Literature review

A literature review has been conducted, followed by the presentation of the proposed problem of detecting inauthentic reviews posted online which have not been left by a genuine consumer.

In this literature review the focus was aimed at reviewing a wide range of literature related to the business of online reviews for products and services. It was necessary to consult a diverse set of sources for this project, including various online journalistic articles and research studies, and many of these are listed below, all of which been cited and can be found in the references section. By consulting a diverse range of sources, including research studies and online journalistic articles, this literature review will provide a comprehensive overview of the subject and lay the groundwork for the proposed research project.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Source, Title,**  **Author** | **Source Type** | **Methodology** | **Performance**  **Metrics** | **Critique Remarks against RO's** |
| [1] How to spot fake  reviews on Amazon, Best Buy, Walmart and other sites, Rick Broida | journal article cnet | internet research | wide, in-depth assessment on other resources | useful assesement of  exisiting methods |
| [2] FakeSpot, private  company, Khalifah | browser extension | NLP + AI | unclear, no stats | no detail on DA  used |
| [3] FTC Puts Hundreds of  Businesses on Notice  about Fake Reviews and  Other Misleading Endorsements, Federal Trade Commission | press release | penalty notice offence issued | undisclosed | shows prevalence of  inauthentic reviews globally |
| [4] amazon-fake-reviews-facebook-groups, Vish Gain | article silicon republic | Identify + target facebook groups who are responsible | no stats, just comments on other methods | useful knowledge of existing social media groups |
| [5] Inside the Underground  Market for Fake Amazon  Reviews, RAJVARDHAN OAK | article, wired magazine | survey on prevalence of people completing fake reviews for refunds | no stats, just comments on other methods | useful knowledge of existing groups |
| [6,7] All You Need to Know  on Fake Reviews and  False Ratings, ECC Ireland | study report | detail business testimonials and review aggregators | free product reimbursement, pillow 20$ | valuable legal background information on this issue. Complete list of companies included |
| [8] Why we usually can't tell when a review is fake, Shabnam Azimi and Alexander Krasnikov of Loyola University of Chicago and Kwong Chan of Northeastern University | study report | participants separated real review from fake ones depending on their on opion | no metrics published. Study suggests were more like to believe negative review | no results published, methodology interesting, valuable methods to incorporated into rule classification |
| [9] Fake Review Watch , Kay Dean | website | investigating user  accounts | unclear, no stats | no DA used, manual research |
| [10] Method to Facilitate E-Commerce Buying Power by Using Machine Learning Techniques, Junzhi Liu | research article, researchgate | Naïve Bayes and Logistic Regression , word clouds | delivery time for commerce | valuable usage of word clouds +other visualisations |
| [11] Illusions of truth—Experimental insights  into human and algorithmic detections  of fake online reviews, Daria Plotkina , Andreas Munzel , Jessie Pallud | research paper,  Science Direct | linguistic analysis tool - Coh-Metrix | unclear, no stats | wide range of techniques used. Valuable paper for research |
| [12] Review Meta, private company | website, app , browser  extension | Independent testing to give user an 'Adjusted Rating' | website claims to analyse 1M + /day | not enough detail on algorithim employed. Valuable resource for dataset on fake reviews |
| [13] A Fake Review Detection System Using  NLP and Machine Learning Techniques, P. Aishwarya Sri, R. Vamshidhar Reddy | reseach paper, International journal of Scientific & Engineering Research | Supervised + Unsupervised learning, NLP, decision tree classifier, a rule-based classifier, Naïve Bayes | unclear, no stats | apart from lack of results a relevant paper for my work |
| [14] Amazon has removed hundreds of thousand of incentivized reviews since it banned the practice, Rob Thubron | techspot , journal article | Review Meta, 5 million reviews across 32,060 products | unclear, no stats | no detail on DA  used, relevant backround information |
| [15] Inside the War on Fake Consumer Reviews, MEGAN MCCLUSKEY | Time magazine, article | how to inform public, consumer advocate | no metrics, theoretical study | useful knowledge of current level of issue |
| [16] Amazon continues to take action against fake review brokers, Amazon staff | Amazon policy news | industry-leading tools to detect and block fake reviews | 2022- Amazon took legal action against 90 bad actors who facilitated and solicited fake reviews | relevant backround information, active team in place from Amazon side |
|  |  |  |  |  |

**Fakespot** [2], this can be added as a browser extension or a mobile app and claims to provide secure shopping on amazon, sephora, ebay and Walmart. Fakespot claims to ‘protect you from getting ripped off when shopping online’ and will ‘get the truth about products, reviews and sellers before you buy’. The website does not provide any technical details on how exactly it is filtering out certain reviews or how it calculates its own star rating for products. It simply claims that it uses ‘AI to detect fraudulent product reviews and third-party sellers in real-time’. Suspiciously the website also contains plenty of five-star positive reviews. They also offer a package for businesses called ‘Trust AI’ which claims to be a powerhouse NLP AI which will work across textual content and extract valuable intelligence from consumers. They have written that their product will find inauthentic accounts and bots on your service for fast and easy removal. The product also contains a review sentiment which will apparently allow you to uncover trends and insights from your customer reviews. Overall, the site promises a lot but does not provide any real evidence to back it up. The browser extension does function and tends to give a slightly lower rating that the shopping website so it is filtering out certain reviews (either real or inauthentic).

**[4]** There are many new and business platforms which have thrown their two-cents worth in the ring**]. Silicon Republic** is an American sci-fi news platform. Vish Gain, a journalist there was the author of a published article in July 2022 which describes a court case led by Amazon suing 10,000 Facebook groups over inauthentic reviews. Amazon was claiming that these groups orchestrate inauthentic product reviews on the website in exchange for money or free products. Amazon claimed at the time, the information would help to ‘complement the technology and continuous monitoring’ that it already did to reduce inauthentic reviews. They requested other social media companies such as Meta, inauthentic book’s parent company to step in at the time to support the case. One of the groups in particular names as ‘Amazon product Review’ had 43,000 members. This article unfortunately doesn’t give much more detailed information about the numbers of reviews involved and the site has not provided an update on this since which makes it difficult to decide which side of the fence, the platform is sitting on.

**ReviewMeta** [12] is another similar site that works only with Amazon, but worldwide. They position themselves as an **independent** checker tool that analyses reviews and ‘helps your shopping experience’. It also comes in the form of a mobile app, a browser extension. Under the ‘How it works’ section are a series of short entertaining video’s, a link to a podcast with the creator (Tommy Noonan), a nice little background story of how he apparently came up with the idea for the website. The site is positively geared towards Amazon and **blames brands** for choosing to ‘abuse the platform that were created to help customers, flooding them with low quality and biased reviews’ which it says the brands do to try and boost their own profits. Like ‘fakespot’ they claim to be performing some statistical modelling to present a truer picture of an online product. The ‘report card’ which the website can generate from an amazon link judges reviewers for their average rating, their word count, repetitive phrases and review history. The analysis this website seems to perform is interesting, and the transparency is commendable, it does seem biased towards Amazon though they do claim to be completely independent.

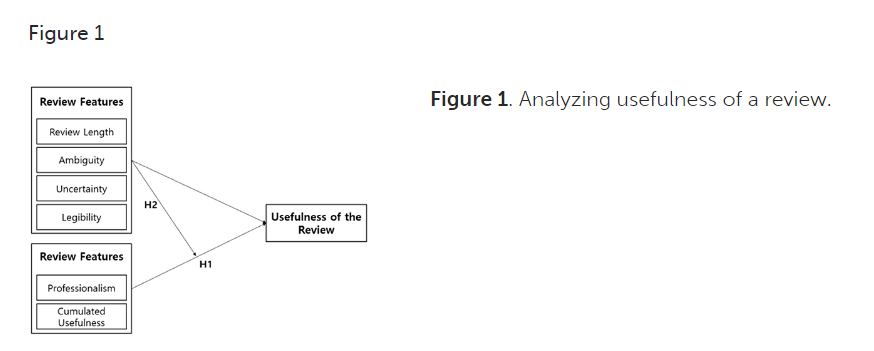
There are of course legal consequences for those who choose to commit what may seem like a petty crime.

[13] **‘A Fake Review Detection System Using NLP and Machine Learning Techniques’** by P. Aishwarya Sri and R. Vamshidhar Reddy describes a method of creating a spam review detection model and ensuring a high level of accuracy through ML methods. Detection feature methods are dived into two categories ‘review centric’ and ‘reviewer centric’, that is detection methods based on a single review or detection methods based on all reviews from a particular reviewer respectively. Pre-processing techniques include standard NLP methods such as stemming, LC conversion, Tokenisation and stop word removal to ensure the dataset sourced from Amazon reviews was as clean and functional as possible. A combination of unigrams, bi-grams and tri-grams were applied to the review information to ensure the adjectives were being grouped correctly with the appropriate nouns as implied by the reviewer. Word embedding allowed the words to be classified into low dimensional vectors.

An in-depth approach was taken by the author through machine learning. Supervised methods such as Decision tree classifier, Bayesian system, Naive Bayes and rule-based classifiers were executed. Rule-based Classifiers [13] were applied as a method of flagging reviews as ‘authentic’ or ‘inauthentic’. Since there is no ‘one size fits all’ rule, a combination of approaches was applied to catch as many indicators as possible. Unsupervised learning methods such as twice-clustering and K-means clustering were also applied. They were justified by their learning strategy of ‘examining the relationship between variables’ which can be suitable for unlabelled datasets. Overall, the article is quite simplistic, but it is well written and straightforward. The techniques outlined are relevant to this paper’s own research, in particular the supervised machine learning methods.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Source, Title, Author** | **Source Type** | **Methodology** | **Performance Metrics** | **Critique Remarks against RO's** |
| [17] Differential Query Semantic Analysis: Discovery of Explicit Interpretable Knowledge from E-Com Search Logs, Sahiti Labhishetty,  ChengXiang Zha,  Min Xie, Lin Gong | E-Com search logs | limited to data format | bridging the vocabulary gap, comparative analysis of search intent, and alleviation of the problem of tail queries and products. | novel strategy using nlp techniques. Limited access to full article |
| [18] Fake review identification and utility evaluation model using machine learning , Wonil Choi, Kyungmin Nam, Minwoo Park1, Seoyi Yang | Corpus-collection of linguistic data | requirement to dig further to read other articles | N/A- not published | Good summary overview of techniques availailability. Doesn’t contain indepth knowledge |
| [19] The Indian repository of resources for language technology, Narayan Choudhary | fifty people and involving thousands of resource persons, covering twenty major languages of India | human resource needed for each language | datasets in 20 scheduled languages of India so far collected | these works are crucial in the development of language technology for Indian languages |
| [20] Natural Language Processing (Almost) from Scratch, Ronan Collobert, Jason Weston, Leon | large unlabeled data sets (∼ 852 million words) | no task-specific engineering | State-of-the-art systems on four NLP tasks. Performances of between 70-90% | wide range of techniques used. Valuable paper for research |
| [21] Commonsense reasoning and commonsense knowledge in artificial intelligence, Ernest Davis, Gary Marcus, NYE | commentry no experiment | eg. Google translate, hand coding required | N/A not published | insightful article, innovative techniques used to imitate common sense |
| [22] Searching Better Architectures for Neural Machine Translation, Yang Fan; Fei Tian; Yingce Xia; Tao Qin; Xiang-Yang Li; Tie-Yan Liu | translation via audio, speech and language processing | resource requirement | permeance model scores | difference approach, not useful to this theis but still interesting |
| [23] Sentiment analysis using product review data, Xing Fang & Justin Zhan | Stanford Sentiment 140 Tweet Corpus | quality of the opinions on Twitter, truth of such online data is not always available. | Performance based on F1 score | valuable legal backround information on this issue. Complete list of companies included |
| [24] GA, MR, FFNN, PNN and GMM based models for automatic text summarization, Mohamed Abdel Fattah, Fuji Ren | 200 Arabic articles in the domain of politics and 150 English articles in the domain of religion from internet archives | semantics such as synonymy, polysemy, and term dependency not taken into account | average nr. Of sentences compressed/min per model type | only baseline approach results included |
| [25] DataTone: Managing Ambiguity in Natural Language Interfaces for Data Visualization, Authors:  Tong Gao, Mira Dontcheva, Eytan Adar, Zhicheng Liu, Karrie G. Karahalios | commentry no experiment | dropdown menu. Needs manual correction from user | dependent on subject | interesting adaption for visualisations |
| [26] Advances in Automatic Text Summarization, Inderjeet Mani and Mark T. Maybury | collection of the most important writings in automatic text summarization | produce an abridged version for a particular user or task | N/A not published | different approaches discussed |
| [27] Natural language processing: state of the art, current trends and challenges, Diksha Khurana, Aditya Koli, Kiran Khatter | Corpus-collection of linguistic data | no research experiment included. General overview | no research experiment included. General overview | no research experiment included. General overview |
| [28] Fake online reviews cost $152 billion a year. Here's how e-commerce sites can stop them, Jonathan Marciano | official figures and self-reporting by e-commerce sites (including Trip Advisor, Yelp, TrustPilot and Amazon | Cost of court cases | direct influence of fake online reviews on global online spending is $152 billion | no technical description of tools availabe, only overview included |
| [29] Text Generation, Kathleen McKeown | Corpus-collection of linguistic data | computational hardware | human judgement | no quantitive performance metric |
| [30] How to implement CNN for NLP tasks like Sentence Classification,  Rajat Newatia | Sentiment Labelled Sentences Data Set from the UCI Machine Learning Repository | nr. Of training samples, hyper parameter tuning | accuracy of CNN model performance | excellent paper with detailed description on code employed |

The article ‘Fake review identification and utility evaluation model using machine learning’ provides some in- depth reading on the subject mentioned in the title [18]. The article was published in January 2023 on the frontier’s platform. The article begins by reiterating the need to monitor fake reviews and highlights some of the consequences of leaving them unchecked. Some of these include platforms which are on the verge of losing credibility and traffic and a decline in sales by other affected vendors. The authors warn that with the general rise in online shopping transactions, the reliance by customers on reviews in making purchasing decisions has also increased dramatically in recent years. The data was sourced through ‘selenium on the **Korean Naver shopping mall platform**. The authors explain that this platform would provide a good representation of review posts and the platform collects reviews from other shopping mall platforms and just republishes them. The aim of the study is to propose an algorithm that utilizes machine learning to firstly remove macroscopic views of fake reviews and also to place reviews that provide useful information to buyers at the top of displayed platform results in order to provide a better experience for all platform participants. A wide variety of data analysis techniques **Neural networks, Generative Pre-Trained transformers and Bidirectional Encoders** were employed in this study. These techniques use the benefits of deep learning and machine translation. Each technique is explained such as the Support Vector Machine (SVM), which was used in this case to define decision boundaries and classify unclassified points, along those boundaries. Several natural language techniques and libraries were also used which may serve as a valuable support for this thesis. Libraries such as BERT and GPT are valuable transformer encoders. Some downfalls of the sentiment analysis are mentioned which shows the authors transparency, such as the adverbs not being included which influence the intensity of a word.



One of the interesting natural language processing techniques which the authors described was tokenizing the emotion analysis data using KoNLPy’s OKT. The reason for using Okt was its function of automatically correcting typos. This can have a great effect on improving accuracy when applied to review data that would have many typos. Regarding clustering, Hierarchical Clustering technique showed the most meaningful results in this study. SVC, LGBM, logical regress and KNN models performed during the supervised learning showed high accuracy with high AUC score values in determining inauthentic models. These results were verified by performing in-depth interviews with customers in this case for a tooth whitening product.

The significance of this study is in its link to from data analysis to actual mobile commerce **sales performance**. The study confirms quantitative and non-quantitative characteristics of customer reviews referred to by customers for decision-making has effect on the financial profits of an enterprise. This bold statement could definitely encourage more interest and investment on the part of businesses to take more of a serious attitude to their online profile. The wish of the authors by undertaking this study is that e-commerce platforms increase service reliability, prevent information overload, prevent participants from leaving the platform, and provide better online shopping experiences to attract more consumers by detecting and filtering out fake reviews using machine learning algorithms.

The paper titled ‘Natural language processing: state of the art, current trends and challenges’ , written by [Diksha Khurana](https://link.springer.com/article/10.1007/s11042-022-13428-4#auth-Diksha-Khurana), [Aditya, Koli](https://link.springer.com/article/10.1007/s11042-022-13428-4#auth-Aditya-Koli), [Kiran Khatter](https://link.springer.com/article/10.1007/s11042-022-13428-4#auth-Kiran-Khatter) & [Sukhdev Singh](https://link.springer.com/article/10.1007/s11042-022-13428-4#auth-Sukhdev-Singh) and published in 2022 presents a fascinating insight into the advances in NLP in recent years [20]. It has spread into areas of information extraction, medial fields, cyber security and summarization, and is of interest to many professionals such as linguistics, psychologists and philosophers. The authors define it as a ‘tract of Artificial Intelligence and Linguistics, devoted to make computers understand the statements or words written in human languages. The paper describes many libraries and applications of NLP which is very interesting for the research of this thesis.

Neural networks are mentioned for example as having revolutionized the field of Natural Language Processing (NLP) by enabling the handling of variable length inputs, which is particularly useful for processing text. The introduction of neural networks brought a significant change in the way NLP problems were approached and solved. For instance, sequence-to-sequence mapping framework is a general approach for mapping sequences of variable length to another sequence of variable length, and has been applied to various NLP tasks such as machine translation, summarization, and question-answering. In this approach, the encoder network processes the input sequence and generates a fixed-length vector representation, which is then used by the decoder network to generate the output sequence. The use of neural networks has led to significant improvements in NLP performance on various tasks, such as sentiment analysis, named entity recognition, and text classification. Moreover, the development of novel neural network architectures such as Convolutional Neural Networks (CNNs) and Transformers has further improved the state of the art in NLP. CNN’s have also been employed in sentiment analysis, classification and machine translation.

The authors give a valuable summary on the process of sentiment analysis. It tends to involves the use of two linguistic resources: the sentiment lexicon and the sentiment pattern database. The sentiment lexicon is used to identify positive and negative words in the documents, and the sentiment pattern database is used to analyse the sentiment patterns in the text. The analysis assigns ratings on a scale of -5 to +5 based on the identified positive and negative words. The currently used tag sets for sentiment analysis are mainly derived from English and designed for Indo-European languages. However, research on Asian and Middle Eastern languages is relatively limited in comparison and may benefit from further research in the future. Sentiment analysis however can also be quite limited, the author’s comment how online, when for example slang is used, it is necessary to consider noun phrases. They use the example of tweets and the Named entity recognition (NER) technique which is used to recognize and separate and aid in classifying text into predefined classes. Considering these metrics in mind, it is necessary to evaluate the performance of an NLP model for a particular application and a particular case.

The reference list for this paper is extremely in-depth and includes books, papers, google scholar articles and executed studies involving the application of NLP techniques on real world problems. The paper focuses not only on various approaches and evaluation metrics of NLP, but also the history of the area and recent developments in literature.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Source, Title, Author** | **Source Type** | **Methodology** | **Performance Metrics** | **Critique Remarks against RO's** |
| [31] Using Natural Language Processing and Network Analysis to Develop a Conceptual Framework for Medication Therapy Management Research, | publication, Towards Data Science | NLTK package python | feature extraction model performance | methods not fully justified |
| [32] Machine Translation: Past, Present, Future, William John Hutchins | research article,  peerj.com | language parsers and emoticons, context-level sentiment analysis techniques, pre-processing methods, and lexical resources | machine + deep learning model performance | detailed article, in depth literature review |
| [33] Sentiment Analysis on Amazon Reviews, Enes Gokce | research article, Towards Data Science | Recurrent Neural Network | no specified | no performance metric detailed |
| [34] Sentiment analysis techniques, challenges, and opportunities: Urdu language-based analytical study, Muhammad Irzam Liaqat1, Muhammad Awais Hassan​1, Muhammad Shoaib1, Syed Khaldoon Khurshid1, Mohamed A. Shamseldin2 | research article, Digital Library | new language model to simultaneously cluster and summarize documents by making use of both the document-term and sentence-term matrices | Experiment on interpretability of the generated summaries. | innovative modelling method used, valuable for data collections when grouping is required |
| [35] Recurrent Neural Networks and Natural Language Processing, Christopher Thomas BSc Hons. MIAP | publication, Science Direct | applying meaning representation language (MRL) that facilitates the uniform interpretation | ACM model performance | Paper doesn’t go into enough detail to describe construct of rules and techniques |
| [36] Integrating Document Clustering and Multidocument Summarization, Dingding Wang,  Shenghuo Zhu,  Tao Li,  Yun Chi,  Yihong Gong | publication, Wired journal | facebook groups offering free refunds for reviews posted | salary level of successful review agents | In-depth research by journalist into inauthentic review groups organisation. Reference to similar online services |
| [37] Semantics and Quantification in Natural Language Question Answering, W.A. Woods | research article, Journal of Scientific + Engineering Research | NLP, feature extraction, training, classification | K means clustering algorithm until convergence is achieved, ideal classifier identified | high level of detail on machine learning algorithms, performance evaluation not included |
| [38] Inside the Underground Market for Fake Amazon Reviews, RAJVARDHAN OAK | research article | problems are formulated as an integer linear program (ILP) and solved using public domain software. | Model performance of both methods presented, ACM | no supervised methods explored |
| [39] A Fake Review Detection System Using  NLP and Machine Learning Techniques, P. Aishwarya Sri, R. Vamshidhar Reddy | research article, Springer Link | memory-based anti-spam filtering | memory-based filter model performance | detailed article, in depth literature review |
| [40] Global unsupervised models for keyphrase based meeting summarization, Korbinian Riedhammer, | book | combination of approaches inc. from neuropsychology, psycholinguistics, and artificial intelligence | context of utterance to determine the proper meanings of words and sentences | broad based approach from various angles, deep understanding of the topic |
| [41] A Memory-Based Approach to Anti-Spam Filtering for Mailing Lists, Georgios Sakkis, Ion Androutsopoulos, Georgios Paliouras, Vangelis Karkaletsis, Constantine D. Spyropoulos & Panagiotis Stamatopoulos | Article, Research Gate | machine learning algorithms to build the classifiers | feature designing and fake review detection models | valuable article for own research. Innovative distinctions between types of fake reviews |
| [42] LEXICAL AMBIGUITY RESOLUTION,  Steven Small, Publisher: Morgan Kaufmann | Article, Research Gate | meta-graph to construct a heterogeneous information network | spamming score per group, overall detection performance, Comparison of P@ k for five methods | logical methodology flow detailed well in graphics |
| [43] Survey on Fake Review Detection Research, L.-Y. Li, B. Qin, T. Liu | Article, Research Gate | Word2Vec model, N nearest neighbour user relationship, DBSCAN algorithm | Experimental results of detection performance | approach not always justified or explained. Good model performance |
| [44] Network Embedding-Based Approach for Detecting Collusive Spamming Groups on E-Commerce Platforms, Jinbo Chao, Chunhui Zhao, Fuzhi Zhang | Article, Research Gate, Department of Telematic Engineering Systems | review scraper, feature computation, fake classifier | 82% F-Score on the classification task, Ada Boost classiﬁer has been proven to be the statistical means according to the Friedman test. | good summary tables, clear framework table |
| [45] Detecting review spammer groups based on generative adversarial networks, Jinbo Chao, Fuzhi Zhang | research study | HanLP package for translation, Latent Dirichlet Allocation (LDA) method for topic modeling, pyLDAvis for modelling | perplexity value and coherence score | interesting approach, no mention of fact that reviews could be false and basing data off them could be biased |
| [46] A framework for fake review detection in online consumer electronics retailers, Rodrigo Barbado, Oscar Araque, Carlos Iglesias | research study, Springer article | Convolution neural network, multidimensional feature representation is used to classify reviews | CNN performances of 0.988, 0.987, and 0.994 | valuable article for own research. Innovative hybrid approach for text, emotions and ratings |
| [47] How Could Consumers’ Online Review Help Improve Product Design Strategy?, Wei Miao, Kai-Chieh Lin , Chih-Fu Wu , Jie Sun , Weibo Sun , Wei Wei and Chao Gu | research article, research ate | Algorithm-Based Filtering | recognition accuracy rate based of punctuation score, sentiment score, vocabulary score | excellent visual flowcharts for rule-based classification |
| [48] DHMFRD – TER: a deep hybrid model for fake review detection incorporating review texts, emotions, and ratings, Ramadhani Ally Duma, Zhendong Niu, Ally Nyamawe, Jude Tchaye-Kondi | research article, research gate | natural language processing; Polish language;machine learning; random forest | F1 score of 0.92 and 0.74 when detecting fake accounts and reviews | large dataset, novel metrics to detect fake review, good summary in lit review |

# The article, ‘Research on False Review Detection Methods: A state-of-the-art review [49] written by [Arvind Mewada](https://www.researchgate.net/profile/Arvind-Mewada) and [RUPESH KUMAR DEWANG](https://www.researchgate.net/profile/Rupesh-Dewang) and published on the research gate platform provides an extremely in depth review into modern analytical methods for detecting fake reviews. The article also contains extremely well laid out methodology through the use of flow charts and tables. The authors have divided the content of spam reviews into 3 categories: untruthful reviews, reviews on brands only and non-reviews. By ‘non-reviews’ the authors mean the review contains no useful information specific information and only generic comments. Reviews were sourced from Yelp website, Tripadvisor Reviews and Amazon book and product reviews. The authors employ feature engineering to detect the clues left by reviewers in fake reviews through lexical, sentiment and syntactic methods. A mathematical model was established to quantify the characteristic values of these behaviours.

# The authors have used rule-based classification to score the reviews based on certain characteristics such as their rating, rating consistency, time frame between reviews and product launches and the percentage of sentiment values. Other methods included linguistic NLP methods such as Bag of Words, POS tagging, Word count features, Grammatical syntactic structure analysis.The discussion and results section is well structured, classifiers and machine learning methods are listed such as SVM, Random Forest. A few possible future improvements are listed such as optimising the labelled data, however the authors do not include why these were not included in this article. Each dataset, method, outcome matrix and model results is listed clearly in Table 5. The article limits itself by only using false review text as the identification target, however future directions are laid out in the conclusion section towards future research in the field of false reviews and false reviewer groups.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Source, Title, Author** | **Source Type** | **Methodology** | **Performance Metrics** | **Critique Remarks against RO's** |
| [49] Research on False Review Detection Methods: A state-of-the-art review, Arvind Mewada, [RUPESH KUMAR DEWANG](https://www.researchgate.net/profile/Rupesh-Dewang?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uRGV0YWlsIiwicGFnZSI6InB1YmxpY2F0aW9uRGV0YWlsIn19) | research article, research gate | Algorithm-Based Filtering | recognition accuracy rate based of punctuation score, sentiment score, vocabulary score | excellent visual flowcharts for rule-based classification |
| [50] Detecting Fake Reviews in Google Maps—A Case Study, Paweł Gryka, Artur Janicki | research article, research gate | natural language processing; Polish language; machine learning; random forest | F1 score of 0.92 and 0.74 when detecting fake accounts and reviews | large dataset, novel metrics to detect fake review, good summary in lit review |
| [51] Aspect‑based classiﬁcation method for review spam detection, Mengsi Cai, Yonghao | research study, Springer article | Bi-LSTM model to automatically extract massive aspect words which are clustered into diﬀerent aspect categories by the K-means algorithm | review spam detection by about 16.11% to 38.86% compared with textual and behaviour features | dataset size not detailed; some assumptions made about spam reviewers |
| [52] Expected and materialised information source use by municipal officials: intertwining with task complexity, Miamaria Saastamoinen | research article, research gate | analyse the use of information sources in the context of varying task complexity and from the perspective of task performers | Mann-Whitney statistically significant , p=0.03 between simple/complex tasks | slightly confusing language, well presented table of results |
| [53] A comprehensive survey of various methods in opinion spam detection, Arvind Mewada | RUPESH KUMAR DEWANG | . Machine learning methods and natural language processing techniques | quantitive comparison to aspects of feature design, model methods, datasets, and rating indicators | clear distinction f types of review eg. Fake/brand/non review/ spammer . No innovative ML modelling used |
| [54] Sentiment Analysis for E-commerce Product Reviews: Current Trends and Future Directions, Salma Elzeheiry, Wael Ali Mohammed Gab Allah, Nagham Mekky, Mohammed Elmogy | research article, research- gate | word2vec, deep learning, sentiment analysis, bigram, and Glove, TF-IDF | Area under AUC , ROC curve | clear methodology flowcharts |
| [55] Method to Facilitate E-Commerce Buying Power by Using Machine Learning Techniques, Junzhi Liu | research article, research gate | Naïve Bayes and Logistic Regression , word clouds | delivery time for commerce | valuable usage of word clouds |
| [56] Whose reviews are most valuable for predicting the default risk of peer‑to‑peer lending platforms?, Liting Li, Haichao Zheng, Dongyu Chen, Bin Zhu | research article, Electronic Commerce Research (2022) | linear regressions of the number of manipulated reviews / average rating on transaction volume. | correlation value between patform duration and manipulated positive review count | Limited to chinese dataset |
| [57] Fake Review Detection: Classification and Analysis of Real  and Pseudo Reviews, Arjun Mukherjee , Vivek Venkataraman , Bing Liu , Natalie Glance | research paper, Google scholar | using the information theoretic measure KL-divergence and its asymmetric  property on 2 types of reviews (real/fake) | classification  accuracy of 89.6% with bigram features | interesting psycholinguistic  phenomena about forced and natural fake reviewers |
| [58] A deep learning approach for detecting fake reviewers, Dong Zhang, Wenwen Li, Baozhuang Niu, Chong Wu | research paper, Science direct | behavior-sensitive feature extractor, context-aware attention mechanism, and fake reviewer detection | long delivery time with deep learning | novel deep learning-based framework for detecting suspicious reviewers |
| [59] Creating and detecting fake reviews of online products, Joni Salminen, Chandrashekhar Kandpal, Ahmed Mohamed Kamel, Soon-gyo Jung, Bernard J. Jansen | research paper, Science direct | 2 models CPT-2 and ULMFit represent different types of NLP architectures | performance – accuracy of 63% with text features and 78% with all available features | well-designed visualizations |
| [60] An Approach for Detecting Spam in  Arabic Opinion Reviews, Ahmad S. J. Abu Hammad | Msc. Thesis | classification method to find a way to classify the  Arabic opinion reviews, whether it should be spam and non-spam | F-measure 99.6% | well laid out thesis, quite basic coding used |
| [61] Distortion as a Validation Criterion in the Identification of Suspicious Reviews, Guangyu Wu, Derek Greene, Barry Smyth, Pádraig Cunningham | research paper, UCD | an assessment of shill detection mechanisms on a dataset of hotel reviews | CPS Score, level of distortion, PPS score | valuable paper for own research, well written, in-depth discussion |
| [62] Removing order effects from human-classified datasets: A machine learning method to improve decision making systems, Dmitry Romanov , Valentin Molokanov , Nikolai Kazantsev , Ashish Kumar Jha | research article, Science direct | basic classification algorithms Naïve Bayes to test our model's efficacy in eliminating the order effect | Naïve Bayes significance level | paper fails to answer how to remove other forms of cognitive bias, such as gender and racial biases. |
| [63] A deep learning approach for detecting fake reviewers: Exploiting reviewing behavior and textual information, Dong Zhang , Wenwen Li , Baozhuang Niu , Chong Wu | research article, Science direct | using 133 unique features from the combination of content and behaviour-based features to detect fake reviews using ML classifiers. | results (accuracy, precision, recall and F1) from Scikit library, 7.73% for the fake class and 99.3% for the genuine class using a Multilayer Perceptron classifier | well discussed, innovative hybrid approach. Results clearly presented |
| [64] Consumers rule: How consumer reviews influence perceived trustworthiness of online stores, Sonja Utz, Peter Kerkhof, Joost van den Bos | research article, Science direct | effects of online reviews on perceived trustworthiness of an online store | opinions of participants document in table | similar experiments out there, nothing innovative about this experiment |
| [65] The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews, Do-Hyung Park , Sara Kim | research article, Science direct | experiment asking participants with varying level of expertise about multimedia product | no significant differences in gender (F(9, 240) = 0.766, p < 0.648), age (F(9, 240) = 0.862, p < 0.560), and frequencies of online purchase (F(9, 240) = 0.896, p < 0.530) | study makes several theoretical contributions |
| [66] Suspicion of online product reviews as fake: Cues and consequences, L. Jean Harrison-Walker, Ying Jiang | research article, Science direct | study of types of cues used by customers to determine if review is authentic | findings discussed not evaluated quantitivly | good insight for brands and market research, useful cues to consider |
| [67] Understanding online fake review production strategies, Snehasish Banerjee , Alton Y.K. Chua | research article, Science direct | participants outline strategy on mehod, challenges faced, demographic details | planning style, knowledge style score and creating style score values to explore mapping between production strategie and cognitive style | Nice use of Anova to differenciate between clusters. Well thought out performance evaluation |
| [68] The more they know: Using transparent online communication to combat fake online reviews, Yiru Wang , César Zamudio , Robert D. Jewell | research article, Science direct | communicating the platforms’ actions online in transparent manner | four-stage framework, VIEW (Verify, Inform, Explore, and Watch), provides a roadmap for online review platform managers | theoretical discussion, missing concrete performance results |
| [69] Mind the fake reviews! Protecting consumers from deception through persuasion knowledge acquisition, Murilo Costa Filho , Diego Nogueira Rafael | research article, Science direct | pilot study with consumers against an original hypothesis | results suggest fake reviews are much more likely to go unnoticed by consumers when they are not equipped with tools to detect them | well written theoretical discussion, support for more transparency with consumers |
| [70] Unfolding the characteristics of incentivized online reviews, Ana Costa , João Guerreiro , Sérgio Moro , Roberto Henriques | research article, Science direct | data mining approach to predict whether or not a new review published was incentivized based on several review features such as the overall rating, the helpfulness rate, and the review length | word count, number of sentences, number of characters, Kruskal-Wallis test | interesting conclusion that incentivised reviews have longer character count and can be used as deciding factor |

**To conclude this literature review.** The continued media focus on inauthentic reviews, driven in part by such websites as ReviewMeta [4] and Fake spot’s [3], their relentless publicity drive is taking attention away from much more serious issues that the media does not cover, such as click farming, bookstuffing, incentivized purchasing, and mass gifting however this goes beyond the subject of this project thesis. The article published on the frontier’s platform [17] is focused on a Korean shopping platform. The author has undertaken a very deep look at natural language techniques combined with several machine learning models which is a valuable piece of research for this thesis. The study demonstrates a strong link between sales data for a particular product and the presence of online fake reviews for that product. This information is then backed up by in-depth interviews from platform participants making overall a very strong case. [12] This report from Amazon shows they acknowledge how widespread the issue is, simply by the fact that they claim to have over 12,000 employees working on the issue and that they have filed six lawsuits against companies in 2023 for fraud and abuse of the platform. The article in Wired provides and interesting insight into the multiple social media groups that are being financially incentivised to purchased targeted items and the write a review about it. Awareness of the darker side to these reviews has widened the research of this thesis greatly and has provided valuable opinions which contribute to the depth of this report. The knowledge of the existence of such reviews has broadened the research of this thesis, providing valuable insights and opinions that contribute to the depth of this report. Therefore, it is crucial to develop accurate methods for detecting fake reviews and ensuring the integrity of review systems to protect consumers and businesses' interests.