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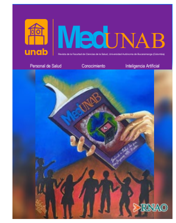

Scoping Review

The Use of Artificial Intelligence Techniques in Nursing Data Systems: Scoping Review

El uso de técnicas de inteligencia artificial en los sistemas de datos de enfermería: Scoping Review

O uso de técnicas de inteligência artificial em sistemas de dados de enfermagem: Scoping Review

Shina Singla
ssingla@rnao.ca
Registered Nurses' Association of Ontario. Toronto, Canada.

Christina Medeiros
cmedeiros@rnao.ca
Registered Nurses' Association of Ontario. Toronto, Canada.

Shanoja Naik
snaik@rnao.ca
Registered Nurses' Association of Ontario. Toronto, Canada.

Lyndsay Howitt
lhowitt@rnao.ca
Registered Nurses' Association of Ontario. Toronto, Canada.

Doris Grinspun
dgrinspun@rnao.ca
Registered Nurses' Association of Ontario. Toronto, Canada.

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Author Contributions

SS. *Conceptualization, software, investigation, validation, formal analysis, data curation, visualization, and writing–original draft, review and editing.* ***CM.*** *Conceptualization, methodology, validation, formal analysis, data curation, visualization, and writing–original draft, review and editing.* ***SN.*** *Conceptualization, methodology, validation, data curation, visualization, writing–review and editing, supervision, and project administration.* ***LH.*** *Conceptualization, methodology, and writing–review and editing.* ***DG.*** *Methodology, writing–review and editing, supervision, and funding acquisition.*

ABSTRACT

Introduction. Artificial intelligence and machine learning are technologies that assist in uncovering patterns in data that can inform clinical decision-making. The Registered Nurses' Association of Ontario has used artificial intelligence techniques to assist in understanding impactful clinical practices and implementation strategies. This scoping review aimed to discover the adaptation and implementation of various artificial intelligence and machine learning techniques in various healthcare settings using different data systems that house nursing-related data. **Methodology.** In March 2022, a scoping review was conducted to search for peer-reviewed literature using the following terms: "nursing", "artificial intelligence", "data systems", "statistics", and "aggregated data". Studies were excluded if they were not relevant to nursing, utilized qualitative or mixed-methods analyses, were literature review articles, and did not focus on artificial intelligence or the use of patient-level data. **Results.** A total of 2,627 articles were retrieved, with 1,518 articles remaining after de-duplication. Through title and abstract screening, 1,347 articles remained. Following the full-text screening, 13 studies remained. Artificial intelligence techniques used by healthcare data systems include regression, neural networks, classification, and graph-based methods, among others. **Discussion.** There is a gap in the application of artificial intelligence methods in data systems that evaluate the impact of implementing best practices in nursing. More data systems are needed that employ artificial intelligence techniques to support the evaluation of best practices in nursing and other health professions. **Conclusions.** Various artificial intelligence techniques in data systems housing nursing-related data were retrieved. However, more data systems and research are needed in this area.

Keywords:
Practice Guidelines as Topic; Evidence-Based Nursing; Machine Learning; Artificial Intelligence; Health Information Systems

RESUMEN

Introducción. La inteligencia artificial y el aprendizaje automático son tecnologías que ayudan a descubrir patrones en los datos que pueden informar la toma de decisiones clínicas. La Asociación de Enfermeras Registradas de Ontario ha utilizado técnicas de inteligencia artificial para ayudar a comprender las prácticas clínicas que generan impacto y las estrategias de implementación. El objetivo de esta revisión es descubrir la adaptación e implementación de diversas técnicas de inteligencia artificial y aprendizaje automático en varios entornos sanitarios, utilizando diferentes sistemas de datos que almacenan datos relacionados con la enfermería. **Metodología.** En marzo de 2022, se realizó una revisión de alcance para buscar literatura revisada por pares utilizando los siguientes términos: «enfermería», «inteligencia artificial», «sistemas de datos», «estadística» y «datos agregados». Se excluyeron los estudios si no eran relevantes para la enfermería, utilizaban análisis cualitativos o de métodos mixtos, si eran artículos de revisión bibliográfica y no se centraban en la inteligencia artificial o en el uso de datos a nivel de paciente. **Resultados.** Se recuperó un total de 2,627 artículos, de los cuales 1,518 quedaron tras la eliminación de duplicados. Tras la revisión de títulos y resúmenes, quedaron 1,347 artículos. Posteriormente, con la revisión del texto completo, quedaron 13 estudios. Las técnicas de inteligencia artificial utilizadas por los sistemas de datos sanitarios incluyen, entre otras, la regresión, las redes neuronales, la clasificación y los métodos basados en gráficos. **Discusión.** Existe un vacío en la aplicación de métodos de inteligencia artificial en los sistemas de datos que evalúan el impacto de la implementación de buenas prácticas en enfermería. Se necesitan más sistemas de datos que empleen técnicas de inteligencia artificial para apoyar la evaluación de buenas prácticas en enfermería y otras profesiones de la salud. **Conclusiones.** Se recuperaron diversas técnicas de inteligencia artificial en sistemas de datos que almacenan datos relacionados con la enfermería. Sin embargo, se necesitan más sistemas de datos e investigación en este ámbito.

Palabras clave:
Guías de Práctica Clínica como Asunto; Enfermería Basada en la Evidencia; Aprendizaje Automático; Inteligencia Artificial; Sistemas de Información en Salud

RESUMO

Introdução. A inteligência artificial e o aprendizado de máquina são tecnologias que ajudam a descobrir padrões em dados que podem informar a tomada de decisões clínicas. A Associação de Enfermeiras Registradas de Ontário vem utilizando técnicas de inteligência artificial para ajudar a entender as práticas clínicas que geram impacto e as estratégias de implementação. O objetivo desta revisão é descobrir a adaptação e implementação de diversas técnicas de inteligência artificial e aprendizado de máquina em diversos ambientes de saúde, utilizando diferentes sistemas de dados que armazenam dados relacionados à enfermagem. **Metodologia.** Em março de 2022, foi realizada uma revisão de escopo para pesquisar literatura revisada por pares usando os seguintes termos: «enfermagem», «inteligência artificial», «sistemas de dados», «estatísticas» e «dados agregados». Foram excluídos os estudos que não se mostravam relevantes para a enfermagem, utilizavam análises qualitativas ou de métodos mistos, se eram de artigos de revisão de literatura e não focavam na inteligência artificial ou no uso de dados no nível do paciente. **Resultados.** Foram recuperados 2,627 artigos no total, dos quais 1,518 permaneceram após a eliminação das duplicatas. Após a revisão de títulos e resumos, restaram 1,347 artigos. Posteriormente, com a revisão do texto completo, restaram 13 estudos. As técnicas de inteligência artificial usadas pelos sistemas de dados de saúde incluem, entre outras, regressão, redes neurais, classificação e métodos baseados em gráficos. **Discussão.** Existe uma lacuna na aplicação de métodos de inteligência artificial em sistemas de dados que avaliam o impacto da implementação de boas práticas de enfermagem. São necessários mais sistemas de dados que implementem técnicas de inteligência artificial para apoiar a avaliação de boas práticas em enfermagem e outras profissões de saúde. **Conclusões.** Diversas técnicas de inteligência artificial foram recuperadas em sistemas de dados que armazenam dados relacionados à enfermagem. No entanto, são necessários mais sistemas de dados e investigação nesta área.

Palavras-chave:
Guias de Prática Clínica como Assunto; Enfermagem Baseada em Evidências; Aprendizado de Máquina; Inteligência Artificial; Sistemas de Informação em Saúde

Introduction

The term "artificial intelligence" was coined by John McCarthy in 1956 during the Dartmouth Summer Research Project on Artificial Intelligence (1). Since then, the definition of this term has evolved from "intelligent machines" (2) to the modern definition of "computer systems that can imitate human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages" (3). Artificial intelligence (AI) and machine learning (ML) use emerging technological advancements and data analytics to unwrap patterns of hidden information (4). These patterns and predictions of future outcomes can inform clinical decision-making and problem-solving, thereby creating a feedback loop to optimize outcomes further. There are numerous applications of AI and ML in health care, including drug development, disease diagnostics, analysis of health plans, health monitoring, drug consultation, surgical treatment, managing medical data, personalized treatment, and medical treatment (5). AI and ML tools and platforms, for example, are used to assist radiologists in identifying lesions, tumors, and suspicious spots on the skin through the collection of medical imaging data (6). In nursing, ML algorithms can be used to manage Big data while informing nursing assessments, interventions, documentation (7), and problem-solving to optimize care provision (8). To support problem-solving, AI is used within clinical decision support (CDS) systems to advance clinical nursing practice (9). For example, AI-based sepsis CDS alert systems have been recently used to trigger rapid responses to patients experiencing sepsis (10). These alert systems use ML techniques to predict a patient's risk of clinical deterioration from vital signs and lab results (11), as seen in the Communicating Narrative Concerns Entered by Registered Nurses (CONCERN) CDS system (12). AI may also play a vital role in contributing to the understanding of how to facilitate the implementation of best practice guidelines (BPGs).

The Registered Nurses Association of Ontario has been funded by the Government of Ontario in Canada since 1999 to develop BPGs (13). RNAO also supports the implementation and sustainability of BPGs through their Best Practice Spotlight Organization® (BPSO®) program since the inception of the BPSO program in 2003 (13). The BPSO program has facilitated BPG implementation provincially, nationally and internationally, leading to improved healthcare outcomes in the academic setting (14) and in the healthcare setting (15,16), related to breastfeeding (17), pain management (18,19), pressure injuries (20,21), stroke (22), mental health (23) and enteral feeding (24). To monitor and evaluate the impact of BPG implementation, RNAO developed two data systems: Nursing Quality Indicators for Reporting and Evaluation® (NQuIRE®) and the MyBPSO reporting system (13,25). The NQuIRE data system consists of the following: demographic data from organizations, data collected on quality indicators, an online data entry form to support BPSOs with data submissions, and a collection of data dictionaries describing quality indicators (13,26). Alternatively, MyBPSO is a reporting system that houses reports consisting of questionnaires and text field forms where BPSOs report on their progress towards achieving deliverables and designation through qualitative contextual information (13). Using the data housed in these two data systems, RNAO launched an artificial intelligence (AI) and machine learning (ML) initiative to identify common patterns in BPG implementation and identify impactful implementation strategies and practice changes associated with improved outcomes. Through this information, BPSOs and health service organizations worldwide can have a list of guideline recommendations, practice changes, implementation strategies, and quality indicators to prioritize, thereby optimizing clinical, organizational, and

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health system outcomes. Therefore, given that AI and ML techniques are being employed to understand the impact of BPG implementation better, it is imperative to know which AI and ML methods exist to support clinical decision-making and BPG implementation further. The purpose of this scoping review is to understand the adaptation and implementation of various AI and ML techniques across multiple healthcare contexts utilizing different data systems housing nursing-related aggregated data through a search of the following databases: MEDLINE, Cumulate Index of Nursing and Allied Health Literature (CINAHL) and Embase.

Methods

This scoping review focused on using AI techniques utilized in different data systems that house nursing-related aggregated data. This scoping review followed the methodological framework proposed by Arksey and O'Malley (27), which has been further advanced by Levac, Colquhoun and O'Brien (28). The five steps of the methodological framework include (Step 1) identifying the research question, (Step 2) identifying relevant studies, (Step 3) study selection, (Step 4) charting the data, and (Step 5) collating, summarizing, and reporting the results. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) provides a checklist of items for scoping review development (29), which was used as a guiding document for this scoping review. A protocol for this scoping review was published in the Open Science Framework database, registration doi: 10.17605/OSF.IO/YNX76 (30).

Step 1: Identifying the research question

The following research question guided the scoping review:

What type of AI/ML techniques have been used in nursing data systems that are built on the use of aggregated data?

Step 2: Identifying relevant studies

The MEDLINE, CINAHL, and Embase databases were searched for peer-reviewed literature in March 2022. The search strategy was reviewed by the authors and thoroughly revised. Scientific peer-reviewed literature was prioritized over grey literature due to some of the inherent flaws in the latter, such as lack of authentication or proper identification. Articles published from the year 2000 to March 2022 were searched to ensure that the evidence on AI and ML techniques was fully captured, recent and accurate. The word search (Annex 1) included "nursing," "artificial intelligence," "data systems," "statistics," and "aggregated data." Relevant Medical Subject Heading (MeSH) terms, CINAHL Subject Headings, and keywords were added and combined using Boolean operators "AND" and "OR."

Step 3: Study selection

The included studies, which form the backbone of our review, focused on AI-based technologies that analyze aggregated data extracted from different nursing data systems. For the scope of this review, only peer-reviewed quantitative studies were included in the final results. Articles required a detailed description of the data systems and the analysis conducted on aggregated data. What set these studies apart was their potential to influence nursing practice or bear a clinical outcome, a key criterion for inclusion. Studies that focused on certain AI methodologies and statistics, such as neural networks, regression or classification of data were included.

To maintain the high quality of the scoping review, the following exclusion criteria were enforced: (a) not relevant to nursing; (b) utilized qualitative or mixed-methods analyses, or were literature review articles; (c) did not focus on the AI-based technologies, use of patient-level data, or non-nursing data systems; (d) published in non-peer reviewed journals; and (e) not published in English.

Step 4: Charting the data

Identified article abstracts were imported into EndNote (31), where duplicates were removed and then uploaded into DistillerSR (32) for screening. Article titles and abstracts were screened independently by two reviewers (SS and CM), and one independent reviewer (SN) addressed conflicts. Studies included in the full-text review were also screened independently by the same reviewers (SS and CM), and discussions with SS, CM, and SN resolved disagreements.

A data extraction template was developed to retrieve relevant information from the included articles. This template was refined through feedback from the other authors. The following data categories were extracted for each article, when applicable:

- RefID (from DistillerSR)
- First author (Year)
- Study design
- Country
- Study setting
- Eligibility criteria
- Objective of study
- Type of AI tool used

- Description of AI method
- Quantitative outcomes
- Clinical outcomes
- Additional comments/notes

Two reviewers (SS and CM) extracted data from half of the citations and subsequently reviewed the other half of the data extracted to ensure the complete assessment of the extracted articles.

Step 5: Collating, summarizing and reporting the results

The data were extracted to a spreadsheet and synthesized using descriptive statistics (33) and content analysis (34). A summary of the review findings is presented in Annex 2.

Results

Overview of included studies:

A total of 2,627 articles were retrieved from three databases. After the removal of duplicates, the remaining 1,518 articles were further screened. A total of 146 articles were retrieved, excluding 1,347 articles through the title and abstract screening process. These final articles were assessed against the inclusion and exclusion criteria. Ultimately, 13 studies met the inclusion criteria and were included in the review, as illustrated in Table 1 (35-47).

Table 1. The process of title and abstract, and full text review.

	Counts	Descriptions (if any)		
IDENTIFICATION				
Number of databases searched	3	MEDLINE, Embase, CINAHL		
Total records identified from databases	2,627	MEDLINE	Embase	CINAHL
		1,024	1,318	285
Duplicated records removed before screening	1,109	There were no records marked as ineligible by automation tools or by means of other reasons		
SCREENING				
Records screened by Title and abstract	1,518			
Records excluded	1,314			
Reports sought for retrieval	171			
Reports not retrieved	25			
Reports assessed for eligibility	146			
Reports excluded	133	Not in English		1
		Published before the year 2000		3
		Conference proceeding and/or not peer reviewed or grey literature		29
		Not about AL/ML in nursing		60
		Not utilized aggregated data		11
		Not using nursing data system		29
INCLUDED STUDIES				
Studies included in review	13			

Depicts the process of title and abstract, and full text review. Databases listed: MEDLINE, Embase and CINAHL

Source: prepared by the authors.

These 13 articles were based on different AI and ML research studies from the following countries: United States (38.5%, n=5, with one being in collaboration with Australia); China (7.7%, n=1); Switzerland (7.7%, n=1); South Korea (7.7%, n=1); Austria (7.7%, n=1); Canada (7.7%, n=1); India (7.7%, n=1); Mozambique (7.7%, n=1); and Italy (7.7%, n=1). The focus of these studies included clinical management of medical conditions (46.2%, n=6), population health (46.2%, n=6), and occupational health (7.7%, n=1). Further information about the included studies can be found in Tables 2 and 3.

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Table 2. Publications from different countries

Place of Publication	n	%
United States	5	38.5
China	1	7.7
Switzerland	1	7.7
South Korea	1	7.7
Austria	1	7.7
Canada	1	7.7
India	1	7.7
Mozambique	1	7.7
Italy	1	7.7

Describes place of publications and corresponding percentages
Source: prepared by the authors.

Table 3. Study Characteristics

Place of Research (Continent)	n	%
North America (one being with Australia) (35,37,38,42,44,47)	6	46.2
Asia (36,40,43)	3	23.1
Europe (39,41,46)	3	23.1
Africa (45)	1	7.7
Study Design	n	%
Retrospective study (35,37,41)	3	23.1
Cross sectional study (44,46)	2	15.4
Time series analysis (45,47)	2	15.4
Other (36,38,39,40,42,43)	6	46.2
Study Setting	n	%
Clinical management (35,36,37,43,44,45)	6	46.2
Population health (38,39,40,42,46,47)	6	46.2
Occupational health (41)	1	7.7

This table contains information about the included studies in this scoping review.
Source: prepared by the authors.

AI-based Technologies:

AI methods and tools utilized by different researchers are included in Table 4. AI tools predominantly included programs such as R, Stata, and others (e.g., Python, MATLAB, SAS and Apache Spark). The AI and ML techniques included regression, neural networks, classification, and graph-based methods, among others.

Table 4. I and ML Methodology and Tools

AI Tool Used	n
Stata (38,45)	2
R (38,39,42,46)	4
Python (39)	1
Apache Spark (39)	1
MATLAB (41)	1
SAS (47)	1
Not specified (35,36,37,40,43,44)	6
AI Method Used	n
Graph-based method (36)	1
Cross validation (36,41,43)	3
Regression (37,38,39,40,42,44,45,47)	11
K-nearest neighbours (KNN) (36,37)	2
Neural network (36,39,43)	3
Classification (37,39,41)	3
Principle Component Analysis (PCA) (41,46)	2
Support Vector Machine (SVM) (41)	1
Statistical methods/ No machine learning (35,37,38,39,40,42,44,45,46,47)	10

This table contains information about the AI and ML methods and tools described in the studies.
Source: prepared by the authors.

The regression analysis technique is widely used in most of the literature reviewed. Different forms of regression analyses were performed in these studies. In some studies, regression analysis was used to predict future outcomes (39,40,42,47). In contrast, in other studies, a relationship between different variables was established using various regression techniques, such as negative binomial regression (37), Poisson regression (38), multinomial logistic regression (44), and segmented regression (45). The regression models depicted a desired association between the variables (37,44) and were highly accurate in determining future outcomes when tested with cross-validation (39,43). The high accuracy can be subject to certain flaws, such as using micro-simulation models. Statistics Canada developed a micro-simulation model to project the prevalence of obesity in South Korea, which may not produce highly accurate results given context-specific variables that may not be present in Statistics Canada's model (40). Another flaw may be caused by self-reporting of data, such as school absenteeism data, where students report the reason for absenteeism through an online system, which is highly unreliable (42). This creates a bias in the data and the associations formed (42). Lastly, the cause of highly accurate results could be the utilization of improper models, for example, using regression analysis instead of other methods, such as longitudinal studies, which may better indicate the data (44).

The statistical methods used in the literature found were rolling mean, regression (logistic, negative binomial, Poisson), Spearman correlation, cross-correlation, exponentially weighted moving average, latent class analysis, likelihood ratio chi-square, Akaike's information criterion, Bayesian information criterion, and Eicker-Huber-White outer product sandwich estimator.

One of the most famous AI techniques, classification, was performed in some studies to classify data. ML methods, such as KNN (37), convolutional neural network (CNN) (39), and Support Vector Machine (SVM) (41) were used for this purpose. These methods predicted the presence or absence of infection in target hospital units (37) and classified patients as healthy or unhealthy based on current status (39). They were used for gait classification using different data aggregation techniques (41). Although different prediction models show high accuracy when tested with cross-validation, chances of publication bias exist, where results showing no outcome are ignored (37).

In conjunction with the graph-based method and KNN, neural networks were also used in computer-aided diagnosis of complex psychological disorders, such as autism spectrum disorder (36). This model had 6.4% higher accuracy than other methods used for analyzing the same dataset. The neural networks utilized in various studies seem to work as anticipated and look promising considering the result (36,39,43).

Novel research on using the Internet of Things (IoT) was also found. IoT is a technological evolution fueled by wireless telecommunication and comprises intelligent communicating 'things,' such as Radio-Frequency IDentification (RFID) tags, sensors, actuators, mobile phones, and so on (48). The IoT was used to determine an integrated solution for combating the COVID-19 pandemic (39). This multi-layer technology utilized CNN, classification, and regression techniques to predict a patient's future state and categorize a patient into infected or uninfected. The study has limitations regarding user experience in using sensors for collecting data from patients and the lack of data in the form of open data repositories related to the outbreak of COVID-19.

Discussion

This scoping review yielded the following AI and ML techniques related to nursing data systems built on the use of aggregated data in the past two decades: regression, neural network, graph-based method, classification, PCA, KNN, and SVM. While reviewing each article, the focus was also on the data collection and aggregation method in which the AI techniques were implemented. Interestingly, most of the literature discloses that the data aggregation is performed either in the same database or while utilizing the AI methodologies.

The results suggest that research on AI and ML methods that could be used for aggregated data, in general, is either not widely pursued or is possibly the first attempt in this direction. The result clearly emphasizes the need for more research in this area, either in nursing or research based on developing AI and ML for the aggregated data system. Fortunately, a few results indicate data aggregated at different levels. Furthermore, this scoping review can be expanded with more descriptive terminologies to improve search strategies and expand the scope to engineering databases related to non-nursing-focused research.

There is a shortage of AI methods being utilized in the field of nursing. Moreover, the studies evaluated were using quantitative data. While focusing on the objective of the RNAO's AI and ML initiative, some studies with focused research on qualitative data analysis were expected to be retrieved. A recent scoping review published on AI-based technologies in nursing is also primarily centered around predictive analytics and does not address the use of nursing databases (49).

The AI and ML techniques and methods that have been elucidated from this scoping review can be utilized in many different data systems utilizing aggregated data for nursing and other health professions. Although this scoping review focused specifically on nursing, the scope of practice of nursing overlaps with that of many health professionals, such as physicians, physiotherapists, occupational therapists, personal support workers, and others (50). Therefore, these AI and ML techniques can be utilized in various data systems collecting aggregated data focused on the broader scope of many health professionals.

In the RNAO context, the findings of this scoping review can further inform the evolution of the AI and ML initiative applied to the NQuIRE and MyBPSO data systems. Among all the techniques retrieved from the studies, neural network and regression analysis are novel to NQuIRE and MyBPSO. These techniques and methods can further inform the AI and ML initiative in RNAO to better understand the impact and factors of BPG implementation.

This scoping review was limited as grey literature and non-English publications were omitted. Only three bibliographic databases were searched, and this can be widened to obtain further information about AI and ML techniques utilized in data systems collecting aggregated data. Lastly, this scoping review was limited to nursing data systems, given that NQuIRE and MyBPSO are both data systems focused on nursing processes. This could be widened in subsequent literature reviews to data systems collecting information on other work by health professionals whose scope of practice aligns with nursing.

This review has demonstrated that developing AI platforms and techniques in nursing practice generally have relevant use cases suitable for academic research. There is a high potential to create fully automated data-driven AI formation, including ML methods. However, the current study and use of cutting-edge machine learning methods (e.g., deep learning using artificial neural networks), when compared to medical imaging and diagnostic support, appear lacking in nursing.

Conclusion

This scoping review summarized the literature published on using various artificial intelligence and machine learning techniques in the nursing field utilizing aggregated data from nursing data systems. There is a gap in applying these methods to the evaluation of qualitative data, especially concerning data systems that house aggregated nursing-related data. Using AI and ML techniques in data systems is imperative to understand how to prioritize practice changes to optimize clinical care and health outcomes. Given the overlap in scope between nursing and other health professions, there is an opportunity to widen future scoping reviews to include data systems related to other health-related disciplines as well. This scoping review lays the foundation for future research on aggregated data systems in various healthcare contexts.

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Conflicts of Interest

The authors declare that they have no conflicts of interest.

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