




Review-Based Recommender System for Hedonic and Utilitarian Products in IoT Framework

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Abstract. With the tremendous increase in product alternatives these days, many businesses rely heavily on recommender systems to limit the number of options they display to their customers on the front end. Many companies use the collaborative filtering algorithm and provide suggestions based on other consumers' choices, like the active user. However, this approach faces a cold start problem and is not suitable for one-time transactions. Thus, this research aims to create a recommender system that uses online customer reviews in the IoT framework to match the attributes of a product important to the shopper. The algorithm makes recommendations by first identifying the product's features essential to a customer. It then performs aspect-based sentiment analysis to identify those features in customer reviews and give them a sentiment score. Each customer review is weighted based on its creditability. As the impact of the recommender systems varies with the product type, an experimental study will be carried out to study the effect of the proposed algorithm differs with hedonic and utilitarian products.

Keywords: Aspect-based sentiment analysis · Recommender systems · Product reviews · Review characteristics · Hedonic product · Utilitarian product

1 Introduction

Due to the current COVID-19 pandemic, lockdown and social distancing laws have pushed a substantial portion of economic activity online. A report by Australian Post showed that in the year 2020, online sales increased up to 57%, with 1.36 million Australians purchasing online for the first time. The emergence of eCommerce as a primary mode of shopping has increased consumers' dependence on product reviews to supplement their knowledge of the product or service being sold (Gao et al. 2022). Several studies have confirmed the importance of customer review on the purchase intention (Jalilvand and Samiei 2012).

These reviews are often in an unstructured textual format, explaining consumers' opinions on different aspects of products based on their own experience (Hussain and Merigó 2022). It offers fine-grained sentiment preferences of various facets of a single object that cannot be extracted from average ratings (Zhang et al. 2015). However, they are in a massive volume making it impossible for an average human reader to monitor and comprehend consumer feedback to find the right product that fits the user's preference. An automated sentiment analysis approach could be used to find what the previous customers have written about the features that the active user is looking for to overcome this issue.

Sentiment analysis uses Natural Language Processing (NLP) and text analytics to extract attributes and components of the item to assess the polarity of consumers' comments (positive, negative, or neutral). Sentiment analysis is divided into three levels, document, sentence, and aspect. However, sentence and document level consider only one topic is expressed in the text, which is not always the case. For example, the sentence "I love all the shades of this eyeshadow palette although I think the pigmentation can be improved." However, it sounds positive, but we cannot evaluate the sentence to be entirely positive as the sentence is optimistic about the palette's shades but pessimistic about the pigmentation of the shades. Aspect based sentiment analysis can help to address the problem. The technique analyzes the user review by categorizing it by aspect and identifying the sentiment associated with them.

Sentiments associated with aspects of the product, unstructured data is converted to structured data, which can be used for qualitative and quantitative assessments.

Nevertheless, the content of the review is not the only variable that influences customers' purchase intention. Several studies have demonstrated how features such as review recency, quality, length, platform, and reviewer characteristics impact the consumer decision-making process (Jia and Lu 2018; Shah and Jha 2021).

The goal of the RS is to filter, prioritize, and effectively deliver personalized content to the user using techniques such as machine learning (Shoja and Tabrizi 2019). Many studies have found that recommender systems significantly affect buyer choice and lead to increased purchase volume. Different organizations use different algorithms to search through a vast amount of dynamically generated data to provide consumers, products that might interest them. However, the collaborative filtering technique is the most successful algorithm (Osman et al. 2019), which generates suggestions based on inter-user comparisons by locating other users who have seen or bought similar products to the user (Hosanagar and Lee 2015; Hussain et al. 2017a; Hussain et al. 2017b). While collaborative filtering is the most promising recommendation technique, its use in e-commerce has revealed well-known shortcomings, sparsity, and cold start (Chen et al. 2015). These problems are caused when customer ratings are insufficient in number to identify similarities in customer interest.

To overcome the sparsity problem, researchers have suggested using the valuable information from customer feedback to improve the performance of the current RS (Chen et al. 2015; Osman et al. 2019). They believe that the rich information embedded in the reviews can enhance the overall recommendation quality. Thus, having a more significant impact on the customer's decision-making process. Nonetheless, many studies have

shown that the product's attribute (Utilitarian vs. Hedonic) moderates the impact of the recommender system (Lee and Hosanagar 2016).

By considering the importance of product attributes in the recommender systems, in this research, we will study the impact of RS developed using the output of aspect-based sentiment analysis on customer feedback and other characteristics of product reviews on purchase intentions. We also aim to investigate how the effect of user review-based recommender systems varies with different product types, such as utilitarian vs. hedonic.

2 Background and Relevant Work

In this section we will discuss the literature that is related to the framework. The section has been divided into seven sub-sections:

- Electronic word of mouth
- Sentiment analysis
- Characteristics of review
- Recommender systems
- Applications of recommender systems in IoT
- Utilitarian and hedonic product selection
- Recommender based on Sentiment Analysis and Review Characteristic.

A comparative analysis of all approaches are presented at the end of the section to analyze and compare all approaches based on different parameters. The discussion of each approaches are discussed as follows:

2.1 Electronic Word of Mouth

The emergence of social and eCommerce media has promoted consumers to share their experiences of specific products or services. These electronic words of mouth (eWOM) have become an integral part of eCommerce. They significantly impact the potential consumer's attitude and behaviour towards the product and other information on the website. Unlike traditional word of mouth (WOM), they are not restricted to the inner consumer circle but target a wider audience. Electronic WOM may be thought of as a social marketing and promotion tool that boosts retailers' knowledge-sharing practices at no expense.

Numerous studies have studied the importance of eWOM in eCommerce and its effect on purchase intention and sales. For instance, Hussain et al. in 2017 found that eWOM tends to reduce perceived risk. According to Jalilvand and Samiei (2012), eWOM is one of the most potent factors affecting brand image and purchasing intention in the automobile industry. A study by Baber et al. in 2016 showed the effect of online word-of-mouth by a reliable and knowledgeable source on the buying intentions of the recipient is influenced by purchasing attitude. Similarly, another study in 2019 revealed that positive sentiment has a significant impact on sales. When investigating the impact on performance, sales of tablets vary with sentiments expressed in the review and their study (Li et al. 2019).

2.2 Sentiment Analysis

Sentiment Analysis (SA) uses Natural Language Processing technique to detect and extract sentiment from textual data (Hussain et al. 2022). Its application has expanded to nearly every possible domain, from consumer goods, utilities, hospitals, and financial services to social events and political campaigns. A system was proposed with an accuracy of 90% that utilized SA on product reviews to classify the comments into different categories, good or bad (Grabner et al. 2012).

Sentiment Analysis is studied at three levels: Document, Sentence, and Aspect. Document-level and sentence level determine that each document or sentence respectively expresses opinion for a single entity. However, this is not always the case. Aspect-based sentiment analysis techniques consist of two steps: aspect extraction and sentiment classification.

Many studies have previously highlighted that implementing aspect-based sentiment analysis (ABSA) on customer reviews is an effective technique to understand people's preferences about the product. Another study used SA to analyze movie reviews on discussion boards to identify different sentiments associated with movies, such as cast, story, director. (Thet et al. 2010).

2.3 Characteristics of Review

Different product review characteristics have a different impact on purchase intention. Features such as time of review, content related to product durability and quality (Zhang et al. 2011), reviewer's profile picture, characteristics, and reputation (Xu 2014) and valence of review, conflicting rating, and product-related attributes (Qiu et al. 2012) affect review credibility. Alkalbani et al. (Alkalbani and Hussain 2021; Alkalbani et al. 2019) proposed Harvesting as a Service (HaaS) crawler that intelligently extract real time consumer reviews from the internet and make it available in different format.

An experimental study by Qiu et al. in 2012 showed how positive reviews have a more significant impact on purchase decisions than negative reviews. The result of this study was confirmed by another experimental study by Jia and Lu in 2018. Thus, customer feedback characteristics and content can be used in a Recommender System (RS) to produce good quality recommendations (Chen et al. 2015; Osman et al. 2019).

2.4 Recommender System

A recommender system is a decision-making strategy; it alleviates information overload by suggesting a list of items that may interest a particular user. They are employed in various websites such as Netflix, YouTube, and Spotify, to provide video and music recommendations; Amazon and Alibaba to suggest a product to buy; Yahoo and Google news to help users decide what to read. In 2014, Hong and Pavlou found that simple acts of recommendation can reduce the perceived risk of buying online and increase purchase probability. Recommenders work by lowering product uncertainty and search cost barriers, as they might hinder purchase decisions Hussain et al. 2022. Literature by Gao et al. 2022 indicated, when a recommender proposes a product, it provides a social

presence by saying ‘people like you preferred X,’ which positively impacts purchase intention.

Recommenders are built using various filtering techniques; each differs from identifying similarities between consumers and objects to identifying well-matched pairs (Osman et al. 2019). These techniques are divided into three categories collaborative filtering, content-based filtering, or hybrid filtering. The collaborative filtering approach is the most successful and commonly implemented. It suggests things by finding other people with similar tastes to the active user and relying on their recommendations. In contrast to collaborative filtering, content-based filtering uses similarities in features of the product to make recommendations. However, the effectiveness of both algorithms is limited when insufficient rating information is available to identify similarities in consumer interest or when a user has little historical data (Chen et al. 2015). The most common type elevates the strengths of collaborative and content-based filtering by merging the results obtained from both types of filtering and presenting a recommendation list. However, these algorithms fail to respond to the disparity of user context, continuously changing user preferences and delivering cross-domain suggestions (Hussain et al. 2018; Hussain et al. 2021a; Hussain et al. 2021b; Hussain et al. 2022).

2.5 Application of Recommender System in IoT

The Internet of Things (IoT) is a new paradigm that envisions a networked infrastructure that allows various devices to communicate with one another at any time and from any location. (Kiraly et al. 2019). It generates diverse artifacts such as services and applications making it difficult for consumers to identify the most relevant ones. Therefore, recommender systems are crucial components of IoT solutions (Cui et al. 2020; Kiraly et al. 2019), making finding relevant applications and services easier.

Examples of recommendations in IoT scenarios include installing apps, relevant data transfer to be deployed and hardware, and software components to complete specific tasks on a gateway. Some domain-specific examples in this context include food suggestions, customized shopping, health and animal monitoring, and smart homes (Kiraly et al. 2019). However, there are some challenges in using traditional recommendation systems in the IoT arena. The data in the IoT service system is enormous, complicated, and growing (Hussain and Sohaib 2019). Thus, it requires users to go through a lot of unnecessary information, leaving them exhausted and unsatisfied. Another issue is that users’ interest varies with time. Traditional recommendation systems presume that users’ interests remain constant, neglecting the intrinsic relationship between time and user choice. Therefore, it is important to design a personalized recommendation system that considers user preferences’ real-time patterns and manages big data reliably and efficiently (Cui et al. 2020).

2.6 Utilitarian vs Hedonic

A product is often classified as utilitarian or hedonic. Hedonic products are fun, entertaining, and enjoyable, whereas utilitarian products are goal-oriented, helpful, functional, and essential. Furthermore, when looking for these items in an e-store, utilitarian products have quantitative characteristics such as memory capacity or screen resolution. In

contrast, hedonic products have subjective attributes, such as fragrance or taste. As a result, when looking for a utilitarian product, the consumer is focused on the goal they hope to achieve with the product, so consumers are more concerned with the possibility of the product failing to meet the goal (Chiu et al. 2014). Hedonic goods, on the other hand, are bought solely for pleasure. Thus, the cost of getting the wrong hedonic product is less than the utilitarian product. Therefore, the increased perceived risk of not finding the right item, a buyer could compare more products suggested by the system to find the perfect utilitarian product. A study by Moon et al. (2017) suggested utilitarian and hedonic products have different influences on consumers' attitudes and purchase decisions. Thus, a recommender system needs to consider the type of product before making suggestions. Research by Park et al. (2011) explored those consumers tend to buy hedonic products when suggested to them in the same way they would buy when advised by people more like them.

2.7 Recommender Based on Sentiment Analysis and Review Characteristics

Sentiment Analysis can be used to detect sentiment from textual reviews with great accuracy (Raza et al. 2021a, 2021b, 2021). This technique can also convert the degree of negativity and positivity of preferences into a numerical rating to integrate with the filtering algorithm (Ricci et al. 2015; Hussain et al. 2020) (Raza et al. 2021). Kumar et al. in 2020, used SA of reviews on Twitter, movie metadata, and social graphs to suggest movies. They found out their proposed system recommended movies more precisely than other models. In another study, sentiment classification was performed on reviews to derive ratings. This rating was incorporated in item-based and user-based Collaborative Filtering algorithms to infer the User-Item Rating Matrix to enhance the working of the recommender (Zhang et al. 2013). Gao et al. (Gao et al. 2020) introduced an implicit knowledge using collaborative learning techniques for an optimal API recommendation in IoT environment. Rosa et al. (2015) proposed a framework for music suggestions for mobile devices, in which songs were recommended based on the user's mood. User's sentiments were extracted using SA of sentences posted on Social Networking Sites (SNS).

The suggested model demonstrated a 91% of customer satisfaction rate. There have been many pieces of research focused on how aspect-based sentiment analysis can improve the impact of the recommender system. A study showed recommendations that using ABSA on customer reviews performs better than traditional Collaborative algorithms (Zhang et al. 2015). In another study, Bauman et al. (2017) suggested a recommendation algorithm that used ABSA to make recommendations and suggest facets of the item to improve consumer's experience further. Osman et al. (2019) merged the numerical rating and rating gathered from ABSA of textual review to optimize the traditional Collaborative Filtering algorithm. However, very few efforts have been made to integrate review characteristics in the recommender system to make more valid and high-quality suggestions.

2.8 Comparative Analysis of Existing Approaches

Table 1 shows how each research is different from the other. From the comparative analysis, we found that none of the studies has studied the varying impact of the review-based recommender system on different product types, which is very important for the decision-making process. Moreover, none of the approaches has considered review characteristics in the decision-making process.

The comparative analysis of different approaches is presented in below table:

Table 1. Analysis of different previous studies

References	Aspect-based sentiment analysis	Review characteristics	Social data	Utilitarian VS hedonic	Recommendation provided
Bauman et al. (2017)	✓	×	✓	×	✓
Kumar et al. (2020)	×	×	✓	×	✓
Zhang et al. (2013)	×	×	×	×	✓
Rosa et al. (2015)	×	×	✓	×	✓
Zhang et al. (2015)	✓	×	×	×	✓
Osman et al. (2019)	✓	×	×	×	✓
Hussain et al. (2022)	✓	×	✓	×	✓
Thet et al. (2010)	✓	×	×	×	×

3 Proposed Approach

The study aims to incorporate aspect-based sentiment analysis (ABSA) of customer reviews and product characteristics in a recommender system. The study analyses the impact of review-based recommender systems on utilitarian and hedonic product purchase intention in an e-commerce setting.

The approach helps to improve the quality and validity of recommendations. Moreover, it has overcome problems like data sparsity and other issues highlighted earlier. However, to utilize customer's opinions and product characteristics in the context of the recommenders, it is important to translate user's textual preferences, not only in terms of negative and positive but to what extent they are pessimistic or an optimist. The proposed approach is comprised of the following steps, as presented in Fig. 1.

3.1 Extraction of Product Feature in Customer Reviews

The initial step in this process is to analyze the credibility of different product reviews on the social media website. This will help us to discard fake reviews by dishonest sellers and spammers and get more accurate product ratings. Reviews will be filtered out based on specified rules stated below.

- They have a lot of grammatical and spelling mistakes
- They are very short
- The same user has more than one review for the same product
- They were posted more than a year ago
- The reviews are not in English

After filtering the reviews, Aspect-based sentiment analysis will be performed using spaCy and TextBlob on the credible product reviews to extract product attributes from reviews. spaCy and TextBlob is a Python library for natural language processing used for sentiment analysis and text processing. The first goal in the extraction will be to split

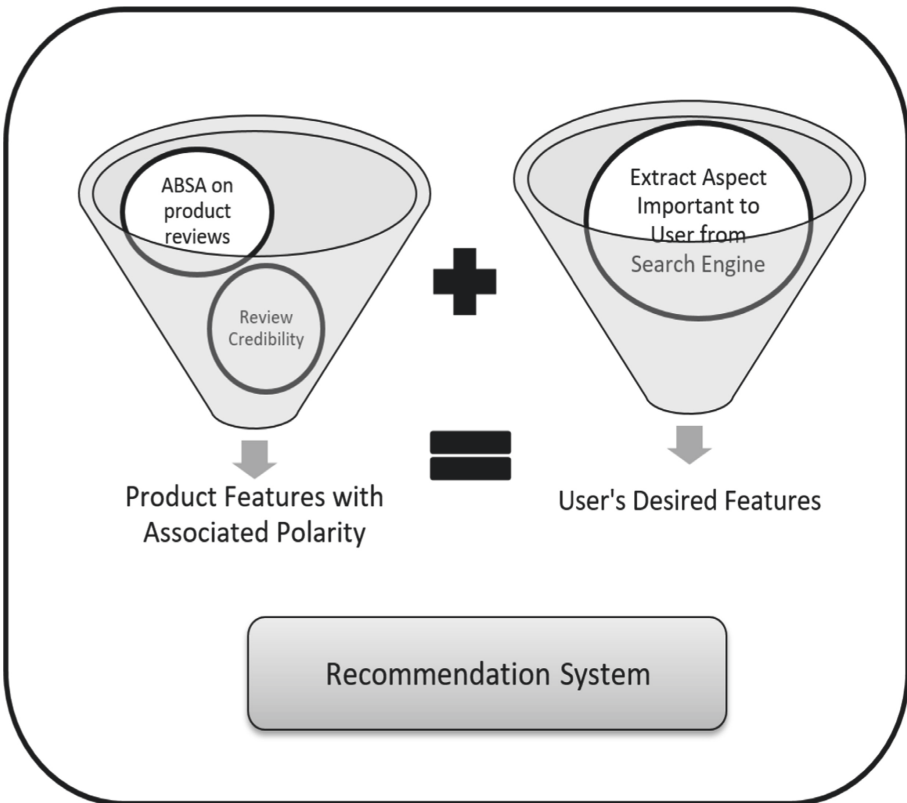


Fig. 1. The proposed recommendation system

sentences and extract product aspects and sentiment descriptions associated with them. Once this is done, we will classify them as positive or negative and associate a score.

3.2 Obtaining user Inputs Regarding Desired Features

User's preferred product features will be obtained by extracting the keywords that have been clearly specified by the user on the eCommerce's websites search engine.

3.3 Acquiring Matching Scores between Preferences and Reviews

The user will achieve a similarity score between a review and the desired attributes using a Natural Language Processing text analysis technique Word Embedding algorithm, word2vec and its pre-trained word vector.

3.4 Testing the Impact of the Review-Based Recommender on Hedonic and Utilitarian Products

Lastly, we will test this approach in an experimental study to explore its impact on different product attributes in the context of this study, Hedonic and Utilitarian. We will incorporate this recommender system in a functional eCommerce website simulation with Hedonic and Utilitarian types of products. And test what kind of product a user is most likely to put in a cart. We will also measure users' satisfaction with the recommendation provided to test the reliability of the recommender system proposed in this research.

This recommender framework will reduce issues associated with traditional models such as data sparsity and domain sensitivity and enhance suggestions' quality. The varying impact of this recommender approach will then be used to study its effect on Utilitarian and Hedonic product purchase decisions. This approach is novel as we will be studying the impact of the Review Based Recommender System on different product types (Utilitarian VS Hedonic).

4 Conclusion

The proposed study depicts how reviews on social media influence customers purchase decisions. Online retailers can leverage the result of this study to determine the most effective social media strategies for targeting and satisfying their target audiences. It enables them to optimize revenues on an e-commerce site. The research presented a novel approach integrating customer review information on social media and customer's interest in different aspects of the product gathered. The study analyzes keywords in the search engine in recommenders to enhance the suggestions compared to other traditional algorithms. This study also aids in determining which product types - hedonic or utilitarian- best serve a customer. The approach overcomes issues related to changing user preferences, changing data, lack of data, and domain sensitivity. In future, we will evaluate the approach in different complex nonlinear decision problems.

References

- Alkalbani, A.M., Hussain, W.: Cloud service discovery method: a framework for automatic derivation of cloud marketplace and cloud intelligence to assist consumers in finding cloud services. *Int. J. Commun. Syst.* **34**(8), e4780 (2021). <https://doi.org/10.1002/dac.4780>
- Alkalbani, A.M., Hussain, W., Kim, J.Y.: A centralised cloud services repository (CCSR) framework for optimal cloud service advertisement discovery from heterogenous web portals. *IEEE Access* **7**, 128213–128223 (2019)
- Australia Post. Inside Australian Online Shopping, Australia, April 2021 (2021). https://auspost.com.au/content/dam/auspost_corp/media/documents/ecommerce-industry-report-2021.pdf
- Baber, A., Thurasamy, R., Malik, M.I., Sadiq, B., Islam, S., Sajjad, M.: Online word-of-mouth antecedents, attitude and intention-to-purchase electronic products in Pakistan. *Telematics Inform.* **33**(2), 388–400 (2016). <https://doi.org/10.1016/j.tele.2015.09.004>
- Bauman, K., Liu, B., Tuzhilin, A.: Aspect-based recommendations: recommending items with the most valuable aspects based on user reviews. In: *Proceedings of KDD 2017*, Halifax (2017). <https://doi.org/10.1145/3097983.3098170>
- Chen, L., Chen, G., Wang, F.: Recommender systems based on user reviews: state of the art. *User Model. User-Adap. Inter.* **25**(2), 99–154 (2015). <https://doi.org/10.1007/s11257-015-9155-5>
- Chiu, C.-M., Wang, E.T., Fang, Y.-H., Huang, H.-Y.: Understanding customers' repeat purchase intentions in B2C e-commerce: the roles of utilitarian value, hedonic value and perceived risk. *Inf. Syst. J.* **24**, 85–114 (2014). <https://doi.org/10.1111/j.1365-2575.2012.00407.x>
- Cui, Z., Xu, X., Xue, F., Cai, X., Cao, Y., Zhang, W., Chen, J.: Personalized recommendation system based on collaborative filtering for IoT scenarios. *IEEE Trans. Serv. Comput.* **13**(4), 685–695 (2020)
- Felfernig, A., Polat-Erdeniz, S., Uran, C., Reiterer, S., Atas, M., Tran, T.N.T., Dolui, K.: An overview of recommender systems in the internet of things. *J. Intell. Inf. Syst.* **52**(2), 285–309 (2019)
- Gao, H., Huang, J., Tao, Y., Hussain, W., Huang, Y.: The joint method of triple attention and novel loss function for entity relation extraction in small data-driven computational social systems. *IEEE Trans. Comput. Soc. Syst.* (2022)
- Gao, H.K., Jung, Y., Hussain, W., Iqbal, M., Duan, Y.: *Intelligent Processing Practices and Tools for E-Commerce Data, Information, and Knowledge*, Springer, Cham (2022). <https://doi.org/10.1007/978-3-030-78303-7>
- Gao, H., Qin, X., Barroso, R.J.D., Hussain, W., Xu, Y., Yin, Y.: Collaborative learning-based industrial IoT API recommendation for software-defined devices: The implicit knowledge discovery perspective. *IEEE Trans. Emerg. Top. Comput. Intell.* (2020). <https://doi.org/10.1109/TETCI.2020.3023155>
- Gräbner, D., Zanker, M., Fliedl, G., & Fuchs, M.: Classification of customer reviews based on sentiment analysis. In: Fuchs, M., Ricci, F., Cantoni, L. (eds.) *Information and Communication Technologies in Tourism 2012*, Springer, Vienna, pp. 460–470, January 2012, https://doi.org/10.1007/978-3-7091-1142-0_40
- Hong, Y., Pavlou, P.A.: Product fit uncertainty in online markets: Nature, effects, and antecedents. *Inf. Syst. Res.* **25**(2), 328–344 (2014). <https://doi.org/10.1287/isre.2014.0520>
- Hussain, S., Ahmed, W., Jafar, R.M.S., Rabnawaz, A., Jianzhou, Y.: eWOM source credibility, perceived risk and food product customer's information adoption. *Comput. Hum. Behav.* **66**, 96–102 (2017a). <https://doi.org/10.1016/j.chb.2016.09.034>
- Hussain, W., Sohaib, O.: Analysing cloud QoS prediction approaches and its control parameters: considering overall accuracy and freshness of a dataset. *IEEE Access* **7**, 82649–82671 (2019). <https://doi.org/10.1109/ACCESS.2019.2923706>

- Hussain, W., Hussain, F.K., Hussain, O.K., Damiani, E., Chang, E.: Formulating and managing viable SLAs in cloud computing from a small to medium service provider's viewpoint: a state-of-the-art review. *Inf. Syst.* **71**, 240–259 (2017b). <https://doi.org/10.1016/j.is.2017.08.007>
- Hussain, W., Hussain, F.K., Hussain, O., Bagia, R., Chang, E.: Risk-based framework for SLA violation abatement from the cloud service provider's perspective. *Comput. J.* **61**(9), 1306–1322 (2018). <https://doi.org/10.1093/comjnl/bxx118>
- Hussain, W., Merigó, J.M.: Centralised quality of experience and service framework using PROMETHEE-II for cloud provider selection. In: Gao, H., Kim, J.Y., Hussain, W., Iqbal, M., Duan, Y. (eds.) *Intelligent Processing Practices and Tools for E-Commerce Data, Information, and Knowledge*, pp. 79–94. Springer Publishing, Cham (2022)
- Hussain, W., Merigó, J.M., Rabhi, F., Gao, H.: Aggregating fuzzy sentiments with customized QoS parameters for cloud provider selection using fuzzy best worst and fuzzy TOPSIS. In: León-Castro, E., Blanco-Mesa, F., Alfaro-García, V., Gil-Lafuente, A.M., Merigó, J.M., Kacprzyk, J. (eds.) *Soft Computing and Fuzzy Methodologies in Innovation Management and Sustainability*, LNCS, vol. 337, pp. 81–92. Springer, Cham (2022). https://doi.org/10.1007/978-3-030-96150-3_6
- Hussain, W., Merigó, J.M., Raza, M.R.: Predictive intelligence using ANFIS-induced OWAWA for complex stock market prediction. *Int. J. Intell. Syst.* (2021a). <https://doi.org/10.1002/int.22732>
- Hussain, W., Merigo, J.M., Gao, H., Alkalbani, A.M., Rabhi, F.: Integrated AHP-IOWA, POWA framework for ideal cloud provider selection and optimum resource management. *IEEE Trans. Serv. Comput.* **01**, 1–1 (2021b). <https://doi.org/10.1109/TSC.2021.3124885>
- Hussain, W., Merigó, J.M., Raza, M.R., Gao, H.: A new QoS prediction model using hybrid IOWA-ANFIS with fuzzy c-means, subtractive clustering and grid partitioning. *Inf. Sci.* (2022). <https://doi.org/10.1016/j.ins.2021.10.054>
- Hussain, W., Raza, M.R., Jan, M.A., Merigo, J.M., Gao, H.: Cloud risk management with OWALSTM predictive intelligence and fuzzy linguistic decision making. *IEEE Trans. Fuzzy Syst.* (2022)
- Hussain, W., Sohaib, O., Naderpour, M., Gao, H.: Cloud marginal resource allocation: a decision support model. *Mob. Netw. Appl.* **25**(4), 1418–1433 (2020). <https://doi.org/10.1007/s11036-019-01457-7>
- Jalilvand, M.R., Samiei, N.: The effect of electronic word of mouth on brand image and purchase intention: an empirical study in the automobile industry in Iran. *Market. Intell. Plan.* (2012). <https://doi.org/10.1108/02634501211231946>
- Jha, A., Shah, S.: Disconfirmation effect on online review credibility: an experimental analysis. *Decis. Support Syst.* **145**, 113519 (2021). <https://doi.org/10.1016/j.dss.2021.113519>
- Jia, Y., Lu, I.: Do consumers always follow “useful” reviews? The interaction effect of review valence and review usefulness on consumers' purchase decisions. *JASIST* **69**(11), 1304–1317 (2018). <https://doi.org/10.1002/asi.24050>
- Kumar, S., De, K., Roy, P.P.: Movie recommendation system using sentiment analysis from microblogging data. *IEEE Trans. Comput. Soc. Syst.* **7**(4), 915–923 (2020). <https://doi.org/10.1109/TCSS.2020.2993585>
- Lee, D., Hosanagar, K., Nair, H.: When do recommender systems work the best? The moderating effects of product attributes and consumer reviews on recommender performance. In: *International World Wide Web Conference Committee (IW3C2)*, pp. 85–97 (2015). <https://doi.org/10.1145/2872427.2882976>
- Li, S., Zhou, L., Li, Y.: Improving aspect extraction by augmenting a frequency-based method with web-based similarity measures. *Inf. Process. Manage.* **51**(1), 58–67 (2015). <https://doi.org/10.1016/j.ipm.2014.08.005>
- Li, X., Wu, C., Mai, F.: The effect of online reviews on product sales: a joint sentiment-topic analysis. *Inf. Manage.* **56**(2), 172–184 (2019). <https://doi.org/10.1016/j.im.2018.04.007>

- Liu, Q., Gao, Z., Liu, B., Zhang, Y.: Automated rule selection for aspect extraction in opinion mining. In: Twenty-Fourth International Joint Conference on Artificial Intelligence, pp. 1291–1297 (2015). <https://www.ijcai.org/Proceedings/15/Papers/186.pdf>
- Moon, M.A., Khalid, M.J., Awan, H.M., Attiq, S., Rasool, H., Kiran, M.: Consumer's perceptions of website's utilitarian and hedonic attributes and online purchase intentions: a cognitive–affective attitude approach. *Spanish J. Market.-ESIC* **21**(2), 73–88 (2017). <https://doi.org/10.1016/j.sjme.2017.07.001>
- Osman, N.A., Noah, S.A.M., Darwich, M.: Contextual sentiment-based recommender system to provide recommendation in the electronic products domain. *Int. J. Mach. Learn. Comput.* **9**(4), 425–431 (2019). <https://doi.org/10.18178/ijmlc.2019.9.4.821>
- Park, D.H., Kim, H.K., Choi, I.Y., Kim, J.K.: A literature review and classification of recommender systems on academic journals. *J. Intell. Inf. Syst.* **17**(1), 139–152 (2011). <https://doi.org/10.13088/jiis.2011.17.1.139>
- Qiu, L., Pang, J., Lim, K.H.: Effects of conflicting aggregated rating on eWOM review credibility and diagnosticity: the moderating role of review valence. *Decis. Support Syst.* **54**(1), 631–643 (2012). <https://doi.org/10.1016/j.dss.2012.08.020>
- Raza, M.R., Hussain, W., Merigó, J.M.: cloud sentiment accuracy comparison using RNN, LSTM and GRU. In: 2021 Innovations in Intelligent Systems and Applications Conference (ASYU) (2021a)
- Raza, M.R., Hussain, W., Merigó, J.M.: Long short-term memory-based sentiment classification of cloud dataset. In: 2021 Innovations in Intelligent Systems and Applications Conference (ASYU) (2021b)
- Raza, M.R., Hussain, W., Tanyıldızı, E., Varol, A.: Sentiment analysis using deep learning in cloud. In: 9th International Symposium on Digital Forensics and Security (ISDFS), Elazig, Turkey (2021)
- Raza, M.R., Varol, A., Hussain, W.: Blockchain-based IoT: An Overview. In: 2021 9th International Symposium on Digital Forensics and Security (ISDFS) (2021)
- Ricci, F., Rokach, L., Shapira, B.: Recommender systems: introduction and challenges. In: Ricci, F., Rokach, L., Shapira, B. (eds.) *Recommender Systems Handbook*, pp. 1–34. Springer, Boston (2015). https://doi.org/10.1007/978-1-4899-7637-6_1
- Rosa, R.L., Rodriguez, D.Z., Bressan, G.: Music recommendation system based on user's sentiments extracted from social networks. *IEEE Trans. Consum. Electron.* **61**(3), 359–367 (2015). <https://doi.org/10.1109/TCE.2015.7298296>
- Shoja, B., Tabrizi, N.: Customer reviews analysis with deep neural networks for e-commerce recommender systems. *IEEE Access.* **1** (2019). <https://doi.org/10.1109/ACCESS.2019.2937518>.
- Thet, T.T., Na, J.C., Khoo, C.S.: Aspect-based sentiment analysis of movie reviews on discussion boards. *J. Inf. Sci.* **36**(6), 823–848 (2010). <https://doi.org/10.1177/0165551510388123>
- Xu, Q.: Should I trust him? The effects of reviewer profile characteristics on eWOM credibility. *Comput. Hum. Behav.* **33**, 136–144 (2014). <https://doi.org/10.1016/j.chb.2014.01.027>
- Zhang, K., Cheng, Y., Liao, W.K., Choudhary, A.: Mining millions of reviews: a technique to rank products based on importance of reviews. In *Proceedings of the 13th International Conference on Electronic Commerce*, pp. 1–8, August 2011. <https://doi.org/10.1145/2378104.2378116>
- Zhang, W., Ding, G., Chen, L., Li, C., Zhang, C.: Generating virtual ratings from Chinese reviews to augment online recommendations. *ACM Trans. Intell. Syst. Technol. (TIST)* **4**(1), 1–17 (2013). <https://doi.org/10.1145/2414425.2414434>
- Zhang, Y., Liu, R., Li, A.: A novel approach to recommender system based on aspect-level sentiment analysis. In *2015 4th National Conference on Electrical, Electronics and Computer Engineering*, pp. 1453–1458. Atlantis Press, December 2015. <https://doi.org/10.2991/nceee-15.2016.259>