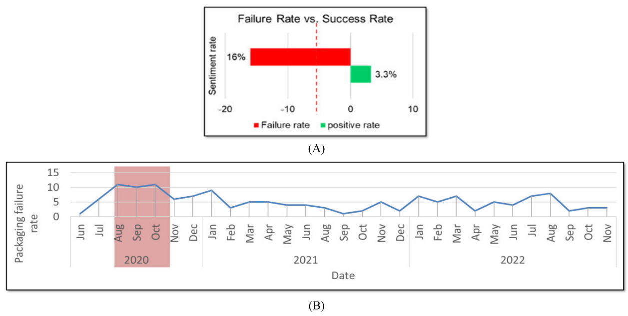


FIGURE 13. (A) Packaging failure and positive rates (B) Packaging failure rate over time.

taken to address emerging issues. This long-term monitoring capability helps businesses stay on top of packaging evaluation and continuously improve customer experiences.

Overall, the WIPE platform offers advanced data analytics techniques to provide valuable insights for improving packaging evaluation and enhancing customer experiences. By automating the data flow of packaging evaluation, correlating images and text, and using FP-growth and sentiment analysis, the platform can quickly identify packaging issues and provide actionable insights for designers to improve their packaging and address customer concerns.

III. RESULT AND DISCUSSION: CASE STUDY

In this study, we successfully implemented the WIPE platform, achieving several crucial objectives. These encompassed automated data processing, correlation of images and text, and the utilization of association rule mining. The efficacy of the WIPE application was validated through two case studies focusing on different variants of laundry detergent products: liquid soap and soap pods. These selections were based on the availability of diverse designs for the same product function and brand, along with an abundance of reviews and ratings for each product. This approach ensured a robust evaluation of the WIPE platform's performance.

A. LAUNDRY DETERGENT LIQUID SOAP

For instance, the laundry detergent liquid soap (Fig. 10) has 31,259 ratings and 922 reviews, and the WIPE platform was able to extract and consider all of these reviews to evaluate the product's packaging.

We used reviews with a rating lower than two stars, and then packaging relevant word lists were generated via the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm. It gives a term more weight when it appears more frequently in a single document and often occurs in many documents. The generation process of the packaging word list is shown in Figure 11.

If there are more than ten reviews on the Amazon platform, they are listed on separate pages. Consequently, since this case study has over 922 reviews, it has 93 pages of reviews. Companies may not desire or have time to read every page review to understand customer satisfaction. The WIPE application's result for the case study highlights the necessity of reading every review because most negative ones are found after page 5, as shown in Figure 12.

The result of the sentiment analysis step in the web-based intelligent packaging evaluation model is shown in Fig. 13-A. The packaging failure rate helps designers rethink the packaging features, and if it is above their assurance level in manufacturing, they should redesign the package and address its problems. However, if the packaging failure rate is lower than the assurance level, it would be acceptable without significant design changes. We should consider all of the unavailable purchases on Amazon for a more accurate failure rate. Figure 13-B displays the monthly packaging failure rate for 2020, 2021, and 2022, indicating higher failure rates in August 2020 and October 2020 and providing valuable insights for designers to analyze and address packaging issues.

The results show that there should be some problems with the box, bottle, cap, and package, as shown in Figure 14. But what are the relationships between these problems? Which parts of the package/product got damaged? The Fp-growth association rule mining algorithm with specific minimum

FIGURE 14. Word Cloud and TF-IDF Comparison for Negative Packaging Reviews.

TABLE 2. Meaningful association rules for consequent of "box".

Antecedent	Consequent	Support	Antecedent	Consequent	Support
leak	box	0.16	cap	box	0.042
inside	box	0.061	wrap	box	0.021
spill	box	0.064	soak	box	0.021
bottle	box	0.064	seal	box	0.021
open	box	0.058	mess	box	0.021
arrive	box	0.048	plastic	box	0.021
box	arrive	0.048	tape	box	0.021
duct	box	0.042			

support and confidence(0.01 and 0.01) values was applied to negative sentences to answer these questions.

From the damaged parts identification aspect, we used a graph showing which words are connected to packaging word lists (directed edges' weight shows support value, and vertices are frequent words in reviews. In Figure 15, the weight of edges is the support value of a rule between two vertices (words). Directed edges between words show an association between rules between ancestors and consequences. If the edges are thicker, there are strict rules between frequent item sets. For example, rules between the box and other frequent words are shown in Table 2 (these words are ordered based on their frequencies). The main issue with the box is leakage, indicating potential design problems with the detergent liquid. Improving these issues could enhance customer satisfaction. Identified factors affecting containment efficiency should be addressed to prevent package failure. Redesigning leak testing during development, particularly for the bottle, cap, wrapping, and tape, is crucial.

B. PODS LAUNDRY DETERGENT SOAP

The second design is a detergent pod. It got an 88% 5-star rating and includes 81 pods. Its number of reviews is 5,650, with 91,706 total ratings. Both products have free shipping on orders over $25.00 shipped by Amazon. The designs of these products and brief descriptions are depicted in Figure 16.

The WIPE platform's packaging evaluation showed that the liquid detergent bottle had a packaging failure rate of 16%, while the detergent pod had the lowest rate at 4%, indicating better performance in protection, containment, and convenience functions. Figure 17 allows designers to compare packaging failure rates of different designs for the same product with 10% assurance level. Therefore, The liquid

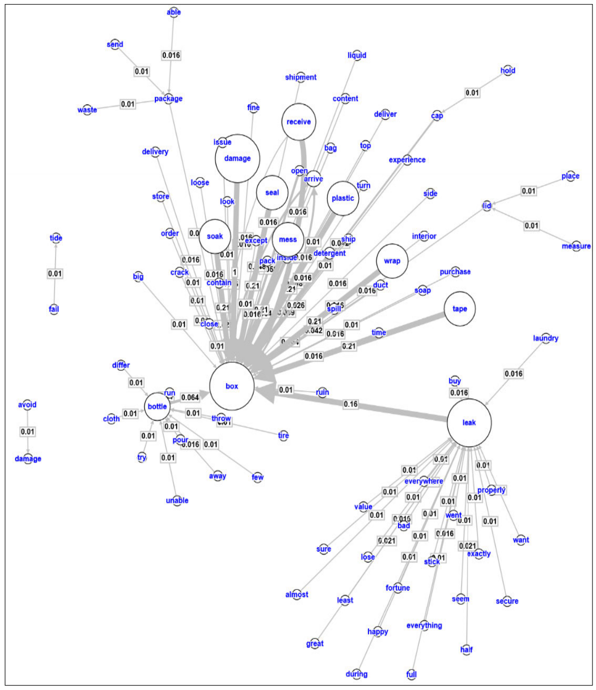


FIGURE 15. Relationships between words based on support value; edges' weight shows support value, and vertices are frequent words in reviews.

FIGURE 16. Detergent pod design and Amazon descriptions.

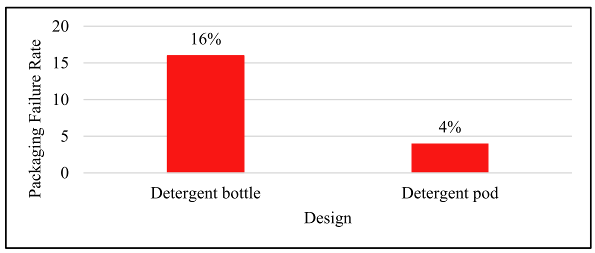


FIGURE 17. Packaging failure comparison for detergent pod and bottle.

detergent bottle's design needs to be reconsidered since its failure rate matches the assurance level.

The results of the associate rule mining yielded several findings related to the detergent pod, including concerns regarding the pod itself, its package, box, leakage, lid, bottle, and cap. Among the association rules generated, two rules were related to the cap: "child → cap" and "lock → cap," as illustrated in Figure 18.

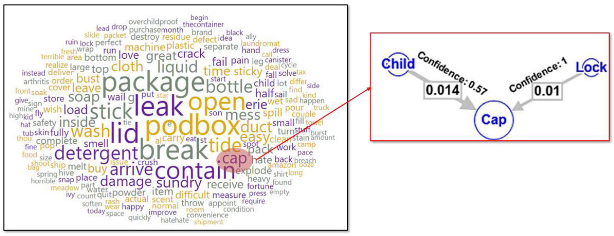


FIGURE 18. Association rules related to cap concerns.

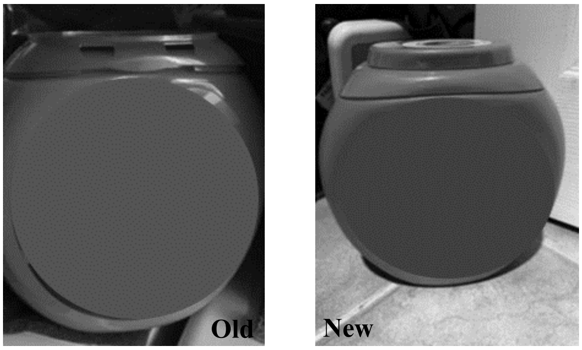


FIGURE 19. Old and new designs of caps based on images attached to online reviews.

Figure 18 shows that the most frequent items mentioned in reviews were lock caps and child-resistance concerns. We correlated images of those reviews, including frequent item sets, to obtain further details about this problem. For instance, Figure 19 demonstrates a change related to the child-proof cap. Although this change improved child resistance, it made opening the cap difficult for adults. Therefore, the designers reconsidered the cap design to both satisfy the adults and prevent the child from opening it. Consequently, the previous design showed convenience failure because, based on the convenience function of the package (as pointed out in section II-A), the pack should have been picked up, opened, and unpacked without potential damage to the content and consumer. More detailed discussion and analysis can be found in [25].

The future development of the WIPE platform will focus on the integration of LLMs and advanced sensing technologies to revolutionize packaging evaluation in e-commerce.

1) THE ROLE OF LLM IN THE FUTURE OF PACKAGING EVALUATION IN E-COMMERCE

In our forthcoming work, we aim to integrate LLMs into the WIPE platform. This integration promises to significantly enhance WIPE's analytical capabilities, currently based on LSTM and association rule mining, by leveraging LLMs' superior natural language processing prowess. LLMs will enable a more nuanced analysis of customer feedback, detecting subtle sentiments and identifying emerging trends in packaging preferences. This approach not only targets direct packaging defects but also deciphers broader customer perceptions, critical in the e-commerce realm where buyers rely solely on online product representations.

The inclusion of LLMs will automate the feedback categorization process, making it both faster and more precise. This efficiency could dramatically shorten the cycle from problem identification to resolution, thereby boosting customer satisfaction and reducing waste. Furthermore, LLMs will facilitate the development of predictive models for packaging performance, incorporating diverse data such as social media trends and environmental factors. By adopting LLMs, WIPE will transition from a reactive assessment tool to a proactive system, adept at foreseeing and adapting to the evolving dynamics of e-commerce and sustainability.

2) THE ROLE OF SENSING TECHNOLOGIES IN THE FUTURE OF PACKAGING AND E-COMMERCE

The rapid evolution of Radio Frequency (RF) and wireless technologies, such as RFID, Wi-Fi, Bluetooth, and 5G, is revolutionizing e-commerce and packaging sectors. These technologies boost product tracking, enhance supply chain transparency, and increase operational efficiency, paving the way for smart warehouses and automated inventory systems. Additionally, remote sensing technology provides indispensable insights for logistics optimization and maintains quality standards for perishable items. Integrating these technologies with AI for predictive management promises to fortify logistics resilience. Our future research will delve into how packaging integrated with sensing systems can streamline logistics, elevate customer satisfaction, and promote eco-friendly practices, signifying a pivotal shift in e-commerce dynamics.

IV. CONCLUSION

In conclusion, this study introduced the WIPE platform as an innovative solution for packaging evaluation that employs artificial intelligence techniques. By analyzing customer reviews on e-commerce websites, the WIPE application automates the evaluation process, reduces the costs of field tests, minimizes errors, and improves packaging qualities. The platform's ability to scrape large amounts of reviews and interpret text and images to identify customers' meaningful patterns and packaging concerns accelerates the problem-solving process by using feedback collected over time. Moreover, the WIPE application was demonstrated to be effective in benchmarking two different designs for the same function, enabling companies to compare packaging failure rates and success reasons of a design. The framework can be used for several products on the Amazon platform to identify trends and realize how packaging and product systems perform as they are changed.

While this study represents a significant improvement in packaging evaluation, future research should focus on addressing the limitations of natural language processing techniques and image interpretation. Enhancing sentiment analysis accuracy is one promising avenue, as more accurate sentiment analysis results can yield more meaningful and reliable rules. This could be accomplished by implementing a vote-based model based on machine learning models such as LSTM, Naïve based, and rule-based models. Additionally, image sentiment analysis could increase the model's accuracy, as it can be challenging to interpret images using current methods. The current platform only considers English reviews, so future research should explore multilingual sentiment analysis. Finally, increasing the sentiment score of packaging words in reviews would allow for packaging-related sentiment analysis, enabling more effective feedback for designers. Overall, the WIPE platform represents a significant step forward in packaging evaluation and offers promising avenues for future research.

REFERENCES

[1] International Trade Administration. *eCommerce Sales & Size Forecast*. Accessed: Nov. 12, 2022. [Online]. Available: https://www.trade.gov/ecommerce-sales-size-forecast

[2] Y. Wang, S. Peng, X. Zhou, M. Mahmoudi, and L. Zhen, "Green logistics location-routing problem with eco-packages," *Transp. Res. E, Logistics Transp. Rev.*, vol. 143, Nov. 2020, Art. no. 102118.

[3] *E-Commerce Packaging Strategy: Design With the End in Mind*. Accessed: Nov. 12, 2022. [Online]. Available: https://www.linkedin.com/pulse/e-commerce-packaging-strategy-design-end-mind-sara-shumpert-dunn

[4] P. Böröcz and B. Molnár, "Measurement and analysis of vibration levels in stacked small package shipments in delivery vans as a function of free movement space," *Appl. Sci.*, vol. 10, no. 21, p. 7821, Nov. 2020.

[5] A. Hagman, R. Economy, B. Timmermann, M. Nygårds, A. Lundin, C. Barbier, M. Fredlund, S. Östlund, B. Innovation, and B.-K. Gruvon, "Experimental and numerical verification of 3D forming," in *Proc. Trans. 16th Fund. Res. Symp. Oxford*, 2017, pp. 3–26.

[6] W. I. Kipp, "Developments in testing products for distribution," *Packag. Technol. Sci.*, vol. 13, no. 3, pp. 89–98, 2000.

[7] J. Bahlau and E. Lee, "Designing moulded pulp packaging using a topology optimization and superimpose method," *Packag. Technol. Sci.*, vol. 35, no. 5, pp. 415–423, May 2022.

[8] M. Upadhyaya and M. Nygårds, "A finite element model to simulate brim forming of paperboard," in *Proc. 28th IAPRI Symp. Packag.*, May 2017, pp. 395–408.

[9] J.-E. Gustafsson and M. Nygårds, "Loading and deformation of cigarette packages," in *Proc. 28th IAPRI Symp. Packag.*, Lausanne, Switzerland, 2017, p. 409.

[10] M. Nygårds, S. Sjökvist, G. Marin, and J. Sundström, "Simulation and experimental verification of a drop test and compression test of a gable top package," *Packag. Technol. Sci.*, vol. 32, no. 7, pp. 325–333, Jul. 2019.

[11] T. Fadiji, T. Berry, C. J. Coetzee, and L. Opara, "Investigating the mechanical properties of paperboard packaging material for handling fresh produce under different environmental conditions: Experimental analysis and finite element modelling," *J. Appl. Packag. Res.*, vol. 9, no. 2, p. 3, 2017.

[12] G. Marin, P. Srinivasa, M. Nygårds, and S. Östlund, "Experimental and finite element simulated box compression tests on paperboard packages at different moisture levels," *Packag. Technol. Sci.*, vol. 34, no. 4, pp. 229–243, Apr. 2021.

[13] B. Liu, *Sentiment Analysis and Opinion Mining*. Cham, Switzerland: Springer, 2022.

[14] S. A. Bini, "Artificial intelligence, machine learning, deep learning, and cognitive computing: What do these terms mean and how will they impact health care?" *J. Arthroplasty*, vol. 33, no. 8, pp. 2358–2361, Aug. 2018.

[15] J. M. Helm, A. M. Swiergosz, H. S. Haeberle, J. M. Karnuta, J. L. Schaffer, V. E. Krebs, A. I. Spitzer, and P. N. Ramkumar, "Machine learning and artificial intelligence: Definitions, applications, and future directions," *Current Rev. Musculoskeletal Med.*, vol. 13, no. 1, pp. 69–76, Feb. 2020.

[16] A. Mehrzad, M. Darmiani, Y. Mousavi, M. Shafie-Khah, and M. Aghamohammadi, "A review on data-driven security assessment of power systems: Trends and applications of artificial intelligence," *IEEE Access*, vol. 11, pp. 78671–78685, 2023.

[17] P. J. Ballester and J. B. O. Mitchell, "A machine learning approach to predicting protein-ligand binding affinity with applications to molecular docking," *Bioinformatics*, vol. 26, no. 9, pp. 1169–1175, May 2010.

[18] L. Deng and X. Li, "Machine learning paradigms for speech recognition: An overview," *IEEE Trans. Audio, Speech, Language Process.*, vol. 21, no. 5, pp. 1060–1089, May 2013.

[19] R. Ireland and A. Liu, "Application of data analytics for product design: Sentiment analysis of online product reviews," *CIRP J. Manuf. Sci. Technol.*, vol. 23, pp. 128–144, Nov. 2018.

[20] A. B. M. R. Islam, "Machine learning in computer vision," in *Applications of Machine Learning and Artificial Intelligence in Education*. Hershey, PA, USA: IGI Global, 2022, pp. 48–72.

[21] A. Akbar, P. Agarwal, and A. Obaid, "Recommendation engines-neural embedding to graph-based: Techniques and evaluations," *Int. J. Nonlinear Anal. Appl.*, vol. 13, no. 1, pp. 2411–2423, Mar. 2022.

[22] V. N. Dornadula and S. Geetha, "Credit card fraud detection using machine learning algorithms," *Proc. Comput. Sci.*, vol. 165, pp. 631–641, Jan. 2019.

[23] M. Tavasoli, M. H. Yaghmaee, and A. H. Mohajerzadeh, "Optimal placement of data aggregators in smart grid on hybrid wireless and wired communication," in *Proc. IEEE Smart Energy Grid Eng. (SEGE)*, Aug. 2016, pp. 332–336.

[24] A. E. Ezugwu, A. M. Ikotun, O. O. Oyelade, L. Abualigah, J. O. Agushaka, C. I. Eke, and A. A. Akinyelu, "A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects," *Eng. Appl. Artif. Intell.*, vol. 110, Apr. 2022, Art. no. 104743.

[25] M. Tavasoli, "Web-based intelligent packaging evaluation (WIPE) platform," M.S. thesis, School Packag., Michigan State Univ., East Lansing, Michigan, 2023.

[26] D. Knoll, D. Neumeier, M. Prüglmeier, and G. Reinhart, "An automated packaging planning approach using machine learning," *Proc. CIRP*, vol. 81, pp. 576–581, Jan. 2019.

[27] N. D. S. E. Silva, F. de Souza Farias, M. M. dos Santos Freitas, E. J. G. P. Hernández, V. V. Dantas, M. E. C. Oliveira, M. R. S. P. Joele, and L. D. F. H. Lourenço, "Artificial intelligence application for classification and selection of fish gelatin packaging film produced with incorporation of palm oil and plant essential oils," *Food Packag. Shelf Life*, vol. 27, Mar. 2021, Art. no. 100611.

[28] T. Wei and S. Xiangbo, "Selection of optimal packaging methods for different food based on big data analysis," in *Proc. IEEE Int. Conf. Power, Intell. Comput. Syst. (ICPICS)*, Jul. 2020, pp. 558–561.

[29] C. Zhao, M. Johnsson, and M. He, "Data mining with clustering algorithms to reduce packaging costs: A case study," *Packag. Technol. Sci.*, vol. 30, no. 11, p. 753, Nov. 2017.

[30] J. Lepine, V. Rouillard, and M. Sek, "On the use of machine learning to detect shocks in road vehicle vibration signals," *Packag. Technol. Sci.*, vol. 30, no. 8, pp. 387–398, Aug. 2017.

[31] T. Archaviboonyobul, R. Chaveesuk, J. Singh, and T. Jinkarn, "An analysis of the influence of hand hole and ventilation hole design on compressive strength of corrugated fiberboard boxes by an artificial neural network model," *Packag. Technol. Sci.*, vol. 33, nos. 4–5, pp. 171–181, Apr. 2020.

[32] Y. S. Chang and H. J. Lee, "Optimal delivery routing with wider drone-delivery areas along a shorter truck-route," *Expert Syst. Appl.*, vol. 104, pp. 307–317, Aug. 2018.

[33] S.-U. Zhang, "Classifying thermal degradation of polylactic acid by using machine learning algorithms trained on Fourier transform infrared spectroscopy data," *Appl. Sci.*, vol. 10, no. 21, p. 7470, Oct. 2020.

[34] Y. Yang, X. Zhang, J. Yin, and X. Yu, "Rapid and nondestructive on-site classification method for consumer-grade plastics based on portable NIR spectrometer and machine learning," *J. Spectrosc.*, vol. 2020, pp. 1–8, Dec. 2020.

[35] S. Holland, M. Tavasoli, and E. Lee, "Evaluating consumer review images for package failure using machine learning," in *Proc. 23rd IAPRI World Packag. Conf.*, 2022, pp. 473–480.

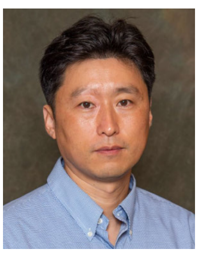
[36] Y. Wu and Y. Lu, "An intelligent machine vision system for detecting surface defects on packing boxes based on support vector machine," *Meas. Control*, vol. 52, nos. 7–8, pp. 1102–1110, Sep. 2019.

[37] X. Yang, M. Han, H. Tang, Q. Li, and X. Luo, "Detecting defects with support vector machine in logistics packaging boxes for edge computing," *IEEE Access*, vol. 8, pp. 64002–64010, 2020.

[38] H. Taheri, P. Riggs, N. Widem, and M. Taheri, "Heat-sealing integrity assessment through nondestructive evaluation techniques," *Packag. Technol. Sci.*, vol. 36, no. 2, pp. 67–80, Feb. 2023.

[39] S. Esfahanian and E. Lee, "A novel packaging evaluation method using sentiment analysis of customer reviews," *Packag. Technol. Sci.*, vol. 35, no. 12, pp. 903–911, Dec. 2022.
[40] Y. Liu, J. Jin, P. Ji, J. A. Harding, and R. Y. K. Fung, "Identifying helpful online reviews: A product designer's perspective," *Comput.-Aided Design*, vol. 45, no. 2, pp. 180–194, Feb. 2013.
[41] J. Ni, J. Li, and J. McAuley, "Justifying recommendations using distantly-labeled reviews and fine-grained aspects," in *Proc. Conf. Empirical Methods Natural Lang. Process. 9th Int. Joint Conf. Natural Lang. Process.*, 2019, pp. 188–197.
[42] *Open Data on AWS*. Accessed: Nov. 16, 2022. [Online]. Available: https://registry.opendata.aws/amazon-reviews-ml/
[43] R. Woodall, D. Kline, M. Modaresnezhad, and R. Vetter, "A cloud-based system for scraping data from Amazon product reviews at scale," in *Proc. Conf. Inf. Syst. Appl. Res.*, Washington, DC, USA, 2021, pp. 23–34.
[44] J. Jin, P. Ji, and C. K. Kwong, "What makes consumers unsatisfied with your products: Review analysis at a fine-grained level," *Eng. Appl. Artif. Intell.*, vol. 47, pp. 38–48, Jan. 2016.
[45] M. Kaur and S. Kang, "Market basket analysis: Identify the changing trends of market data using association rule mining," *Proc. Comput. Sci.*, vol. 85, pp. 78–85, Jan. 2016.
[46] R. Agrawal and R. Srikant, "Fast algorithms for mining association rules," in *Proc. 20th Int. Conf. Very Large Data Bases*, vol. 1215, 1994, pp. 487–499.
[47] J. Han, J. Pei, and Y. Yin, "Mining frequent patterns without candidate generation," *ACM SIGMOD Rec.*, vol. 29, no. 2, pp. 1–12, Jun. 2000.
[48] Islamiyah, P. L. Ginting, N. Dengen, and M. Taruk, "Comparison of priori and FP-growth algorithms in determining association rules," in *Proc. Int. Conf. Electr., Electron. Inf. Eng. (ICEEIE)*, vol. 6, Oct. 2019, pp. 320–323.
[49] H. C. Wu, R. W. P. Luk, K. F. Wong, and K. L. Kwok, "Interpreting TF-IDF term weights as making relevance decisions," *ACM Trans. Inf. Syst.*, vol. 26, no. 3, pp. 1–37, Jun. 2008.

MAHSA TAVASOLI received the M.Sc. degree in computer engineering from the Ferdowsi University of Mashhad, Mashhad, Iran, in 2016, and the M.Sc. degree in packaging from Michigan State University, East Lansing, MI, USA, in 2023. She is currently pursuing the Ph.D. degree in information technology with North Carolina Agricultural and Technical State University, USA, specializes in machine learning (ML) and digital twins (DT). Her research interests include ML and DT technologies to system implementations, communication network security, and privacy, with a particular focus on smart cities, including autonomous vehicles, smart healthcare, smart supply chains, and smart farming.



EUIHARK LEE received the Ph.D. degree in mechanical and aerospace engineering from Rutgers, The State University of New Jersey. He is currently an Assistant Professor with the School of Packaging, Michigan State University, where his recent research focuses on optimizing engineering designs in the packaging field. His work involves resource-efficient design enhancements, the development of tailored numerical analysis methods for packaging systems to streamline the design process, and the integration of artificial intelligence (AI) to enhance accuracy and automation in packaging design and evaluation.

YASHAR MOUSAVI (Member, IEEE) received the Ph.D. degree from Glasgow Caledonian University, Glasgow, U.K., in 2023. He is currently a Senior Analytical Engineer with American Axle & Manufacturing, Detroit, MI, USA. He is majored in artificial intelligence-based modeling, simulation, and analysis of combustion-based and electric vehicles' power transfer units, gear shift actuation systems, eLocker electric drive units, and full-vehicle driveline systems. He has carried out various projects for top-notch companies, such as General Motors, Stellantis, Ford, Mercedes Benz, and Volkswagen. He is also a Controls Integration Researcher with the Power and Renewable Energy Systems (PRES) Team, Glasgow Caledonian University. His research interests include control theory and applications, vehicle dynamics modeling and analysis, artificial intelligence, power systems analysis, robust nonlinear control, fault-tolerant control, renewable energy, and robotic systems modeling and control. He is a member of the IEEE Young Professionals. He served as a reviewer and the guest editor for numerous journals and conferences.

HANNANEH BARAHOUEI PASANDI (Member, IEEE) is currently a Postdoctoral Fellow Researcher with the EECS Department, University of California, Berkeley. Her research interests include wide spectrum of mobile systems and mobile computing, with a focus on systems-based on wireless technologies. She is also deeply immersed in research centered around privacy auditing and mitigations in 5G networks and developing cutting-edge intelligent wireless and embedded systems, designed for advanced communication and sensing with application in smart package tracking, smart farming, autonomous vehicles, mixed reality environments, and the Internet of Things (IoT).

AFEF FEKIH (Senior Member, IEEE) received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from the National Engineering School of Tunis, Tunisia, in 1995, 1998, and 2002, respectively. She is currently a Full Professor with the Department of Electrical and Computer Engineering and the Chevron/BORSF Professor of engineering with the University of Louisiana at Lafayette. Her research interests include control theory and applications, including nonlinear and robust control, optimal control, and fault tolerant control, with applications to power systems, wind turbines, unmanned vehicles, and automotive engines. She is a member of the IEEE Control Systems Society, IEEE Power and Energy Society, and the IEEE Women in Engineering Society. She is an Appointed Member of the Board of Governors of the IEEE Control Systems Society (2023–2024). She is also a member of the IFAC Technical Committee on Power and Energy Systems, American Automatic Control Council (AACC) Technical Committee on Control Education, the IEEE Systems Council on Diversity and Inclusion Committee, and the IEEE Technology Conference Editorial Board. She is the Co-Chair and the Media Coordinator of the IEEE Control System Society Women in Control Group (WiC). She served as a reviewer and the guest editor for numerous journals and conferences. She serves as an Associate Editor for the IEEE-IAS Industrial Automation and Control Committee.