ESCOLA POLITÉCNICA DE SAÚDE JOAQUIM VENÂNCIO

Ministério da Saúde
FIOCRUZ
Fundação Oswaldo Cruz

Ciclo de talleres
La formación y el trabajo de los técnicos en salud en el mundo post-Covid

Taller 4 – "Información y registros en salud: el papel de los técnicos"

Alicia Ferreira Maia. MD,MSc

12 de diciembre de 2022

La Escuela Universitaria de Tec
Médica (EUTM)

- La Escuela Universitaria de Tecnología Médica de Uruguay, depende de la Facultad de Medicina de la Universidad de la República.
- Comparte el edificio con la Facultad de Enfermería, la Escuela de Parteras y la Escuela de Nutrición.
- Fue creada en el Hospital de Clínicas en 1950 como Sección de Auxiliares del Médico, luego como Colaboradores del Médico, Escuela de Tecnología Médica, hasta el nombre que tiene ahora.

Fuente: Historias Universitarias de la reseña histórica de la EUTM. Reseña histórica de la EUTM elaborada por el Área de Investigación Histórica del Archivo General de la Universidad de la República (AGU)

En el año 1978, al pasar a llamarse "Escuela de Tecnología Médica", los egresados pasaron a denominarse "Técnicos", y a obtener títulos en vez de certificados.

En 1994 cambia la denominación de "Escuela de Tecnología Médica" a "Escuela Universitaria de Tecnología Médica". Se instala por primera vez la Asamblea del Claustro de la Escuela Universitaria de Tecnología Médica.

En 1995 se realizan los "1os talleres de Reestructura de la EUTM" Se propone como Título de egreso el de Licenciado para las carreras de 4 años de duración. Se apoya el cambio de la denominación de Técnico por el Tecnólogo en los demás.

Fuente: Historias Universitarias de la reseña histórica de la EUTM. Reseña histórica de la EUTM elaborada por el Área de Investigación Histórica del Archivo General de la Universidad de la República (AGU)

En la actualidad, la EUTM tiene 18 carreras de formación de grado, y funciona en dos sedes: en la capital del país y en una ciudad del norte (Paysandú)

- Técnico/a en Anatomía Patológica	- Licenciado/a en Imagenología
- Tecnólogo/a en Cosmetología Médica	- Licenciado/a en Neurofisiología Clínica
- Técnico/a en Hemoterapia	- Licenciado/a en Instrumentación Quirúrgica
- Técnico/a en Podología Médica	- Licenciado/a en Laboratorio Clínico
- Técnico/a en Radioisótopos	- Licenciado/a en Neumología
- Tecnólogo/a en Radioterapia	- Licenciado/en Oftalmología
- Tecnólogo/a en Salud Ocupacional	- Licenciado/a en Psicomotricidad
- Licenciado/a en Fisioterapia	- Lic y Tecnólogo/a en Registros Médicos
- Licenciado/a en Fonoaudiología	- Licenciado/a en Terapia Ocupacional

Carrera: Registros Médicos

Son 4 años de curso para obtener la Licenciatura.

A los 2 años se obtiene un título intermedio: Tecnólogo de Registros Médicos.

Además de los contenidos específicos, los estudiantes deben cursar materias generales a todas las carreras de la EUTM: Ciclo ESFUNO (Estructura y Funciones Normales), Salud Pública y Metodología de la investigación.

Carrera: Registros Médicos

Contenido curricular específico

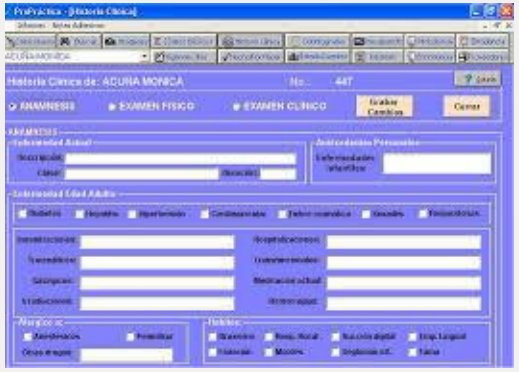
- Administración
- Procesamiento de imágenes
- Registros Médicos I, II y III
- Técnicas de oficina
- Ciencias Médicas y Terminología
- Informática en Registros Médicos
- Estadísticas asistenciales I y II
- Planificación y organización

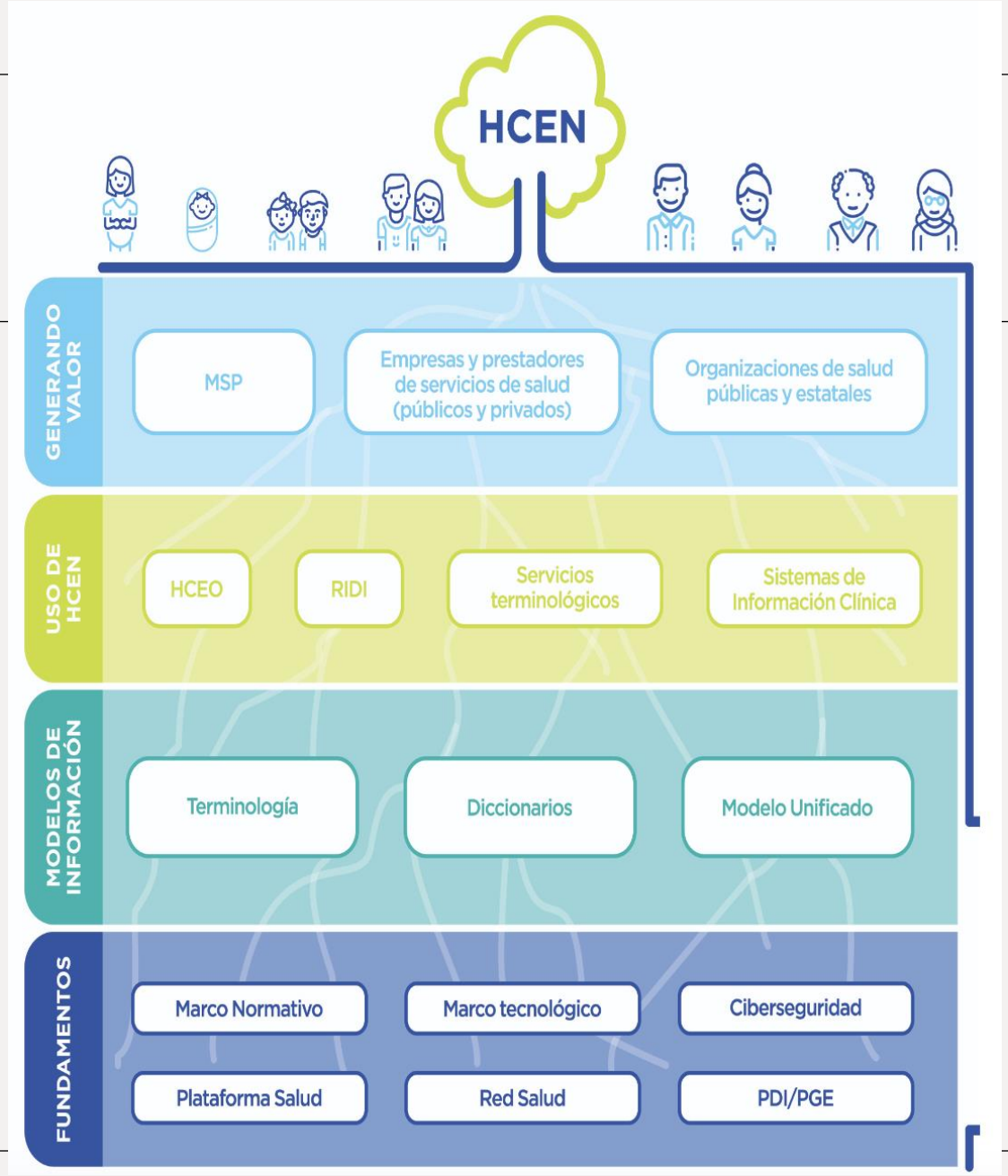
Licenciatura en Registros Médicos

Competencias y Funciones

- Manejo y custodia de la historia clínica
- Registro de pacientes en la admisión (ingreso, transferencia, egreso) a la hospitalización, y mantenimiento del censo diario de pacientes hospitalizados.
- Registro de pacientes en las consultas ambulatorias y en la coordinación quirúrgica
- Estadísticas asistenciales (en los diferentes niveles de atención)
- Codificación de egresos hospitalarios
- Apoyo en las auditorías médicas

Evolución de la Historia Clínica





Fuente de la imagen: Programa Salud.uy. https://www.gub.uy/agencia-gobierno-electronico-sociedad-informacion-conocimiento/node/312

- Salud.uy es una iniciativa de Presidencia de la República, el Ministerio de Salud Pública (MSP), el Ministerio de Economía y Finanzas (MEF) y la Agencia de Gobierno Electrónico y Sociedad de la Información y del Conocimiento (Agesic).

- Su objetivo es promover el uso intensivo de las Tecnologías de la Información y la Comunicación (TIC) en el sector de la salud para mejorar la calidad y continuidad asistencial.

- Desde su origen en el año 2012, el programa ha definido estándares y lineamientos de informática médica así como ha establecido el contexto técnico y regulatorio habilitante para hacer posible y segura la historia clínica electrónica nacional (HCEN).

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Documentación

Guía de Introducción a SNOMED CT. Documento de SNOMED International que realiza una introducción a la terminología SNOMED CT. Descargar la Guía de Introducción a SNOMED CT.pdf (201402)

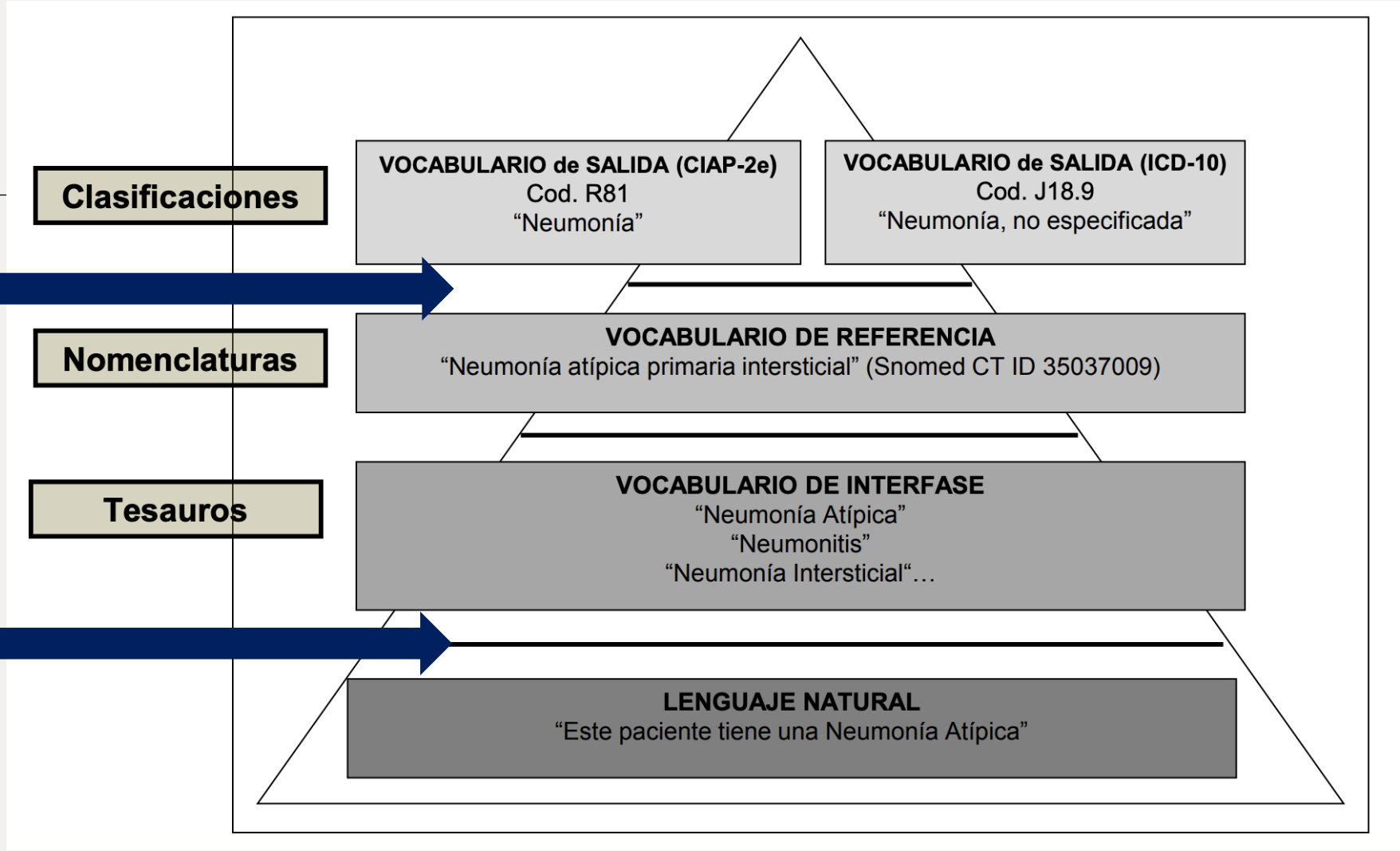
Códigos para registrar los motivos de consulta y diagnósticos relacionados a COVID-19 para notificación al MSP. Descargar Descargar Motivos y diagnósticos para COVID-19 - Versión 2.0.xls (20210112)

`Códigos destacados:`

COVID-19 Confirmado: 840539006 / enfermedad causada por coronavirus del síndrome respiratorio agudo severo 2 (trastorno).

Sospecha de COVID-19: 840544004 / sospecha de enfermedad causada por coronavirus del síndrome respiratorio agudo severo 2 (situación).

Exposición a COVID-19: 840546002 / exposición a coronavirus del síndrome respiratorio agudo severo 2 (evento).



Tomado de: Carlos Otero. MD, MS. Utilización de Terminologías Clínicas y su aplicación a una Historia Clínica Electrónica. Presentación en el webinar de Salud.uy. 22/10/2020

Formación y nuevas competencias

- Apoyo en la investigación con Datos de la Vida Real (RWD)para generar Evidencia de la Vida Real (RWE).
- Apoyo en la investigación de Salud Pública Basad en la Evidencia
- Apoyo en la gestión de Servidores de Terminologías – Vocabularios de interfase, vocabularios de referencia (SNOMED-CT)
- Especialización: Científico de Datos (Data Science), y en Data wrangling
- Manejo de Big Data, y Datalake

Leveraging electronic health records for data science: common pitfalls and how to avoid them

Christopher M Sauer, Li-Ching Chen, Stephanie L Hyland, Armand Girbes, Paul Elbers, Leo A Celi

Analysis of electronic health records (EHRs) is an increasingly common approach for studying real-world patient data. Use of routinely collected data offers several advantages compared with other study designs, including reduced administrative costs, the ability to update analysis as practice patterns evolve, and larger sample sizes. Methodologically, EHR analysis is subject to distinct challenges because data are not collected for research purposes. In this Viewpoint, we elaborate on the importance of in-depth knowledge of clinical workflows and describe six potential pitfalls to be avoided when working with EHR data, drawing on examples from the literature and our experience. We propose solutions for prevention or mitigation of factors associated with each of these six pitfalls—sample selection bias, imprecise variable definitions, limitations to deployment, variable measurement frequency, subjective treatment allocation, and model overfitting. Ultimately, we hope that this Viewpoint will guide researchers to further improve the methodological robustness of EHR analysis.

Introduction and context: use of data from electronic health records

Electronic health records (EHRs) are increasingly used to survey population health,[1,2] develop classification and prediction models for decision support,[3] identify optimal treatment policies,[4] or even simulate randomised clinical trials.[5] Compared with alternative data sources and study approaches, such as cohort studies or randomised controlled trials, the main advantage of EHR analysis is the use of data that are already captured, thus reducing administrative efforts, costs, and sample selection bias. EHRs are more representative of the total target population and less subject to inclusion bias than randomised controlled trials, because EHR data are obtained from all individuals who interact with health systems.[6] Although important epidemiological considerations remain,[7] such as those discussed in this Viewpoint, EHRs include more comprehensive data from patients as they evolve over time and provide access to large dataset sizes, especially when EHR analysis involves large integrated health-care systems or a network of health-care providers who use interoperable information systems. Ultimately, large sample sizes can provide increased statistical power to do subgroup analyses and reduce the risk of type II errors.

Importance of methodological robustness

Although EHR data analysis offers promising research opportunities, the applicability and robustness of EHR research are often limited by methodological shortcomings inherent to the complexity of EHR data.

First, compared with clinical repositories and clinical trials, the likelihood of variation in data collection for EHRs is increased because many variables are measured by use of different technologies and sampling frequencies. Second, the retrospective nature of most EHR data analyses means that cohorts, exposures, and outcomes are defined retrospectively. This retrospective approach allows for such definitions to be adjusted in light of analysis outcomes, resulting in potentially misleading findings, because of multiple hypothesis testing and without appropriate statistical adjustment. Finally, the type and quality of data, including which patients are included in the analysis, are heavily dependent on clinical practice patterns, which introduce sample selection biases that lead to spurious associations. One should keep in mind that EHR data are not primarily collected for research purposes; instead, they store all patients' information collected during clinical care, or, in some cases, serve an administrative function such as billing. Therefore, analysis of EHR data should not be undertaken without the involvement of investigators with specialist knowledge of the domain of interest, spanning from care practices to data processing.[8–11]

Goals of this Viewpoint

Over the past two decades, with ever increasing use of EHR data, previous investigations[7,12,13] and our research have observed that issues arising during clinical care (eg, people from minority ethnic groups seeking health care less frequently) are also reflected in the EHR data, thus introducing bias in EHR studies. We believe that an integrated and comprehensive discussion of how clinical workflows and information system design affect EHR data analyses is still missing in the literature. In this Viewpoint, we extend these concepts by integrating machine learning, epidemiological, and statistical considerations with important clinical considerations, by reviewing the literature and case examples. Although most pitfalls we present are mainly relevant to machine learning models, others are also crucial for all types of EHR studies.

In this Viewpoint, we identify six common clinical and methodological pitfalls using a mixed approach, both relying on expert opinion and a literature review. We cross-checked our literature review and references of the identified publications to include additional relevant publications. Inclusion of papers was at the authors' discretion (CMS, SLH, and LAC). By discussing these six pitfalls of crucial importance, we hope to guide

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Steps	Identified pitfalls	Potential solutions
Cohort building	1) Sample selection bias	Discuss design choices with an experienced clinician Use gold-standard cohort definitions Perform sensitivity analyses
Definitions of variables	2) Imprecise variable definitions	Develop definitions in a multidisciplinary team, involving clinicians, epidemiologists, statisticians, social scientists, and patients
Feature selection	3) Limitations to deployment	Check if registration time is a…with result time Only include information tha…ailable at baseline Ensure there is no patient ov…etween the training dataset and the test dataset
Feature selection	4) No adjustment for association between frequency of measurements and severity of disease	Consult experts and adjust va…s using epidemiological or statistical strategies such as weighting, …le imputation, or removal of unreliable variables
Study design	5) Subjective treatment allocation affecting causal inference studies	Aim to adjust for interphysici…d intraphysician differences in treatment allocation
Study or results validation	6) Model overfitting and reduced generalisability to other settings	Question how local policies n…ffect generalisability Potentially adjust effect size e…tes on the basis of known differences in prevalence

Figure: **Six recurrent clinical and methodological pitfalls in studies using electronic health records and potential sol…s**

Develop definitions in a multidisciplinary team, involving clinicians, epidemiologists, statisticians, social scientists, and patients

https://www.thelancet.com/action/showPdf?pii=S2589-7500%2822%2900154-6

Original research

Toward a better understanding about real-world evidence

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ABSTRACT

Background There has been an interest in real-world evidence (RWE) in recent years. RWE is usually generated from data derived from routine healthcare, such as electronic healthcare records and disease registries. While RWE has many advantages, it is often open to various biases, which may distort results. Appropriate understanding and interpretation are critical to the best use of RWE in healthcare decisions.

Methods On the basis of a literature review and empirical research experience, we summarised the concept and methodological framework of RWE, and discussed in detail methodological issues specific to routinely collected healthcare data and observational studies using such data.

Results RWE is derived from a spectrum of data generated from the real-world setting, using two broad study designs including observational studies and pragmatic clinical trials. Real-world data may usually be collected through routine practice or sometimes actively collected with a research purpose. Observational studies using routinely collected data (RCD) are the most common type of RWE, although they are prone to biases. When planning and implementing RWE studies, coherent working steps are warranted, including definition of a clear and answerable research question, development of a research team, selection of a fit-for-purpose data source, choice of state-of-the-art study design, establishing a database with transparent data processing, performing multiple statistical analysis to control bias, and reporting results in accordance with established guidelines.

Conclusions RWE has been mounting over the years. The appropriate interpretation and use of such evidence often warrant adequate understanding about methodology. Researchers and policymakers should be aware of the methodological pitfalls when generating and interpreting RWE.

In recent years, the concept of real-world evidence (RWE) has become widely accepted. In particular, with the release of the 21st Century Cure Act in the USA, the interest in RWE was fuelled among researchers and policymakers.[1] RWE may have a wide spectrum of applications, such as understanding about treatment patterns, informing treatment outcomes in vulnerable populations, and assessing treatment effects in real-world practice.

However, misunderstanding or confusion is still common concerning what RWE is and how one should interpret the evidence. For example, a common misconception about RWE is that it can only be generated using data from routine clinical care and does not involve new data collection over a pre-defined protocol.[2] Another common misconception is that RWE merely refers to evidence generated from observational studies.[3]

In reality, the methodological framework for RWE is more complex than classical clinical trials. Lack of strong methodological and statistical expertise may sometimes lead to inappropriate handling of data, thus producing unreliable or even incorrect conclusions.[3] Therefore, it is important to better understand the concept and methodological issues regarding RWE.

CONCEPTUAL FRAMEWORK OF REAL-WORLD EVIDENCE

The term 'real-world evidence' is often used to refer to clinical evidence about utilisation (eg, treatment pattern or compliance), benefits and harms of medical products in a defined population or a subgroup population. The evidence is typically derived from analyses of healthcare data outside of classical clinical trials.[2]

Data sources for generating RWE usually come in two main forms, including routinely collected healthcare data (RCD) and actively collected healthcare data in routine clinical practice settings.[4] While RCD are often generated from routine practice for non-research purposes, such as electronic medical records, claims data and health surveillance data, actively collected healthcare data are often collected with certain research purposes. These two forms of data are important sources of real-world data, and their common features are that the data are derived from routine clinical practice.

RWE is derived from the analyses of real-world data, and in many cases is based on observational study designs. However, such studies are susceptible to bias due to the complexity in the healthcare setting, data, and observational nature of the design. Both researchers and evidence users must be highly cautious about observational studies using real-world data. It is also worth noting that RWE is not equivalent to observational study. An interventional study can also be used to generate RWE, and one such design is a pragmatic clinical trial.[3 5] This study design is often prioritised where the treatment effect on a heterogeneous population is urgently needed, the optimal treatment is largely unknown in routine practice, or medical needs (typically those related to patient welfare) are insufficiently met.[6] In this paper, we specifically discuss issues about observational studies using real-world data, especially routinely collected healthcare data.

ISSUES ABOUT DATA SOURCES: FOCUSING ON ROUTINELY COLLECTED DATA

Routinely collected healthcare data represent the most common type of real-world data. Because these data are typically collected in routine

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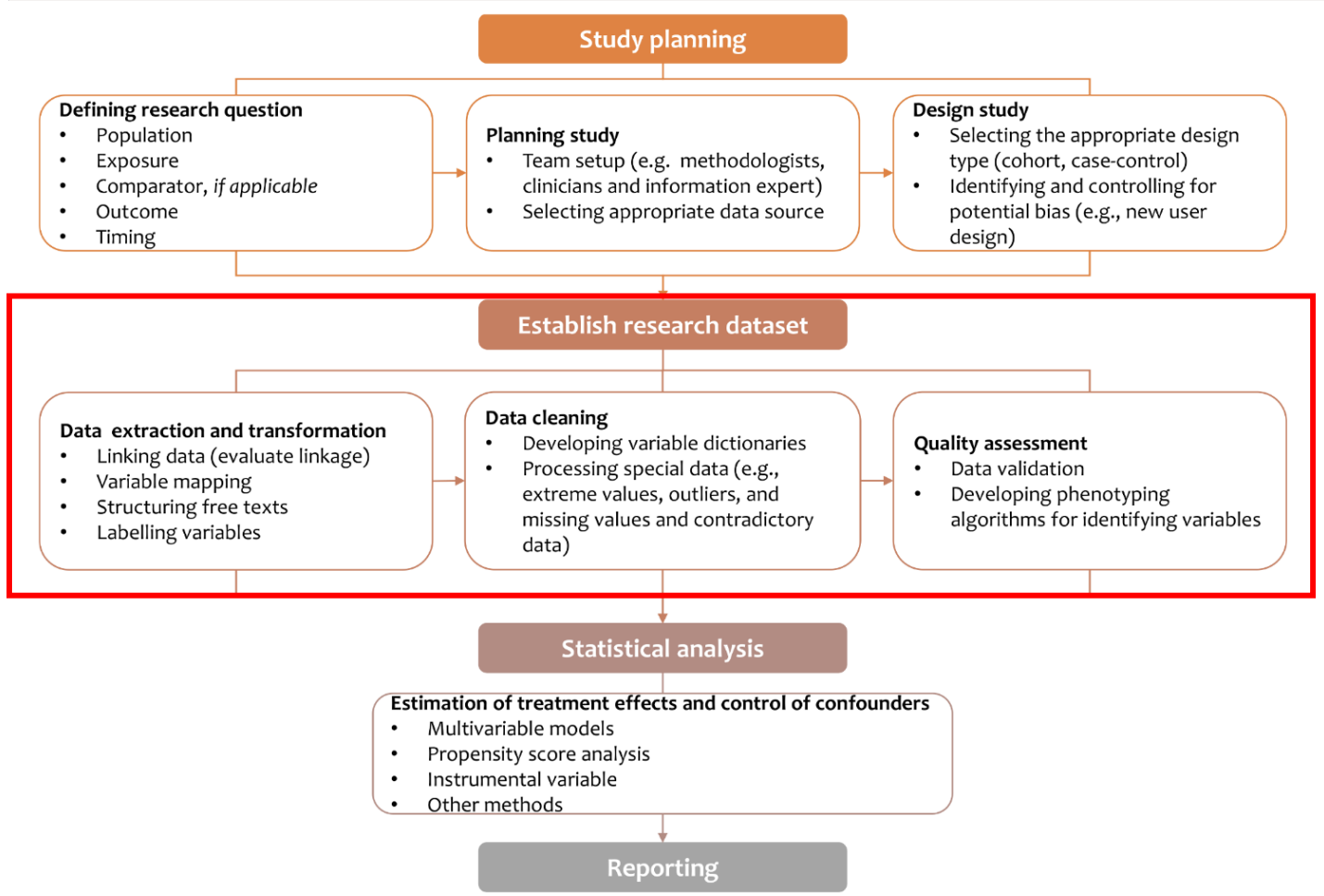

Figure 1 Schematic flow of observational study using routinely collected data.

Liu M, Qi Y, Wang W, et al Toward a better understanding about real-world evidence European Journal of Hospital Pharmacy 2022;29:8-11

Competencias que se mantienen

- Codificación de los certificados de defunción
- Estadísticas vitales
- Apoyo a la gestión y a la toma de decisiones en salud
- Registro y orientación de pacientes en los diferentes niveles de atención

Algunas conclusiones

- La formación de técnicos y licenciados con conocimientos específicos en sistemas de información en salud es un valor agregado importante.

- Integrar a estos profesionales en el equipo multidisciplinario que desarrolla, implementa y gestiona los sistemas de información en salud, mejora la calidad de los registros y por tanto de los resultados.

- Se requiere actualización continua y fortalecimiento de la formación en herramientas tecnológicas actuales (y futuras), para acompasar los vertiginosos cambios en los sistemas de información.

Gracias por su atención

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