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Review Article

Digital Surveillance and Artificial Intelligence in Detection of AEFI: A New Frontier in Vaccine Safety Monitoring

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ABSTRACT

The integration of digital surveillance and Artificial Intelligence (AI) technology constitutes a significant shift in Adverse Event Following Immunization (AEFI) monitoring. This review explores the artificial intelligence based approaches such as machine learning, Natural Language Processing (NLP), and blockchain technology to improve vaccination safety surveillance. Artificial intelligence provides the immediate and accurate identification of safety signals by using a variety of data sources, such as electronic health records, social media platforms, and mobile health applications. Social media analytics have shown great promise for early detection of AEFIs, but blockchain protects the integrity and transparency of safety data. Despite these advances, difficulties remain, including underreporting, inequities in healthcare infrastructure, and ethical considerations including data privacy and biased algorithms. Low-resource environments, in specifically, experience challenges due to insufficient digital infrastructure and employee abilities. The assessment emphasizes the importance of combining old passive reporting systems with modern digital tools to develop a comprehensive and balanced AEFI monitoring framework. By addressing these barriers enabling global collaboration, digital technologies can increase the effectiveness of AEFI surveillance, increase confidence in vaccination programs, and improve emergency response times. This innovation in vaccine safety monitoring has the ability to address existing gaps and provide a strong framework for global immunization safety.

Keywords: Adverse Event Following Immunization, Artificial Intelligence, Digital Surveillance, Vaccine Safety.

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INTRODUCTION

Maintaining public confidence in vaccination programs and ensuring the detection of unusual Adverse Event Following Immunization (AEFI) that may not be observed in clinical trials requires monitoring vaccine safety (Buttery and Clothier, 2022). Artificial Intelligence (AI) and digital surveillance are becoming more effective techniques for improving vaccine safety monitoring, especially when it comes to the identification of adverse events following vaccination. With the use of digital surveillance and artificial intelligence technologies, safety warnings might be identified more proactively and surveillance could occur almost instantly. Active surveillance systems that combine administrative, claims data and electronic health records are quickly emerging as a major global development trend in post-marketing vaccine safety monitoring (Sun *et al*., 2021).

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Compared to more conventional passive monitoring techniques, this strategy enables the earlier identification of any safety concerns. Utilizing natural language processing techniques for social media monitoring has also demonstrated potential for early identification of mentions of Vaccine Adverse Events (VAEMs) (Khademi Habibabadi *et al*., 2022). AEFI surveillance includes mobile health technology as an additional frontier. Compared to typical passive reporting, the use of SMS prompts for consumer-based vaccination safety monitoring greatly increased AEFI detection rates (Gold *et al*., 2021).

It's significant to note that while digital approaches have benefits, conventional passive reporting systems continue to have issues. Only 56.2% of nations reported ≥10 AEFI per 100,000 surviving newborns in 2019, according to a worldwide review, pointing to limitations in regular AEFI reporting (Salman, 2021). Artificial intelligence-enabled natural language processing and picture analysis can quickly identify possible adverse events by extracting valuable insights from unstructured data, including social media posts and electronic medical records (Zeng *et al*., 2021). Digital surveillance and artificial intelligence will probably become more crucial as vaccination systems develop, especially in response to global health emergencies like COVID-19, in order to ensure vaccine safety and maintain confidence in immunization programs (Teo, 2021). By improving vaccine safety surveillance systems and enhancing their capacity to proactively identify and promptly resolve safety problems, the use of these innovative techniques may eventually improve public confidence in immunization programs (Ball, 2014).

The Evolution of AEFI Monitoring: From Paper to Pixels

Adverse Events Following Immunization monitoring has advanced significantly, switching from paper-based to computerized methods. Conventional AEFI monitoring was dependent on pre-existing reporting systems, which frequently resulted in delays between the reporting of an event and its occurrence (Khademi Habibabadi *et al*., 2022). Underreporting and a lack of timeliness were two issues with these passive monitoring techniques (Laryea *et al*., 2019). Modern methods, on the other hand, improve AEFI monitoring by utilizing digital technology (Psihogios *et al*., 2022). Using smartphone technology, for example, the SmartVax program actively requests AEFI reports from vaccination recipients through automated SMS questionnaires (Westphal *et al*., 2016). Even with older populations, this approach showed great acceptability and response rates, indicating that it is a potential tool for almost real-time vaccination safety monitoring. It's interesting to observe that social media has become a valuable additional resource for tracking side effects of vaccinations. High accuracy has been achieved in extracting mentions of vaccine adverse events from Twitter tweets using the VAEM-Mine approach, which blends topic modeling and classification techniques (Khademi Habibabadi *et al*., 2022).

The speed, completeness, and sensitivity of vaccination vigilance have all greatly increased with the switch from paper-based to digital AEFI monitoring systems. SafeVac and other mobile apps have demonstrated the viability of collecting AEFI data over extended periods (Nguyen *et al*., 2021). Tracking vaccination safety has shown to be successful using traditional AEFI monitoring methods, such as China's National Adverse Event Following Immunization Surveillance System (NAEFISS) (Hu *et al*., 2023). It is become more and more obvious that advances are moving into the digital realm. According to an evaluation of Ethiopia's preparedness for deploying active AEFI surveillance, technologies that support both paper-based and electronic-based recording are required (Zeleke *et al*., 2023). The utilization of international databases such as VigiBase for AEFI signal disproportionality analysis serves as another example of this transformation (Kim *et al*., 2024). The shift to digital has been accelerated by the COVID-19 pandemic. The vaccine safety service in Victoria, SAEFVIC, quickly modified its systems to handle higher report volumes by combining data from both active and spontaneous surveillance. They generated public-facing vaccination safety reports, created databases specifically for AESI for improved monitoring, and deployed technologies to automate, filter, and triage reports (Laemmle Ruff *et al*., 2022).

Harnessing Big Data: Social Media and AEFI Signal Detection

Social media platforms have become important sources of information for tracking vaccination safety signals and adverse occurrences after immunizations. Research has indicated the effectiveness of using social media data, specifically Twitter, in order to obtain a basic understanding of vaccination safety concerns (Habibabadi *et al*., 2023; Khademi Habibabadi *et al*., 2022). Using natural language processing techniques, the VAEM-Mine approach developed in one research, extracted mentions of vaccination adverse events from Twitter tweets with good accuracy (F1 score of 0.91) (Khademi Habibabadi *et al*., 2022). Additional studies showed that 3 million tweets on COVID-19 vaccinations were gathered and examined. Topic modeling and machine learning were used to detect individual vaccine reactions (Habibabadi *et al*., 2023). Through the provision of more timely data and the opportunity to capture instances that may be unreported through official channels, these social media-based initiatives can serve as a valuable supplement to standard AEFI reporting systems (Habibabadi *et al*., 2023; Khademi Habibabadi *et al*., 2022).

Additionally, social media and internet search engine results might be helpful tools for finding reports of AEFIs connected to cluster anxiety that might not be included in Conventional scientific research (Suragh *et al*., 2018). After developing which extracted Vaccine Adverse Event Mentions (VAEMs) from Twitter with high accuracy, 8,992 VAEMs were found among the more than 800,000 tweets pertaining to vaccines (Khademi Habibabadi *et al*., 2022). In the same way, different research found people who had directly experienced COVID-19 vaccination responses on Twitter and confirmed its findings using an established method for reporting vaccine reactions (Habibabadi *et al*., 2023). These methods get over the drawbacks of passive systems, such as their underreporting and lack of timeliness. Utilizing the potential of big data from social media and other digital sources to improve vaccination pharmacovigilance and AEFI signal detection is significant (Khademi Habibabadi *et al*., 2022).

Machine Learning Algorithms in AEFI Pattern Recognition

In multiple aspects, AEFI detection and monitoring has been enhanced via machine learning and advanced data analysis techniques including (i) Near real-time surveillance: to detect any potential risks more efficiently, experts are investigating into techniques to gather data closer to real-time (Sun *et al*., 2021). (ii) Utilization of electronic healthcare data: there is an opportunity to improve AEFI signal monitoring with the increasing quantity of electronic healthcare data (Mesfin *et al*., 2020). (iii) Social media monitoring: Vaccine-related adverse events are gathered from social networking platforms such as Twitter using natural language processing techniques (Khademi Habibabadi *et al.*, 2022). (iv) SMS-based surveillance: SMS-based surveillance significantly improved AEFI detection rates compared to conventional passive monitoring techniques (Gold *et al.*, 2021).

Machine Learning (ML), which offers various advantages over conventional techniques, is becoming more widely acknowledged as a useful tool for tracking vaccination safety. Large amounts of data from a variety of sources, such as national claim databases and electronic health records, may be processed effectively by ML algorithms, which can then identify possible adverse effects following vaccination with high accuracy (Kim *et al.*, 2021). For active surveillance systems, which proactively detect information on AEFI and promptly look into any safety warnings, this feature is extremely significant (Sun *et al.*, 2020). Random forests, logistic regression, and support vector machines are a few supervised machine-learning techniques that have demonstrated potential for AEFI identification (Carrell *et al.*, 2023). These techniques are capable of identifying possible safety signs by analyzing intricate patient data. While less common, artificial neural networks and naive Bayes classifiers have also been used (Koutanaei *et al.*, 2015).

Improvements were observed in the prediction and detection of the severity of adverse effects following immunization using ML models. XG Boost models had been used in identifying and predicting mild to severe side effects (Levi *et al.*, 2024). Clinical report AEs have been successfully identified and cataloged using Large Language Models (LLMs) (Li *et al.*, 2024). Remarkably, other machine learning techniques have also been used in research related to vaccines, even though LLMs demonstrate promise in AE identification.

Electronic medical data have been analyzed using natural language processing algorithms in order to identify potential side effects of vaccinations. Using confidential coding, the MediClass system was able to identify both gastrointestinal-specific and generic AEFIs in clinical notes, surpassing conventional approaches that just use diagnostic codes (Hazlehurst *et al.*, 2009).

Machine learning algorithms have shown significant results in a range of medical applications, such as the identification and categorization of unfavorable events that occur after vaccination schedules (Ghaffar Nia *et al.*, 2023). Their ability to analyze large datasets, identify complex patterns, and make accurate predictions has made them invaluable tools in the field of public health surveillance (Zeng *et al.*, 2021). Predictive analytics is one of the main uses of machine learning in adverse event after vaccination pattern detection (An *et al.*, 2023). Healthcare practitioners may be able to detect high-risk people or populations for adverse events after vaccination by utilizing machine learning algorithms (Sidey-Gibbons *et al.*, 2019).

Natural Language Processing: Decoding Patient-Reported AEFIs

An increasingly useful technique for examining and comprehending patient-reported adverse events after immunizations is natural language processing, or NLP. Natural language processing techniques might be utilized for gathering appropriate information from social media posts, patient records, and medical reports in order to identify relevant AEFI signs (Dong *et al.*, 2024). These methods evaluate on a both syntactic and semantic level, addressing problems such as identified categorization, sentiment analysis, and determined classification (Pattanayak, 2023). Handling language appropriate to a certain area and individualized comprehension is one of the challenges in using natural language processing to the identification of AEFI signals (Gour, 2020).

Numerical language processing approaches have the potential to extract meaningful information from huge quantities of text data, such as reports on vaccination safety and patient suggestions (Dong *et al.*, 2024). NLP-based methods have demonstrated potential in vaccination safety surveillance by recognizing and eliminating disproportionality signals associated with listed AEFIs, thereby enhancing signal management. 17% of disproportionality signals for COVID-19 vaccinations might be rejected using an NLP-based method, according to research that used the Vaccine Adverse Event Reporting System (VAERS). This might result in a better use of time and resources in signal management (Dong *et al.*, 2024).

Researchers and medical practitioners may examine huge patient-reported adverse event file index databases more quickly and effectively by using natural language processing. This might result in better vaccination safety monitoring and more focused actions to allay public fears (Dong *et al.*, 2024). The analysis of patient-reported data has become an essential component of modern healthcare due to the increased emphasis on patient-centered treatment and the increasing implementation of electronic health records (Li *et al.*, 2022). Particularly, natural language processing methods have become an effective means of drawing conclusions from the unstructured textual data present in adverse event reports submitted by patients (Allabun and Soufiene, 2023). Although these details can be difficult to collect using typical structured data fields alone, natural language processing's ability to effectively extract and assess the occurrence and severity of adverse events is a considerable benefit (Young *et al.*, 2019). In the context of patient safety monitoring and quality improvement activities, the utilization of computational approaches to analyze free-text notes may provide an enhanced understanding of the patient experience (Ozonoff *et al.*, 2022).

Blockchain Technology: Ensuring Data Integrity in AEFI Reporting

Adverse Events Following Immunization reporting can greatly benefit from the Distributed Ledger Technology (DLT) of blockchain (Xu *et al*., 2022). AEFI data integrity and traceability may be guaranteed by blockchain's distributed and immutable nature (Liu *et al*, 2020; Roberts *et al*., 2023). The distributed ledger technology's Data Block Matrix (DBM) version permits controlled data revision or deletion while maintaining integrity (Roberts *et al*., 2023). DLT on blockchain improves data security, privacy, and integrity for healthcare applications. It enables the secure transmission and administration of confidential medical information, such as AEFI reports and patient records (Liu *et al*, 2020; Thakur, 2022). Enhancing confidence and transparency in the healthcare field blockchain's decentralized structure ensures that data is immutable and resistant to modification (Alkan, 2021; McBee and Wilcox, 2020). Blockchain can offer a simple to use, transparent, and safe way to record and track adverse events in the background of AEFI reporting. Further, Data Block Matrix (DBM), a DLT variation that permits controlled data alteration or deletion while ensuring integrity assurance. DBM is particularly useful for applications that must adhere by privacy requirements that require the deletion of user data upon request due to its unique features. The integrity of the data is preserved since the system can keep an immutable ledger of each transaction, guaranteeing that once AEFI data is stored, it cannot be modified or withdrawn (Dhanalakshmi and Babu, 2019). It is important, while that the immutability of blockchain may provide difficulties in maintaining to privacy laws including General Data Protection Regulation (GDPR), which mandate the capability to eliminate personal information upon request (Suripeddi and Purandare, 2021). However, to address this, developments like the Data Block Matrix have been developed, which permits regulated data modification or deletion while maintaining the blockchain's integrity-preserving aspects (Roberts *et al*., 2023).

Ethical Considerations in AI-Driven AEFI Surveillance

AI-driven AEFI surveillance systems raise important ethical considerations that need to be carefully addressed. Privacy and data protection are key concerns when implementing AI-based surveillance of AEFI. These systems often rely on collecting and analyzing large amounts of personal health data, which must be handled securely and in compliance with regulations (Zeleke *et al*., 2023). Ensuring public confidence requires transparency, responsibility, accountability and comprehensibility in the AI systems used for AEFI identification and analysis (Cheong, 2024; Habli *et al*., 2020). The ethical implications of AI applications in healthcare must be carefully assessed since they have the potential to greatly affect patient outcomes, privacy, and overall quality of treatment (Rogers *et al*., 2021; Solomonides *et al*., 2022). In order to address concerns like beneficence, nonmaleficence, autonomy, and justice—basic concepts in medical practice—ethical standards for AI in healthcare are required (Solomonides *et al*., 2022). These suggestions might help in ensuring that sure AI systems are developed and utilized in an approach that prioritizes patient safety first, maintains individual rights, and encourages impartial healthcare findings (Tahri *et al*., 2023).

Global Implications:Bridging AEFI Reporting Gaps in Low-Resource Settings

Public trust and safety in vaccination programs are the primary concerns, but in low-resource areas with potentially inadequate healthcare infrastructure and diagnostic abilities, it might be difficult to conduct thorough monitoring and reporting of adverse events that occur after immunization (Constantine *et al*., 2018; Lamichhane and Neupane, 2022). Over the past ten years, aims to improve vaccination safety monitoring systems across the world had made progress, but there are still large gaps, especially in low-resource settings (Salman, 2021). To improve AEFI surveillance, some countries have used digital methods. Australia has established programs such as Vaxtracker and SmartVax, as well as Canada utilizes the Canadian National Vaccine Safety (CANVAS) Network (Psihogios *et al*., 2022). A major challenge is Healthcare Workers' (HCWs') lack of training and understanding of reportable AEFIs, reporting systems, and processes (Abdu *et al*., 2022; Aborigo *et al*., 2022). Research showed that healthcare workers frequently are hesitant to disclose AEFIs as they concern about the consequences for themselves and the public's opinion (Lv *et al*.,2022; Thomas *et al*., 2021). The fear of raising unnecessary public alarm about vaccines is a prominent barrier, with 61.76% of healthcare workers citing this as a reason for not reporting AEFIs (Lv *et al*.,2022). Furthermore, 15.7% of respondents reported that the fear of facing personal consequences discourages them from reporting (Thomas *et al*., 2021). Reporting is also discouraged by fear of consequences on an individual's part or of getting blamed by superiors (Aborigo *et al*., 2022; Gidudu *et al*., 2020). Additionally, AEFI surveillance participation among HCW is decreased by excessive workloads, a lack of enthusiasm, and insufficient feedback on reports that are turned in (Aborigo *et al*., 2022). Further, AEFI discussion during supervisory visits was substantially linked to an increase in HCW reporting (Gidudu *et al*., 2020). This emphasizes how crucial it is for leaders to continue to communicate and offer assistance. Structural challenges might be addressed by making reporting procedures simpler, providing rewards, and including AEFI reporting into regular monitoring (Aborigo *et al*., 2022). Multiple strategies are required to close these gaps. More timely AEFI identification may also be supported by utilizing digital advances and social media monitoring (Gold *et al*., 2021; Nyambayo *et al*., 2022). Strong pharmacovigilance programs are ultimately necessary to sustain public confidence in vaccinations and overcome resistance (Nyambayo *et al*., 2022; Yamoah *et al*., 2023).

The Future of AEFI Monitoring:Predictive Models and Real-Time Analysis

Technological developments in artificial intelligence and machine learning changed the health care sector while unlocking up possibilities for innovative techniques of post-licensure vaccination safety surveillance (de hond *et al*., 2022). Increasingly, adverse reactions following vaccination signals are being detected in near real-time by using routinely obtained electronic healthcare data, such as immunization and medical records (Mesfin *et al*., 2019). In AEFI surveillance, data comparability and standardization are essential. To compare data from surveillance systems and clinical trials, common case definitions and protocols for case classification, recording, and data presentation must be developed (Bonhoeffer *et al*., 2002).

There is a trend towards implementing active surveillance and other methods into vaccination safety programs, as passive reporting systems have certain limits. These include keeping a look toward new data sources, actively screening for certain illnesses, and utilizing real-time techniques to identify changes in vaccination safety data (Crawford *et al*., 2014). The utilization of predictive analytics in monitoring unfavorable occurrences after vaccination has increased in significance as healthcare organizations work to improve patient safety and outcomes (Buttery and Clothier, 2022). Predicting and analyzing AEFI data is gradually utilizing machine learning and deep learning algorithms (Sghir *et al*.,2023). Large numbers of various data forms, including unstructured and structured information from several sources, may be processed according to these strategies. Platforms for real-time streaming, such as Apache Flink, can collect, transfer, and preprocess data streams in order to use deep learning models for predictive analytics (Dinakar and Vagdevi, 2023).

Challenges and Limitations of Digital AEFI Surveillance System

In digital AEFI reporting, completeness and data quality are key considerations. Two major issues that need to be addressed are incomplete AEFI case investigations and delays in prompt AEFI identification (Mesfin *et al*., 2020). Limitations in some nations are also mentioned, such as the lack of data provided through passive surveillance systems and the delays in investigating into serious adverse events. In particular circumstances, there are problems with regulatory policies, guidance documents, and reporting requirements. For instance, the pharmacovigilance system in Pakistan was lacking enough regulatory policies or reporting requirements at initially (Hagos *et al*., 2024). The absence of rules, regulations and proclamations pertaining to AEFI surveillance was also identified as a gap in Ethiopia. It could be challenging to accommodate recording methods that are both paper-based and electronic-based. It was determined that in order to successfully execute active AEFI surveillance, a system that can handle both forms was required (Zeleke *et al*., 2023). Compared with standard reporting systems, social media monitoring has potential as an additional data source, but there are still difficulties in authenticating and analyzing the data (Habibabadi *et al*., 2023). Underreporting remains a major problem in the field of digital AEFI monitoring systems. For instance, between 1991 and 2001, just 2.7 AEFI incidents per 100,000 vaccination doses were documented in Switzerland, indicating a significant underreporting rate (Schumacher *et al*., 2010). Similarly, with recent modifications to the surveillance system, the number of major AEFIs reported in India remains significantly lower than predicted (Joshi *et al*., 2018). According to Zimbabwe's AEFI surveillance system review, incomplete case investigations and delays in AEFI detection are ongoing challenges (Nyambayo *et al*., 2022). International data comparison is limited by the lack of consistency in AEFI definitions and reporting throughout monitoring systems. According to a comprehensive evaluation of 74 research on maternal immunization, there was an abundance of variation in the definition, estimation, and reporting of AEFIs (Fulton *et al*., 2015).

CONCLUSION

The integration of AI and digital surveillance in AEFI monitoring has completely transformed vaccine safety surveillance. While traditional systems faced challenges like underreporting, delays, and inconsistent data quality, advances in AI-driven tools, such as machine learning algorithms and natural language processing, have enabled real-time detection and analysis of adverse events. The usage of blockchain protects data security, while social media and mobile health apps have increased the rate and depth of safety signal detection, particularly during health emergencies. Despite these advances, issues like as data privacy, ethical concerns, and poor acceptance in low-resource areas remain.

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ABBREVIATIONS

AEFI: Adverse Event Following Immunization; **AI:** Artificial Intelligence; **ML:** Machine Learning; **NLP:** Natural Language Processing; **LLMS:** Large Language Models; **EHR:** Electronic Health Record; **DLT:** Distributed Ledger Technology; **GDPR:** General Data Protection Regulation.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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