# Detecting Adverse Drug Events from social media

# Detecting Adverse Drug Events from social media: A brief literature review

**Imane Guellil** University of Edinburgh
**Nidhaleddine Chenni** ESI Algiers Algeria
**Yousra Berrachedi** ESI Algiers Algeria
**Massinissa Abboud** ESI Algiers Algeria
**Jinge Wu** University College London
**Honghan Wu** University College London
**Beatrice Alex** University of Edinburgh

## Abstract

The aim of this paper is present and regroup 70 research works that have been done for detecting Adverse Drug Events from social media. For each work, we focus on its description, its aim, its approach, the used models, the used datasets, its novelty and its limitation.

## 1 Introduction

Detection of ADEs (drug side effects) is one of the main tasks in the pharmaceutical industry. ADEs can have profound effects on patients' quality of life and is one of the leading causes of increased mortality internationally. The massive use of social media, and the abundance of discussions relating to healthcare in general (where drugs and ADEs are the most widely discussed categories), let them represent an excellent source for extracting ADEs. More recently, different works have been proposed for extracting ADEs from social media. The role of this paper is to briefly present, classify and analyse these works. To the best of our knowledge, no prior survey was proposed on ADEs detection in social media.

## 2 Adverse drug Events in social media: Background

*An adverse Drug Event (ADE), also noun as ADR for Adverse Drug Reaction or drug side-effect, refers to any injuries resulting from medication use, including physical harm, mental harm, or loss of function, that is greatly threatening public health and have become a leading cause of death* (Liu et al., 2018; Lavertu et al., 2021). Detection of ADEs is one of the main tasks in the pharmaceutical industry. Monitoring drug side effects is a crucial task for the pharmaceutical companies developing the drugs and the Food and Drug Administration (FDA) (Hsu et al., 2021). Social media platforms such as Twitter, Facebook, Instagram, Pinterest, etc. have been used extensively used for market analysis of various products. Among large volumes of patient-generated content, drugs and ADEs are the most widely discussed categories, (Liu et al., 2018).

## 3 Adverse Drug Events in social media: related works

The works on ADEs detection in social media can be grouped into different categories: classification, extraction, normalisation, corpus creation and other analysis related to ADEs such as the correlation between Drugs-ADEs or sentiment analysis regarding ADEs.

### 3.1 ADEs classification

The classification corresponds to assigning the right class to tweets, posts, texts, etc. In the majority of cases, it is a binary classification where we only have two classes ADE (for texts including ADEs) and NoADE (for texts without ADEs). The classification represents the first step for detecting if a given text includes reference to ADEs or not. Hence different works focus on this tasks (Liu et al., 2019; Ribeiro et al., 2021; Dai and Wang, 2019; Booth et al., 2018; Rakhsha et al., 2021; Aji et al., 2021; Kayastha et al., 2021; Mane et al., 2018; Hsu et al., 2021; Pimpalkhute et al., 2021; Wang et al., 2018; Habibabadi et al., 2022).

### 3.2 ADEs detection

Two common approaches have been used for medical entity extraction in general (including ADEs extraction): lexicon-based and machine learning methods (Xie et al., 2018). The majority of the most recent studies rely on the machine learning approach (Wahbeh et al., 2021; Xie et al., 2018; Gattepaille et al., 2020; Wang et al., 2021; Lavertu et al., 2021; Shen et al., 2020, 2021; Zhang et al., 2020, 2021; Rakhsha et al., 2021; Bollegala et al., 2018b). However, we also observe that some approaches can not be classified into those categories where the authors are extracting ADEs from a corpus that was manually annotated without using any lexicon or machine learning technics (Alex et al., 2020). Some other approaches exploit various lexical, semantic, and syntactic features, and integrated ensemble learning and semi-supervised learning in order to detect ADEs (Liu et al., 2018). Some authors start by training their own embedding model that they use after for the detection (Hoang et al., 2018) (where AC-SPASM, a Bayesian model for the authenticity and credibility aware detection of potential ADEs from social media is trained and used). Finally, in addition to detecting ADEs, some approaches also highlight the correlation between drugs and ADEs (De Rosa et al., 2021)

### 3.3 Normalisation

The normalisation consists in assigning(mapping) ADEs to their corresponding codes in medical ontologies such as Unified Medical Language System (UMLS), SNOMED CT, Medical Dictionary for Regulatory Activities (MedDRA), etc. This task is in most cases associated with the detection (extraction) where the ADEs are first extracted automatically and then mapped to an existing ontology. To the best of our knowledge, it has no works dedicated to normalisation only without involving the detection (Ji et al., 2021). To map the extracted ADEs to MedDRA, these authors first apply Neural Transition-based Model for named entity recognition (NER) and then link each extracted mention to its MedDRA code.

### 3.4 Resources creation

Some authors start dedicating their efforts to constructing such resources (Dietrich et al., 2020; Laksito et al., 2018; Alvaro et al., 2017; Karimi et al., 2015). Other studies focus in validating the constructed corpus either by classifying ADEs (Smith et al., 2018; Shen et al., 2019; Habibabadi et al.; Duval and Silva, 2019; Jiang et al., 2018; Li et al., 2020) or by extracting them (Li et al., 2020; Arnoux-Guenegou et al.). For this category of works, Twitter was also the predominant source for collecting data.

### 3.5 Classification, detection and normalisation

Some works focus on a pipeline including both tasks, such as (Yaseen and Langer, 2021), which did not only perform binary classification of the ADE text, but also extracted them. Many other studies (Fuentes-Carbajal et al., 2022; Wang et al., 2022; Guo et al., 2021; Zhang et al., 2019; Bollegala et al., 2018a; Tang et al., 2018; Saha et al., 2021; Kim et al., 2020) followed the same pattern,while others (Sakhovskiy et al., 2021; Zhou et al., 2021; El-karef and Hassan, 2021; Magge et al., 2021; Jagannatha et al., 2019; Dima et al., 2021; Ramesh et al., 2021; Barry and Uzuner, 2019) have added normalisation to the pipeline as a technique for transforming features to be on a similar scale like associate or map extracted ADEs to code.

### 3.6 ADEs analysis

The last category of work is dedicated to carrying on some analysis related to ADEs (Golder et al., 2019; Lentzen et al., 2022; Lyu et al., 2020; Golder et al., 2021; Clemens et al., 2022; Chalasani et al., 2018; Saha et al., 2021; Nawar et al., 2022; Zhou et al., 2020; Suragh et al., 2018). These analyses could be related to the sentiments, expectations, and anxiety of the users related to ADE (Golder et al., 2019; Lentzen et al., 2022; Clemens et al., 2022; Suragh et al., 2018). They can also be related to some linguistic features validated by clinical experts for detecting ADEs (Lyu et al., 2020) or to a comparison of the ADE related to a given drug with others or evaluating the Complementary and Alternative Medicine (CAM) (Golder et al., 2021; Saha et al., 2021; Nawar et al., 2022). Finally, some analyses are dedicated to evaluating the precision and the accuracy of the ADEs reported on Social media (Zhou et al., 2020).

## 4 Conclusion

In total, we collected 70 papers that we synthesise and summarise (for more detail, refer to the appendix part). These works were classified into 6 different categories: works on classification, detection, normalisation, classification and extraction and normalisation, resources construction and ADEs analysis. To sum up, many challenges are related to extracting data from social media including the proportion of noise, diversity in content, expressions, language and posting formats, non-textual content used as text, and use of symbols, emoticons and jargon (Indani et al., 2020). Finally one of the most important challenges behind working on collected data from social media is to obtain imbalanced corpora. Few studies only focus on these issues and the majority of the works that did, are focusing on oversampling the data. Many other techniques for balancing a dataset have been proposed. Hence more experiments are required in this part.

## References


Alham Fikri Aji, Made Nindyatama Nityasya, Haryo Akbarianto Wibowo, Radityo Eko Prasojo, and Tirana Fatyanosa. 2021. Bert goes brrr: A venture towards the lesser error in classifying medical self-reporters on twitter. In *Proceedings of the Sixth Social Media Mining for Health (# SMM4H) Workshop and Shared Task*, pages 58–64.

Saira E Alex, Christopher Wong, Alay Shah, Pooja Reddy, Logan DeBord, and Harry Dao Jr. 2020. Social media as a surveillance tool for monitoring of isotretinoin adverse effects. *Cureus*, 12(9).

Nestor Alvaro, Yusuke Miyao, Nigel Collier, et al. 2017. Twimed: Twitter and pubmed comparable corpus of drugs, diseases, symptoms, and their relations. *JMIR public health and surveillance*, 3(2):e6396.

Armelle Arnoux-Guenegou, Yannick Girardeau, Xiaoyi Chen, Myrtille Deldossi, Rim Aboukhamis, Carole Faviez, Badisse Dahamna, Pierre Karapetiantz, Sylvie Guillemin-Lanne, Nathalie Texier, et al. Protocol for evaluating the extraction of adverse drug reactions information in social media, the adr-prism project.

Paul Barry and Ozlem Uzuner. 2019. Deep learning for identification of adverse effect mentions in twitter data. In *Proceedings of the Fourth Social Media Mining for Health Applications (# SMM4H) Workshop & Shared Task*, pages 99–101.

Danushka Bollegala, Simon Maskell, Richard Sloane, Joanna Hajne, Munir Pirmohamed, et al. 2018a. Causality patterns for detecting adverse drug reactions from social media: text mining approach. *JMIR public health and surveillance*, 4(2):e8214.

Danushka Bollegala, Richard Sloane, Simon Maskell, Joanna Hajne, and Munir Pirmohamed. 2018b. Learning causality patterns for detecting adverse drug reactions from social media. *Journal of Medical Internet Research*.

A Booth, S Halhol, E Merinopoulou, M Oguz, S Pan, and A Cox. 2018. Pmu1-frequency of reportable adverse events in health-related social media posts. *Value in Health*, 21:S309.

Sai Chalasani, Vahin Vuppalanchi, Luke Tilmans, Kayla Petersen, Regina Weber, Naga Chalasani, and Craig Lammert. 2018. Novel approach leveraging social media indicates complementary and alternative medicine use highly prevalent and is sometimes associated with serious adverse events in patients with autoimmune hepatitis. *The American Journal of Gastroenterology*, 113:S526–S526.

Kelly S Clemens, Kate Faasse, Winston Tan, Ben Colagiuri, Luana Colloca, Rebecca Webster, Lene Vase, Emily Jason, and Andrew Geers. 2022. Social pathways to side-effects: Personal contacts and social media predict covid-19 vaccine side-effect expectations and experience.

Hong-Jie Dai and Chen-Kai Wang. 2019. Classifying adverse drug reactions from imbalanced twitter data. *International journal of medical informatics*, 129:122–132.

Michela De Rosa, Giuseppe Fenza, Alessandro Gallo, Mariacristina Gallo, and Vincenzo Loia. 2021. Pharmacovigilance in the era of social media: discovering adverse drug events cross-relating twitter and pubmed. *Future Generation Computer Systems*, 114:394–402.

Juergen Dietrich, Lucie M Gattepaille, Britta Anne Grum, Letitia Jiri, Magnus Lerch, Daniele Sartori, and Antoni Wisniewski. 2020. Adverse events in twitter-development of a benchmark reference dataset: results from imi web-radr. *Drug safety*, 43(5):467–478.

George-Andrei Dima, Dumitru-Clementin Cercel, and Mihai Dascalu. 2021. Transformer-based multi-task learning for adverse effect mention analysis in tweets. In *Proceedings of the Sixth Social Media Mining for Health (# SMM4H) Workshop and Shared Task*, pages 44–51.

Felipe Vieira Duval and Fabrício Alves Barbosa da Silva. 2019. Mining in twitter for adverse events from malaria drugs: the case of doxycycline. *Cadernos de saude publica*, 35.

Mohab El-karef and Lamiece Hassan. 2021. A joint training approach to tweet classification and adverse effect extraction and normalization for smm4h 2021. In *Proceedings of the Sixth Social Media Mining for Health (# SMM4H) Workshop and Shared Task*, pages 91–94.

José Alberto Fuentes-Carbajal, Manuel Montes-y Gómez, and Luis Villaseñor-Pineda. 2022. Does this tweet report an adverse drug reaction? an enhanced bert-based method to identify drugs side effects in twitter. In *Mexican Conference on Pattern Recognition*, pages 235–244. Springer.

Lucie M Gattepaille, Sara Hedfors Vidlin, Tomas Bergvall, Carrie E Pierce, and Johan Ellenius. 2020. Prospective evaluation of adverse event recognition systems in twitter: Results from the web-radr project. *Drug safety*, 43(8):797–808.

Su Golder, Arabella Scantlebury, Helen Christmas, et al. 2019. Understanding public attitudes toward researchers using social media for detecting and monitoring adverse events data: multi methods study. *Journal of medical Internet research*, 21(8):e7081.

Su Golder, Karen Smith, Karen Oâ€™Connor, Robert Gross, Sean Hennessy, and Graciela Gonzalez-Hernandez. 2021. A comparative view of reported adverse effects of statins in social media, regulatory data, drug information databases and systematic reviews. *Drug safety*, 44(2):167–179.

Yuting Guo, Yao Ge, Mohammed Ali Al-Garadi, and Abeed Sarker. 2021. Pre-trained transformer-based classification and span detection models for social media health applications. In *Proceedings of the Sixth Social Media Mining for Health (# SMM4H) Workshop and Shared Task*, pages 52–57.

Sedigheh Khademi Habibabadi, Pari Delir Haghighi, Frada Burstein, and Jim Buttery. Mining vaccine adverse events mentions from social media using twitter as a source.

Sedigheh Khademi Habibabadi, Pari Delir Haghighi, Frada Burstein, Jim Buttery, et al. 2022. Vaccine adverse event mining of twitter conversations: 2-phase classification study. *JMIR medical informatics*, 10(6):e34305.

Tao Hoang, Jixue Liu, Nicole Pratt, Vincent W Zheng, Kevin C Chang, Elizabeth Roughead, and Jiuyong Li. 2018. Authenticity and credibility aware detection of adverse drug events from social media. *International journal of medical informatics*, 120:157–171.

Dennis Hsu, Melody Moh, Teng-Sheng Moh, and Diane Moh. 2021. Drug side effect frequency mining over a large twitter dataset using apache spark. In *Handbook of Artificial Intelligence in Biomedical Engineering*, pages 233–259. Apple Academic Press.

Ashish Indani, Devraj Goulikar, Akhil Nair, Pratibha Potare, and Sonal More. 2020. Reporting social media-based adverse events with artificial intelligence: Elaborating the challenges -mitigating with innovation.

Abhyuday Jagannatha, Feifan Liu, Weisong Liu, and Hong Yu. 2019. Overview of the first natural language processing challenge for extracting medication, indication, and adverse drug events from electronic health record notes (made 1.0). *Drug safety*, 42(1):99–111.

Zongcheng Ji, Tian Xia, and Mei Han. 2021. Paii-nlp at smm4h 2021: Joint extraction and normalization of adverse drug effect mentions in tweets. In *Proceedings of the Sixth Social Media Mining for Health (# SMM4H) Workshop and Shared Task*, pages 126–127.

Keyuan Jiang, CHEN Tingyu, A Ricardo, and Gordon R Bernard. 2018. Identifying consumer health terms of side effects in twitter posts. *Studies in health technology and informatics*, 251:273.

Sarvnaz Karimi, Alejandro Metke-Jimenez, Madonna Kemp, and Chen Wang. 2015. Cadec: A corpus of adverse drug event annotations. *Journal of biomedical informatics*, 55:73–81.

Tanay Kayastha, Pranjal Gupta, and Pushpak Bhattacharyya. 2021. Bert based adverse drug effect tweet classification. In *Proceedings of the Sixth Social Media Mining for Health (# SMM4H) Workshop and Shared Task*, pages 88–90.

Myeong Gyu Kim, Jungu Kim, Su Cheol Kim, and Jaegwon Jeong. 2020. Twitter analysis of the nonmedical use and side effects of methylphenidate: machine learning study. *Journal of medical Internet research*, 22(2):e16466.

Arif Dwi Laksito, Heri Sismoro, Fita Rahmawati, Mochammad Yusa, et al. 2018. A comparison study of search strategy on collecting twitter data for drug adverse reaction. In *2018 International Seminar on Application for Technology of Information and Communication*, pages 356–360. IEEE.

Adam Lavertu, Tymor Hamamsy, Russ B Altman, et al. 2021. Quantifying the severity of adverse drug reactions using social media: Network analysis. *Journal of medical Internet research*, 23(10):e27714.

Max-Philipp Lentzen, Viola Huebenthal, Rolf Kaiser, Matthias Kreppel, Joachim E Zoeller, and Matthias Zirk. 2022. A retrospective analysis of social media posts pertaining to covid-19 vaccination side effects. *Vaccine*, 40(1):43–51.

Ying Li, Antonio Jimeno Yepes, and Cao Xiao. 2020. Combining social media and fda adverse event reporting system to detect adverse drug reactions. *Drug safety*, 43(9):893–903.

Jing Liu, Gang Wang, and Gang Chen. 2019. Identifying adverse drug events from social media using an improved semisupervised method. *IEEE Intelligent Systems*, 34(2):66–74.

Jing Liu, Songzheng Zhao, and Gang Wang. 2018. Sselade: a semi-supervised ensemble learning framework for extracting adverse drug events from social media. *Artificial intelligence in medicine*, 84:34–49.

Tianchu Lyu, Andrew Eidson, Jungmi Jun, Xiajie Zhou, Xiang Cui, and Chen Liang. 2020. Data veracity of patients and health consumers reported adverse drug reactions on twitter: Key linguistic features, twitter variables, and association rules. *medRxiv*.

Arjun Magge, Elena Tutubalina, Zulfat Miftahutdinov, Ilseyar Alimova, Anne Dirkson, Suzan Verberne, Davy Weissenbacher, and Graciela Gonzalez-Hernandez. 2021. Deepademiner: a deep learning pharmacovigilance pipeline for extraction and normalization of adverse drug event mentions on twitter. *Journal of the American Medical Informatics Association*, 28(10):2184–2192.

Priyanka S Mane, Manasi S Patwardhan, and Ankur V Divekar. 2018. Medicinal side-effect analysis using twitter feed. In *Progress in Intelligent Computing Techniques: Theory, Practice, and Applications*, pages 59–69. Springer.

Nevine Nawar, Omar El-Gayar, Loknath Sai Ambati, and Giridhar Reddy Bojja. 2022. Social media for exploring adverse drug events associated with multiple sclerosis. In *Proceedings of the 55th Hawaii International Conference on System Sciences*.

Varad Pimpalkhute, Prajwal Nakhate, and Tausif Diwan. 2021. Iiitn nlp at smm4h 2021 tasks: Transformer models for classification on health-related imbalanced twitter datasets. In *Proceedings of the Sixth Social Media*

*Mining for Health (# SMM4H) Workshop and Shared Task*, pages 118–122.

Mahsa Rakhsha, Mohammad Reza Keyvanpour, and Seyed Vahab Shojaedini. 2021. Detecting adverse drug reactions from social media based on multichannel convolutional neural networks modified by support vector machine. In *2021 7th International Conference on Web Research (ICWR)*, pages 48–52. IEEE.

Sidharth Ramesh, Abhiraj Tiwari, Parthivi Choubey, Saisha Kashyap, Sahil Khose, Kumud Lakara, Nishesh Singh, and Ujjwal Verma. 2021. Bert based transformers lead the way in extraction of health information from social media. In *Proceedings of the Sixth Social Media Mining for Health (# SMM4H) Workshop and Shared Task*, pages 33–38.

Luiz APA Ribeiro, Daniel Cinalli, and Ana Cristina Bicharra Garcia. 2021. Discovering adverse drug reactions from twitter: A sentiment analysis perspective. In *2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pages 1172–1177. IEEE.

Koustuv Saha, John Torous, Emre Kiciman, Munmun De Choudhury, et al. 2021. Understanding side effects of antidepressants: large-scale longitudinal study on social media data. *JMIR mental health*, 8(3):e26589.

Andrey Sakhovskiy, Zulfat Miftahutdinov, and Elena Tutubalina. 2021. Kfu nlp team at smm4h 2021 tasks: Cross-lingual and cross-modal bert-based models for adverse drug effects. In *Proceedings of the Sixth Social Media Mining for Health (# SMM4H) Workshop and Shared Task*, pages 39–43.

Chen Shen, Zhiheng Li, Yonghe Chu, and Zhongying Zhao. 2021. Gar: Graph adversarial representation for adverse drug event detection on twitter. *Applied Soft Computing*, 106:107324.

Chen Shen, Hongfei Lin, Kai Guo, Kan Xu, Zhihao Yang, and Jian Wang. 2019. Detecting adverse drug reactions from social media based on multi-channel convolutional neural networks. *Neural Computing and Applications*, 31(9):4799–4808.

Chen Shen, Hongfei Lin, Zhiheng Li, Yonghe Chu, Zhengguang Li, and Zhihao Yang. 2020. A graph-boosted framework for adverse drug event detection on twitter. In *2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pages 1129–1131. IEEE.

Karen Smith, Su Golder, Abeed Sarker, Yoon Loke, Karen Oâ€™Connor, and Graciela Gonzalez-Hernandez. 2018. Methods to compare adverse events in twitter to faers, drug information databases, and systematic reviews: proof of concept with adalimumab. *Drug safety*, 41(12):1397–1410.

Tiffany A Suragh, Smaragda Lamprianou, Noni E MacDonald, Anagha R Loharikar, Madhava R Balakrishnan, Oleg Benes, Terri B Hyde, and Michael M McNeil. 2018. Cluster anxiety-related adverse events following immunization (aefi): an assessment of reports detected in social media and those identified using an online search engine. *Vaccine*, 36(40):5949–5954.

Buzhou Tang, Jianglu Hu, Xiaolong Wang, and Qingcai Chen. 2018. Recognizing continuous and discontinuous adverse drug reaction mentions from social media using lstm-crf. *Wireless Communications and Mobile Computing*, 2018.

Abdullah Wahbeh, Tareq Nasralah, Omar El-Gayar, Mohammad A Al-Ramahi, and Ahmed El Noshokaty. 2021. Adverse health effects of kratom: An analysis of social media data.

Junxiang Wang, Liang Zhao, Yanfang Ye, and Yuji Zhang. 2018. Adverse event detection by integrating twitter data and vaers. *Journal of biomedical semantics*, 9(1):1–10.

Xuqi Wang, Xianfeng Wang, and Shanwen Zhang. 2022. Adverse reaction detection from social media based on quantum bi-lstm with attention. *IEEE Access*.

Yefeng Wang, Yunpeng Zhao, Dalton Schutte, Jiang Bian, and Rui Zhang. 2021. Deep learning models in detection of dietary supplement adverse event signals from twitter. *JAMIA open*, 4(4):ooab081.

Jiaheng Xie, Xiao Liu, and Daniel Dajun Zeng. 2018. Mining e-cigarette adverse events in social media using bi-lstm recurrent neural network with word embedding representation. *Journal of the American Medical Informatics Association*, 25(1):72–80.

Usama Yaseen and Stefan Langer. 2021. Neural text classification and stacked heterogeneous embeddings for named entity recognition in smm4h 2021. *arXiv preprint arXiv:2106.05823*.

Mengxue Zhang, Meizhuo Zhang, Chen Ge, Quanyang Liu, Jiemin Wang, Jia Wei, and Kenny Q Zhu. 2019. Automatic discovery of adverse reactions through chinese social media. *Data mining and knowledge discovery*, 33(4):848–870.

Tongxuan Zhang, Hongfei Lin, Yuqi Ren, Zhihao Yang, Jian Wang, Xiaodong Duan, and Bo Xu. 2021. Identifying adverse drug reaction entities from social media with adversarial transfer learning model. *Neurocomputing*, 453:254–262.

Ying Zhang, Shaoze Cui, and Huiying Gao. 2020. Adverse drug reaction detection on social media with deep linguistic features. *Journal of biomedical informatics*, 106:103437.

Tong Zhou, Zhucong Li, Zhen Gan, Baoli Zhang, Yubo Chen, Kun Niu, Jing Wan, Kang Liu, Jun Zhao, Yafei Shi, et al. 2021. Classification, extraction, and normalization: Casia_unisound team at the social media mining for health 2021 shared tasks. In *Proceedings of the Sixth Social Media Mining for Health (# SMM4H) Workshop and Shared Task*, pages 77–82.

Zeyun Zhou, Kyle Emerson Hultgren, et al. 2020. Complementing the us food and drug administration adverse event reporting system with adverse drug reaction reporting from social media: Comparative analysis. *JMIR Public Health and Surveillance*, 6(3):e19266.