Journal of Infection and Public Health 17 (2024) 102514

Contents lists available at ScienceDirect

Journal of Infection and Public Health

journal homepage: www.elsevier.com/locate/jiph

Enhanced event-based surveillance: Epidemic Intelligence from Open Sources (EIOS) during FIFA World Cup 2022 Qatar

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ARTICLE INFO

Article history:
Received 15 February 2024
Received in revised form 24 July 2024
Accepted 1 August 2024

Keywords:
FIFA World Cup 2022 Qatar
Epidemic Intelligence from Open Sources
Digital disease surveillance
Risk prediction

ABSTRACT

Background: Public health threats can significantly impact mass gatherings and enhancing surveillance systems would thus be crucial. Epidemic Intelligence from Open Sources (EIOS) was introduced to Qatar to complement the existing surveillance measures in preparation to the FIFA World Cup Qatar 2022 (FWC22). This study estimated the empirical probability of EIOS detecting signals of public health relevance. It also looked at the factors responsible for discerning a moderate-high risk signal during a mass gathering event.
Methods: This cross-sectional descriptive study used data collected between November 8th and December 25th, 2022, through an EIOS dashboard that filtered open-source articles using specific keywords. Triage criteria and scoring scheme were developed to capture signals and these were maintained in MS Excel. EIOS' contribution to epidemic intelligence was assessed by the empirical probability estimation of relevant public health signals. Chi-squared tests of independence were performed to check for associations between various hazard categories and other independent variables. A multivariate logistic regression evaluated the predictors of moderate-high risk signals that required prompt action.
Results: The probability of EIOS capturing a signal relevant to public health was estimated at 0.85 % (95 % confidence interval (CI) [0.82 %–0.88 %]) with three signals requiring a national response. The hazard category of the signal had significant association to the region of occurrence (χ^2 (5, N = 2543) = 1021.6, $p < .001$). The hazard category also showed significant association to its detection during matchdays of the tournament (χ^2 (5, N = 2543) = 11.2, $p < .05$). The triage criteria developed was able to discern between low and moderate-high risk signals with an acceptable discrimination (Area Under the Curve=0.79).
Conclusion: EIOS proved useful in the early warning of public health threats.

Abbreviations: CBRN, Chemical, biological, radiological, and nuclear; COVID-19, Coronavirus disease 2019; EBS, Event Based Surveillance; ECDC, European Centre for Disease Prevention and Control; EIOS, Epidemic Intelligence from Open Sources; EMRO-WHO, Eastern Mediterranean Regional Office - World Health Organization; EWARS, Early Warning and Alert Response System; FIFA, Fédération Internationale de Football Association; FWC22, FIFA World Cup 2022; IBS, Indicator-Based Surveillance; IHR, International Health Regulations; MERS-CoV, Middle East Respiratory Syndrome-related Coronavirus; MOPH, Ministry of Public Health; PHEOC, Public Health Emergency Operation Center; RSV, Respiratory Syncytial Virus; WHO, World Health Organization

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https://doi.org/10.1016/j.jiph.2024.102514

Introduction

The FIFA World Cup 2022 (FWC22) was held in Qatar between November 20th and December 18th, 2022. Approximately 1.5 million visitors from over 32 nations attended the tournament's 64 matches [1]. Mass gatherings such as the World Cup can promote social cohesion and cultural exchange, while generating positive economic impacts [2]. However, mass gatherings can pose potential public health risks due to the concentration of large crowds in a compact geography, facilitating the transmission of infectious diseases such as influenza or coronavirus disease 2019 (COVID-19), as well as heat-related illnesses, injuries, and crowd-related incidents such as stampedes or riots [3]. Because of these factors, mass gatherings require an essential expansion and enhancement of public health surveillance.

In preparation to FWC22, Qatar strengthened its existing electronic system of Indicator-Based Surveillance (IBS) through accelerated and frequent reporting of notifiable diseases [4]. Event-Based Surveillance (EBS) was enhanced through an improved regional media scan, community engagement initiatives and it aimed to cover the drug consumption trends, animal and environmental health during FWC22. The Epidemic Intelligence from Open Sources (EIOS) initiative led by the World Health Organization (WHO) aimed to automatize and enhance internet media scanning. The application aggregated reports from official traditional media, aligning with the goals of an international surveillance system to quickly detect health events [5]. Open-source data, despite its wide availability online, needs to be processed to achieve relevant and true reports of potential health hazards [6]. Independent monitoring of various databases (Global Public Health Intelligence Network, Global Health Security Initiative, ProMed, HealthMap etc.) [7] gave way to newer applications include BlueDot, Metabiota and Epitweetr, all of which process data to tackle distinct aspects of surveillance. The EIOS conveniently integrates multiple public health intelligence platforms. The real-time updates, automated filtering, specific dashboards, and convenient visualization were other key factors which deemed EIOS the tool of choice for the FWC22 [8].

It was introduced in Qatar in March 2022 as part of the planned expansions to EBS [9]. EIOS utilized publicly available information from various surveillance networks and systems to strengthen public health intelligence in a unified all-hazards, One Health approach [10]. The system enabled early detection, verification, assessment, and communication of public health signals by filtering open-source articles through pre-determined keywords.

The Ministry of Public Health (MOPH) Qatar and the Eastern Mediterranean Regional Office - World Health Organization (EMRO-WHO) instituted an EBS team six months prior to the tournament. In addition, the European Centre for Disease Prevention and Control's (ECDC) Epidemic Intelligence Group was established to exchange daily findings. A global collaboration fostered transparency and trust, promoted knowledge exchange, and ensured collective health security [11,12]. The partnership was strategically conceived, leveraging the technical expertise and health intelligence capabilities of EMRO-WHO in the Middle East and the ECDC across European countries.

Epidemic intelligence can be defined as all the activities related to the early identification of potential health threats, their verification, assessment, and investigation to recommend public health measures to control them [13,14]. Data sourcing and analytics are key in this regard. Internet based surveillance systems have complemented traditional methods in the early detection of communicable diseases like Ebola [15] Monkeypox [16] and COVID-19 [17]. After information extraction, a risk assessment is conducted for targeted prevention and control measures. While most of these assessments are carried out through expert review, developing a framework can standardize the process. The results of these risk assessments may not suit all geographical regions alike and needs to be continually customized to improve its performance. However, documenting its use in various countries and regions can pave the way for cross-border collaboration and development of methods to automate signal assessment. [18,19].

The EIOS was adopted in several countries to significantly improve the functionality of their EBS [9,20–24]. It served the WHO as one of the key information sources for public health intelligence during the COVID-19 pandemic [25,26]. A detailed study on the impacts of COVID-19 on healthcare workers utilized EIOS to process 3299,158 media reports, effectively narrowing down to 5131 relevant articles, representing approximately 0.15 % of the total [27]. The EIOS effectively mapped the risk of Crimean-Congo hemorrhagic fever and identified high risk areas. The system retrieved 365 articles of which 141 (37 %) were considered as occurrence points for the disease [28]. The World Organization for Animal Health relied on EIOS as one of their data sources to evaluate the sensitivity of their notification system. The results suggest that EIOS had contributed to identifying unreported disease incidents [29].

Despite EIOS being widely employed for surveillance and detailed analysis of open-source data, there are few studies describing its results and evaluating its role in early warnings and subsequent impact [30]. In Qatar, the main objectives of using EIOS during a mass gathering event were to boost the existing EBS and incorporate a near real-time surveillance to detect public health threats that may impact the FWC22 tournament. We anticipated a greater volume of signals during matchdays compared to training days. Likewise, a higher number of signals were expected to fall under the category of air-borne diseases due to the ongoing pandemic. We also considered various factors like geography, disease spread, and severity while designing the data collection method.

This study aimed to explore the probability of capturing signals relevant to public health and describe their characteristics using EIOS during the FWC22. It studied the relationship between various health hazard categories and their region of occurrence. It analyzed whether signal detection on matchdays was related to the type of hazard. It also attempted to model the likelihood of identifying a moderate-high risk event with the triage criteria developed for public health surveillance during a mass gathering event in Qatar. The findings of this study contribute valuable insights to the growing body of evidence on how epidemic intelligence through EIOS can enhance EBS systems in detecting early warnings [8,31,32]. Additionally, the paper documents the EIOS experience, detailing its customization for use in a mass gathering event, which can stand as a reference for other stakeholders in their preparations for similar events.

Methodology

Study design and data collection

This cross-sectional descriptive study used data retrieved from the EIOS between November 8th and December 25th, 2022. MOPH, with assistance from EMRO-WHO, established an EIOS dashboard which employed machine learning to filter and categorize open-source articles. Authorized staff de-duplicated, and triaged the signals, ensuring real-time processing [33]. Disease name, characteristics (priority level, potential to spread, healthcare system impact etc.), region and date of occurrence were captured from corresponding media reports and maintained in Microsoft Excel. The EMRO-WHO and ECDC offices shared relevant signals with MOPH daily, where these were compiled and finalized. The activity focused on detecting a pre-identified list of infectious diseases and public health threats from selected countries (See Supplementary Material A for the list of keywords used to filter the articles). These were categorized into six general hazard categories for ease of analyses.

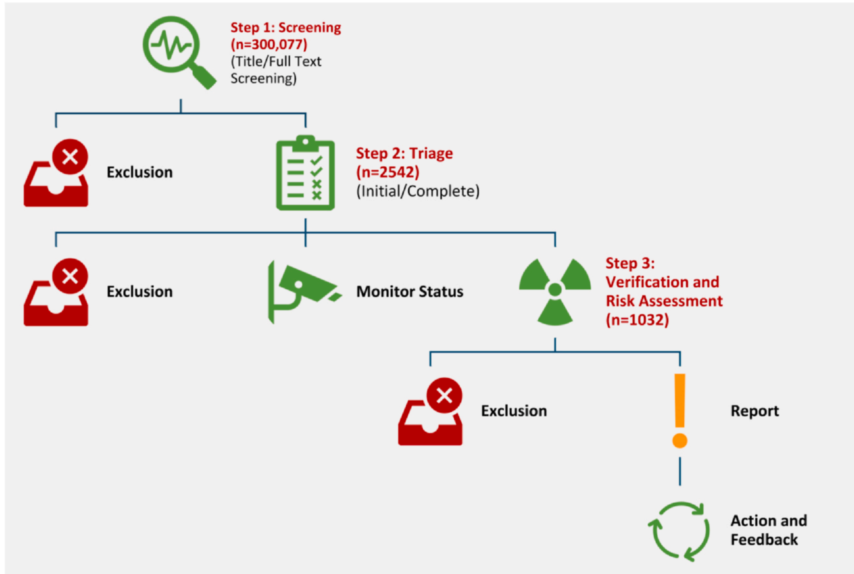

Fig. 1. Steps followed in processing the articles filtered by the EIOS FWC22 dashboard.

The steps followed in processing the articles filtered by the EIOS dashboard is as follows (Fig. 1):

Step 1 (Screening): All articles (n = 300077) that appeared on the EIOS FWC22 dashboard were title screened. This step excluded irrelevant, duplicate, incomplete, or unconfirmed news/articles. The remaining articles underwent a full text screening. Those relevant to public health were considered signals (n = 2543).

Step 2 (Triage): The triage was a two-step process — initial and complete — performed according to pre-determined criteria. The scoring received during triage decided whether the article was eligible for verification, risk assessment and reporting. The initial triage was based on only criteria 1: 'Is the signal in Qatar or likely to be imported to Qatar?'. If the article scored at least 1 in the initial triage, it proceeded to a complete triage (n = 1811), covering the rest of the criteria (Table 1).

Step 3 (Verification and Risk Assessment): Following triage, the signals that scored 3 and above were subjected to verification and an immediate risk assessment by a group of three experts at MOPH. The factors considered for the risk assessment are laid out in Table 2. The signals were classified into low, and moderate-high risk categories, based on an overall risk status (n = 1032).

The high-risk signals were sent to the Public Health Emergency Operation Center (PHEOC) at the MOPH for a national response coordination. This was done through a unified command center at the "Surveillance and Response to Epidemics" section at the MOPH, Qatar which generated epidemic intelligence by integrating information from all the different surveillance approaches employed [9].

Table 1
Criteria and scoring used for Triage of EIOS signals.

SN	Criteria	Score
1	**Is the signal in Qatar or likely to be imported to Qatar**	0: Not in Qatar; Not likely to be imported to Qatar (**Discarded**) 1: Could be imported to Qatar 3: Signal is in Qatar
2	Priority/unusual/eliminated/ eradicated disease?	0: No 1: Yes
3	Had potential to highly impact the health care system?	0: No 1: Yes
4	Had potential for international spread or interference to trade?	0: No 1: Yes
5	Chemical, biological, radiological, and nuclear (CBRN) or terroristic threats?	0: No 1: Yes
6	Highly political, sensitive issue/ media attention expected?	0: No 1: Yes
Result		0: Discard Signal 1 –3: Monitor Signal 3 and Above: Risk Assessment

Statistical methodology

Signal characteristics were reported with frequency and percentage. The probability of capturing articles relevant to public health from EIOS was calculated using an empirical probability estimation. The number of articles triaged was divided by the total number of articles that appeared on the dashboard. Chi-square test for independence and post hoc-analysis with Bonferroni adjusted p-values was done to determine if there is a significant association between the hazard categories and other variables (region, detection on matchdays, etc.). Contribution of variables was assessed by calculating standardized Pearson's residuals and percentage contribution.

For signals that underwent risk assessment, we estimated the relationship between the assigned risk status and other independent variables including triage criteria using a non-weighted multivariate binary logistic regression. The risk categories were collapsed to 'low' and 'moderate-high' for this purpose. The model was checked for interactions and adjusted using the AIC (Akaike Information Criterion) mixed selection method. Irrelevant predictor variables were dropped to optimize the model. The quality of the model was measured by plotting the Receiver Operating Characteristic (ROC) curve.

R v 4.3.1 was used for all statistical analyses. The glm package was used to perform the logistic regression.

Ethical considerations

The study does not involve human subjects, and all data utilized were obtained from open-source repositories using EIOS. Therefore, ethical approval was not required.

Data availability

The raw data were generated at the Ministry of Public Health, Qatar. Derived data supporting our findings are available from the corresponding author upon request.

Table 2
Risk assessment matrix for EIOS signals that received a score of 3 and above during triage.

Risk Level	Potential impact on the tournament	Potential IHR Response	Event transmission augmented by mass gatherings	Incubation period	Ability to cause severe morbidity or death.	Familiarity/system capacity to respond	Political/media attention	Recommended Actions
Low	Minor impact	No IHR communication required/if event outside Qatar.	Not augmented.	More than 5 days.	No admission/ death.	Event happened many times in Qatar, control measures available.	No political or media attention.	Managed according to standard response protocols, routine control programs and regulation (e.g., routine surveillance).
Moderate	Moderate impact	Not notifiable under the IHR. Requires communication to WHO & National Agencies as FYI	Slightly augmented.	2–5 days.	Small proportion admitted, low CFR and not rising.	Event occasionally happened in Qatar.	Low political or media attention/no spread of news in the community.	Specific roles assigned for response, monitoring or control measures were required (e.g., enhanced surveillance, additional vaccination campaigns).
High	Significant impact	Notifiable under IHR. Requires communication between National Agencies.	Severely aggravated (e.g., direct transmission, food borne).	Less than 2 days.	High proportion admitted, CFR rising daily.	Event rarely/never happened in Qatar.	Highly political/ widespread news in the community.	Involvement of senior management: establishment of command-and-control structures; control measures targeting significant outcomes.

Results

A total of 2543 articles were triaged from 300,077 articles that appeared on the dashboard, estimating the probability of detecting signals relevant to public health at 0.85 % (95 % confidence interval (CI) [0.82 %–0.88 %]). From these, 1032 signals underwent a risk assessment and 343 (0.1 %, 95 % CI [0.10 %, 0.13 %]) moderate-high risk signals with potential impact on the games were identified. Three signals were declared events of concern that required immediate attention from the PHEOC. These reports included mostly rumors about the Middle East Respiratory Syndrome coronavirus (MERS-CoV) and were treated and managed as infodemics. None of the signals required the activation of the IHR communication mechanism.

The chi-squared test of independence found significant association between hazard categories and the region of signal occurrence, (χ^2 (5, N = 2543) = 1021.6, $p < .001$). After post-hoc comparison with Bonferroni adjusted p-values, we concluded that a higher number of 'Miscellaneous' signals (percentage contribution =75.24) were noted among those that occurred in Qatar. In comparison, the frequency of other category signals occurring in Qatar were statistically similar. The test also found a significant association between hazard categories and detection of signals during matchdays, (χ^2 (5, N = 2543) = 11.2, $p < .05$). Vector-borne diseases were less likely to be reported during matchdays while other categories showed statistically similar trends (Table 3).

In the multiple binary logistic regression, hazard categories, region of occurrence, healthcare system impact, international spread and political sensation emerged as independent predictors for differentiating between high-moderate and low risk signals (Table 4). Based on the receiver operating characteristic (ROC) curve, the model performed decently, with an area under the curve (AUC) score of 0.79 and can be relied on to predict the risk status of a random signal.

Discussion

Instances where EIOS was previously employed for health surveillance include Tokyo Paralympic Games [34] and implementation of epidemic intelligence in Africa [32]. It can be noted that the proportion of relevant signals captured from through EIOS was low as reported in the previous studies ranging between 0.15 % and 37 % [27,28]. In our study, the probability of capturing relevant signals was estimated at 0.85 %, which concurred with previous findings.

The signals (n = 2542) were distributed among various hazard categories with the highest proportion related to 'air-borne diseases' (39.9 %, 95 % CI [37.9 %–41.9 %]). This was an expected finding owing to the COVID-19 pandemic [35] and the high interest and advancements in the field of influenza surveillance [36,37]. However, while vector-borne diseases were a concern, they could have been deprioritized during the tournament, considering the socio-economic status and absence of mosquito vectors responsible for dengue and chikungunya in Qatar [38,39]. We also found that signals that occurred in Qatar were more likely to be categorized as 'miscellaneous' (which included chemical, biological, radiological, nuclear (CBRN) events, fake news, sensationalism, bioterrorism etc.). From examining these studies and our findings, it appears that EIOS worked better in detecting early warnings of 'airborne diseases' at a global scale and 'miscellaneous' threats at a regional scale. The high number of 'miscellaneous' signals detected locally is likely due to the greater media attention that the FWC22 tournament garnered and how news-reports shaped public perception in terms of the health measures adopted by Qatar [40].

According to results of the logistic regression, the signals that occurred in Qatar had 6.02 times the odds for signals that occurred elsewhere to be deemed moderate-high risk. Similarly, the signals

Table 3
Descriptive statistics and chi-squared test results for signals detected from EIOS.

Characteristics comparison between general hazard categories (n = 2543)	**n (%, 95 % CI [LL%, UL%])***	**χ^2 (df)***	***p*-value**
Total articles	300077		
No of signals (n)	2543 (0.85, [0.82, 0.88])		
General Hazard	**n = 2543**		
Airborne diseases	1015 (39.9, [37.9, 41.9])		
Food and water-borne diseases	316 (12.4, [10.4, 14.5])		
Zoonosis	532 (20.9, [18.9, 22.9])		
Vector-borne diseases	290 (11.4, [9.4, 13.4])		
STD/direct transmission	121 (4.8, [2.8, 6.8])		
Miscellaneous	269 (10.6, [8.6, 12.6])		
Region of occurrence		1021.6 [5]	**< 0.001**
Qatar	314 (12.3, [11.1, 13.7])		
Outside Qatar	2229 (87.6, [86.3, 88.9])		
Signal detected on matchdays		11.221 [5]	**< 0.05**
No	1274 (50.1, [48.1, 52.1])		
Yes	1269 (49.9, [47.9, 51.9])		

* CI: Confidence Interval; LL: Lower Limit; UL: Upper Limit; df: degrees of freedom

with high political and sensational value, those with an impact on the healthcare system and those that spread internationally has significantly higher odds of being considered moderate-high risk. Our findings corroborate other papers which underscores the risks of global transmission [41] and mass casualty incidents [42] that occur during mass gathering events. It also points to how media sensationalism and fake news reduces the trust and behavioral intentions of the public [43,44]. The results also indicate that the triage criteria developed for the purpose of FWC22 has achieved a decent accuracy in identifying moderate-high risk signals (AUC score = 0.79). Though the syndromic surveillance and IBS in Qatar was quicker in identifying local public health threats, EIOS effectively identified global signals of concern. Comparing the epidemic intelligence gathered from the overall public health surveillance system in Qatar, the EIOS contributed to identifying around 5 % of the events of concern that were reported to the PHEOC, which is noteworthy [9].

Limitations

Human resources prove essential in using the EIOS platform [45]. Having to process huge data to achieve relevant results raises a question of resource efficiency and sustainability. Manual triaging, time constraints in de-duplication, misclassification of signals, and difficulties in uniform data capture were challenges that may have affected the data quality. Usually, the accuracy of a model is judged

Table 4
Results of multivariate binomial logistic regression for risk assessed signals.

Multivariate binary logistic regression (n = 1032)	**n (%, 95 % CI [LL%, UL%])***	**adjusted OR***	**95 % CI***	***p*-value**
No of articles that underwent risk assessment (n)	1032			
Risk Status				
Moderate-High risk	343 (33.2, [30.4, 36.2])	_	_	_
Low risk	689 (66.7, [63.8, 69.6])	_	_	_
General Hazard				
Airborne diseases	359 (34.8, [31.6–38.0])	_	_	
Food and water-borne diseases	157 (15.2, [12.1–18.4])	0.45	0.29,0.71	< 0.001
Zoonosis	252 (24.4, [21.3–27.6])	0.35	0.23,0.52	< 0.001
Vector-borne diseases	131 (12.7, [9.6–15.9])	0.18	0.09,0.33	< 0.001
STD/direct transmission	9 (0.87, [0–4.1])			> 0.9
Miscellaneous	124 (12.0, [8.9–15.2])	0.28	0.14,0.56	< 0.001
Region of occurrence				
Outside Qatar	933 (90.4, [88.4–92.1])	_	_	
Qatar	99 (9.6, [7.9–11.6])	6.02	2.91,12.9	< 0.001
Signal detected on matchdays				
No	466 (45.1, [42.1–48.2])	_	_	_
Yes	566 (54.8, [51.8–57.9])	_	_	_
Predictors from Triage Criteria				
Priority/unusual/eliminated/eradicated disease				
No	83 (8.0, [6.5–9.9])	_	_	_
Yes	949 (91.9, [90.1–93.5])	_	_	_
Potential high impact to healthcare system				
No	780 (75.6, [72.8–78.2])	_	_	
Yes	252 (24.4, [21.8–27.2])	14.9	8.91,25.6	< 0.001
Potential for international spread/interference to trade				
No	620 (60.1, [57.0–63.1])	_	_	
Yes	412 (39.9, [36.9–42.9])	5.83	3.62,9.64	< 0.001
Chemical, biological, radiological, and nuclear (CBRN)/Terroristic threats				
No	36 (3.5, [2.5–4.8])	_	_	_
Yes	996 (96.5, [95.2–97.5])	_	_	_
Political/media sensation				
No	731 (70.8, [67.9–73.6])	_	_	
Yes	301 (29.2, [26.4–32.0])	20.1	11.8,35.5	< 0.001

* CI: Confidence Interval; LL: Lower Limit; UL: Upper Limit; OR: Odd's Ratio

by its performance with new data. Though it was not feasible — FWC22 being a one-time event — this study did not attempt to train the model on existing data and compare the predictions. It would also have been advantageous to incorporate metrics such as the proportion of misclassified, duplicated, or irrelevant signals through a review of the signal data. Furthermore, the criteria employed for signal processing were tailored exclusively for the Qatari context, precluding generalizability and direct comparisons with EIOS use in other countries.

Significance

Nevertheless, our study used a standardized framework to generate data. At present, few studies have described and reported on the criteria and scoring used to determine signals of public health importance and their roles in predicting the risk status. Our study laid out the use-case scenario during FWC22 and estimated the quality of the model that was employed.

Recommendations

Optimizing the EIOS algorithms to reduce data noise would allow for better use of resources. Implementing features such as advanced filtering, detection of changes in volume of information per category, automated data capture and extraction of metadata could alleviate most of the challenges. Linking captured data to an event management system will further reduce manual efforts and enhance data quality. There are several advanced avenues that could be explored in the future, for example, time series and geographical analysis of global data [46,47], risk-mapping and modelling for specific diseases and other health threats [28]. Interinstitutional collaboration [12] to work on shared dashboards, could increase the system's sensitivity. Further research evaluating the usefulness of EIOS can compare the improvements made.

Conclusion

In conclusion, EIOS was effective as a complementary surveillance measure, with a 0.85 % probability of detecting signals relevant to public health during the FWC22 tournament. The triage criteria developed for this purpose were able to discern high priority signals. Qatar's approach may serve as a model for other nations implementing EIOS in similar circumstances.

Funding statement

The authors received no funding for this work.

Declaration of Competing Interest

The authors declare that no competing financial, research and/or publication interests exist. All authors have approved the final article.

Acknowledgements

We extend our profound gratitude to our colleagues from the Epidemic Intelligence, European Centre for Disease Prevention and Control (ECDC) - Gianfranco Spiteri, Grazina Mirinaviciute, Jon Bilbatua, and Hasan Tareq for their invaluable expertise, insights, and contributions to this research paper. Their support has significantly enhanced the quality and depth of our work.

Individual Contributions

M Sallam and S Himatt conceived the idea and supervised the project and findings of this work. RJ developed the research goals, performed data analyses, visualizations and drafted the original manuscript. LM and TE contributed to writing and finalizing the manuscript. MD, HA, DM, RS, EB, MM, S Heikal, and SA conceived and carried out the data collection. AC, M Sadek, MH, and FA contributed to the interpretation of results. MA and HA were in charge of resources and overall supervision. All authors provided critical feedback and helped in shaping the manuscript.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jiph.2024.102514.

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