Clinical Information Capture in the Electronic Health Record:

Literature Review and Key Considerations

Office of the Nursing & Midwifery Services Director

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Foreword

Welcome to this report *Clinical Information Capture in the Electronic Health Record (EHR): Literature Review and Key Considerations* which identifies several clinical data types in the EHR and several methods of entering this clinical data into the EHR. The advantages and disadvantages of each of these data types and methods of entering the clinical data are identified and discussed in this report. This report also outlines twenty-one key considerations during design, development and ongoing optimisation of capturing clinical information in the EHR derived from the literature presented and the experience of the Advisory Group members.

This report was commissioned by the Office of the Nursing and Midwifery Services Director, Health Service Executive to support services who are or will be embarking on the digital transformation journey of implementing an EHR.

The advantages and disadvantages of each of these data types and methods of entering the clinical data are drawn from an extensive international literature review; a review of national literature that includes grey literature; and the experiences of our colleagues on the Advisory Group who have engaged with or worked on digital transformation projects across Ireland.

The Advisory Group were fundamental to driving, reviewing and providing direction for this work. Their combined experience and insights added considerable value to this report and more specifically the derivation of the key considerations. Thank you for your time, energy and commitment.

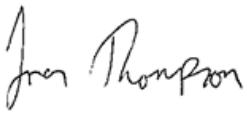
We would like to thank Dr Orna Fennelly, who authored this report for her expertise, dedication and commitment in completing this important piece of work. In addition, we would like to thank her colleagues in UCD in particular Dr Catriona Cunningham and Professor Neil O'Hare for their support and guidance to Orna.

Sláintecare outlines clear goals for the eHealth agenda to both digitally connect the health service and digitally connect the citizen (to health). The EHR is the cornerstone of this Programme. We hope this document will be of value to clinicians, managers and technicians alike to provide meaningful information and offer key insights into clinical information capture in the EHR as we go forward.

Getting clinical information capture right is about ensuring the right data about the right patient is in the right place and at the right time to ensure safe quality care, improve efficiency and healthcare outcomes for people that use our services. It's also about empowering and enabling people who use our services to experience better care.

Loretto Grogan

National Clinical Information Officer for Nursing and Midwifery, ONMSD



Fran Thompson

Chief Information Officer, Interim, HSE

Prof. Neil O'Hare

Group CIO, Ireland East Hospital Group; Prof. Health Informatics, School of Public Health, Physiotherapy and Sports Science, UCD

Author and Advisory Group

Authored by:

Dr. Orna Fennelly	School of Public Health, Physiotherapy and Sports Science, and the Insight Centre for Data Analytics, University College Dublin (UCD).

Advisory Group Members:

Jason Chandler	Information Communication Technology (ICT) Project Manager, Office of the Chief Information Officer, Health Service Executive (HSE)
Dr. Heather Cronin	Senior Clinical Psychologist in Neuropsychology and Clinical Health and Social Care Professions (HSCP) Lead, Clinical Management System for Specialised Care Services, National Rehabilitation Hospital (NRH).
Dr. Caitriona Cunningham	Associate Professor, School of Public Health, Physiotherapy and Sports Science, UCD.
Rita Darcy	Community Electronic Health Record (EHR) Senior Project Manager, HSE
Loretto Grogan	Chair of Advisory Group and National Clinical Information Officer for Nursing and Midwifery, HSE
Fiona Lawlor	Business Manager with the National Project Team on the Maternal and Newborn-Clinical Management System (MN-CMS) project.
Prof. Neil O'Hare	Prof. of Health Informatics, School of Public Health, Physiotherapy and Sports Science, UCD and Group Chief Information Officer, Ireland East Hospital Group
Dr. Conor O'Shea	General Practitioner and National Co-ordinator of the General Practice Information Technology (GPIT) Project at the Irish College of General Practitioners (ICGP)
Angela Reed	Senior Professional Officer, Northern Ireland Practice and Education Council for Nursing and Midwifery (NIPEC).
Miriam Roche	Electronic Patient Record (EPR) Project Manager, St. James' Hospital (SJH)

Glossary of terms

Term:	Definition:
Aggregation terminology	A body of terms linked to a code set which facilitates simple hierarchy relationships between the terms and is used for administrative purposes
Artificial Intelligence (AI)	System which interprets data, reasons through the knowledge derived from this data, decides on the best action(s) to take (according to pre-defined parameters) to achieve a given goal and learns to adapt its behaviour by analysing how the environment was affected by its previous actions
Barcode medication administration (BCMA)	Technology which ensures the right patient, right dose, right drug, right time and right route and automatically documents medication administration into the electronic record via scanning both the patient's wristband and the medication to be administered
Clinical decision support (CDS)	Software which matches the characteristics of an individual patient to a computerised clinical knowledge base, and patient-specific assessments or recommendations are then presented to the clinician to aid decision-making
Clinical Information System	A repository of clinical data stored on a computer within a healthcare organisation
Clinical record	Summary of the assessment of a person's physical, psychological and social well-being, and whenever necessary, the views and observations of family members, evidence of decision-making and care delivery, and evaluation of the care provided
Clinical scribe	An unlicensed individual employed to transcribe the patient history and assessment as verbally stated by the healthcare professional (HCP)
Computerised Provider Order Entry / Computerised Physician Order Entry (CPOE)	Computer system for requesting medications or tests (e.g., radiology, laboratory) for a patient
Content Importing Technology	Technology which moves information from one section of a patient's clinical record into another or from an external device into the electronic health record (EHR)
EHR-integrated device	Commercially available device which has been integrated with an EHR system to automatically or semi-automatically (i.e., with clinician approval) capture and document patient-generated health data
Electronic Health Record (EHR)	**Longitudinal record of information regarding the health status of a subject of care which follows them from one practice or specialist to the next, in computer processible form**
Electronic Patient Record (EPR) / Electronic Medical Record (EMR)	Longitudinal record of health information of a patient within a single institution
Emergency Department (ED)	A medical treatment facility specialising in emergency medicine , also known as accident and emergency (a & e)
End-user	Person accessing and using the EHR system
Front-line staff	Person interacting with health-service users
General Practitioner (GP)	Medical doctor based in the community who assesses and treats acute and chronic illnesses and provides preventive care and health education to patients
Go Live	Point at which EHR becomes operational
Healthcare Information and Management Systems Society (HIMSS)	A global, not-for-profit organisation focused on better health through information and technology
Health Information Quality Authority (HIQA)	An independent authority that exists to improve health and social care services for the people of Ireland
Healthcare organisation	Utilised throughout the report to describe all facilities which provide healthcare (e.g., hospital, primary care setting)
Healthcare professional (HCP)	Provider of healthcare who may be from any discipline including medicine, nursing, midwifery, pharmacy, allied health.
Health information exchange (HIE)	Sharing of patient data across organisational and geographical boundaries
Health Information Technology for Economic and Clinical Health (HITECH)	An Act in the United States (US) which provided monetary incentives to HCPs who demonstrated meaningful use of EHRs (i.e., CDS, HIE)

Information Communication Technology (ICT)	An extension of the term information technology (IT) that stresses the role of communication
Interface terminology	A terminology which provides terms with more granularity and clinical intent for a specific healthcare discipline or speciality
Internet of things (IoT)	System of interrelated computing devices, mechanical and digital machines, objects, animals or people that are provided with unique identifiers and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction.
Interoperability	Ability of different information systems, devices or applications to connect and 'talk' effectively to one another in a coordinated manner, within and across organisational boundaries
KLAS	An organisation which conducts research on health information technology to provide accurate, honest and impartial insights by building relationships with the buyers and sellers
Language	Use of words in a structured and conventional way
Natural Language Processing (NLP)	Application of computational techniques to analysis and synthesis natural language
Patient	Utilised in this report to describe a person accessing health services
Patient Portal	Healthcare information documented and managed by a healthcare organisation which is accessible to a patient
Personal Health Record (PHR)	Patient-held record comprising of information provided by a healthcare provider, the patient, a device or a combination of the above
Reference terminology	A clinical terminology which facilitates the combination of concepts to create terms which are clinically meaningful
Semantic interoperability	The shared meaning and understanding of clinical data across organisational and geographical boundaries
Shared care record	Enables providers in primary care or hospitals to view patient records with the patient's consent and is usually stored locally
Summary care record	A structured summary of a clinical record which is held on a national database and continuously updated with key patient information from the local system (e.g., patient's name, address, age, allergies, current medications and diagnoses) and is accessible to authorised staff over a secure internet connection
Super-user	Regular staff member who learns the system prior to implementation so that s/he can expedite IT support and provide problem-solving to other staff
Systematized Nomenclature of Medicine - Clinical Terms (SNOMED-CT)	Clinical reference terminology with thousands of codes which can be utilised to capture all clinical notes including allergies, vitals, past history, family history, symptoms, clinical findings and diagnosis
Standardised terminology	Defined body of words or expressions used in relation to a particular subject or activity
Usability	Effectiveness, efficiency and satisfaction with which specific users can achieve a specific set of tasks in a particular environment
Vendor	An enterprise selling goods or services
Workflow	Pattern of activity of the end-user

Contents

Executive Summary

Healthcare faces major challenges to tackle the current and future demands of a growing and ageing population [1]. Information and knowledge are a core asset of health systems and the creation and use of this asset in an effect manner is critical to improve the performance of the system and ensure a sustainable, quality and safe healthcare service [2, 3]. This sensitive personal information usually includes a summary of the assessment of the person's physical, psychological and social well-being, and whenever necessary, the views and observations of family members, evidence of decision-making and care delivery, and evaluation of the care provided [4, 5]. The ability to record and share key information on patients' and service-users' interaction across organisations and care settings will provide benefits to patients, service-users, carers, healthcare professionals (HCPs) and wider stakeholders in the health system [1, 6].

The electronic health record (EHR) provides a longitudinal health record of an individual from one practice or specialist to the next in computer processable form and enables authorised access to patient records in real-time which reduces duplication in work. The EHR is the key capability requirement for delivering integrated healthcare [7, 8]. Additionally, the EHR expands the capacity to capture and utilise patients' clinical information to improve healthcare with more legible information, improved patient safety with flagging of crucial patient information, ability to retrieve information regarding patients (e.g., conditions or medications) and aggregation of big data for service development, research and planning [1, 7, 9-17]. These benefits are extended via adjunct technologies such as clinical decision support (CDS) software which matches patient clinical information with a computerised knowledge base to provide recommendations to the HCP and the Internet of Things (IoT) which could provide more comprehensive and accurate patient information to the EHR [3].

However, many of the EHR-related benefits can only be derived if the necessary clinical information is captured in an appropriate manner. Therefore, during the procurement, design, development, implementation and optimisation of an EHR as well as any adjunct technologies (e.g., CDS, wearables), the type of clinical data and method of data entry onto the EHR need to be considered in relation to the clinical needs and objectives of the healthcare organisation. This may include collecting information in a format which enables interoperability and information exchange with another system or organisation and comprehensive retrieval of data for analytics and reporting. However, the clinical information must also retain its overarching aim which is to track a patient's condition and communicate this to other members of the healthcare team to inform clinical decision-making [18, 19].

To inform decisions in relation to the type of clinical data which should be collected in the EHR and the methods of data entry onto to the EHR, a review of the literature was conducted focused on clinical data in text format and an expert Advisory Group was convened. Following the initial identification of the clinical data types and data entry methods in the EHR (Fig. 1), a scoping review of the literature was conducted with the following objectives:

1) To identify the advantages and disadvantages of capturing clinical information in the EHR using data which was: (i) Unstructured; (ii) Structured; (iii) Coded; and (iv) Semi-structured.
2) To identify the advantages and disadvantages of HCPs entering data onto the EHR using the following data entry methods: (i) Personal Entry; (ii) Content Importing Technology; (iii) Technology Speech Recognition; and (iv) Clinical Scribes.

Key findings from the Literature:

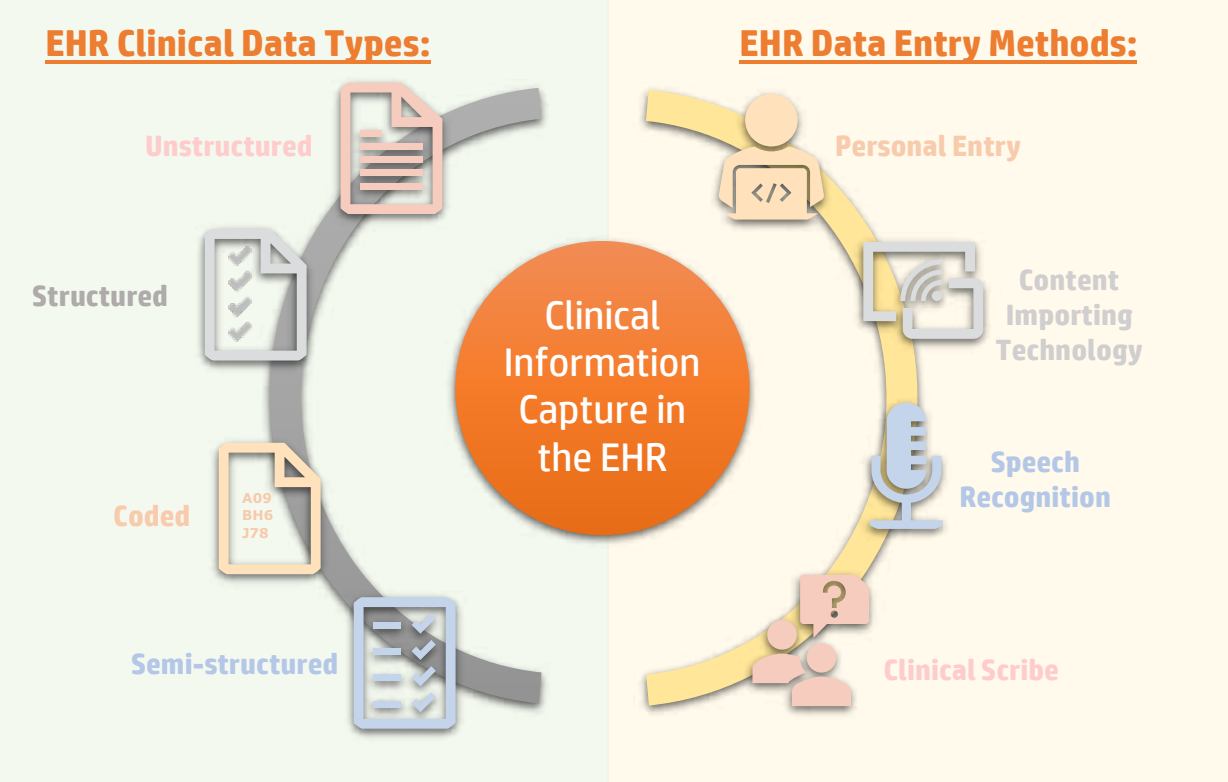


Figure 1. Clinical data types (text) and data entry methods utilised in an EHR identified via the literature review and consultation with the Advisory Group

Clinical Data Types in the EHR:

1. **Unstructured data:** Also known as free or narrative text, unstructured data is often preferred by HCPs as it is more familiar and unrestrictive. However, critical information may be obscured by long narrative text unless natural language processing is utilised.

2. **Structured data:** Including structured templates, drop-down lists, tick boxes and radio buttons, structured data fields help flag critical clinical information and prompt more comprehensive collection of information by HCPs. However, it has often been considered restrictive by HCPs.

3. **Coded data:** Standardised terminologies which are associated with codes have been utilised to promote consistent collection and understanding of clinical information. This also facilitates more comprehensive and accurate data retrieval and the use of CDS software to improve quality of care.

4. **Semi-structured data:** A hybrid model of structured, unstructured and coded data is commonly utilised to gain the benefits of structured and coded data, whilst also enabling free text entry when clinically-relevant data does not fit into the structured templates or where context needs to be added to the structured data element.

Data Entry Methods in the EHR:

1. **Personal entry:** The HCP manually enters the clinical data using the keyboard and mouse, stylus or touch screens. Personal entry usually produces the most accurate data however, it can be time-consuming to type long narrative notes, especially for those with poor computer literacy.

2. **Content importing technology:** Technology which automatically or semi-automatically imports text into the EHR either from another field of the EHR (e.g., copy-and-paste, autofill) or from another device (e.g., barcode scanning, EHR-integrated devices). Although use of content importing technology can save time for the end-user, as well as improve accuracy and timely availability of data, it also poses new risks such as importing of irrelevant or outdated information which may be excessive and cause 'note bloat', obscuring key clinical information.

3. **Speech recognition (SR):** Technology which translates spoken word into text. SR can reduce report turnaround times but high error rates, with potential safety implications, have been identified. This technology is however constantly evolving, and the benefits will vary between vendors and depend on time spent conditioning the SR to the environment and accent of the HCP using it.

4. **Clinical scribe:** An individual who is employed to transcribe the patient information verbally stated by the HCP during the patient encounter and help the HCP to navigate the EHR. Initially clinical scribes were introduced in the United States (US) due to the burden on HCPs of documenting clinical information for insurance companies but more recently, scribes been utilised in Australia and Canada. Although scribes have potential to increase clinical productivity of HCPs, there are legal, governance and privacy issues related to their employment as well as additional costs.

Key Considerations from the Literature and Advisory Group

Based on findings from the literature and input from the Advisory Group during several consultative meetings, a consensus was reached regarding the key considerations for capturing clinical information in the EHR:

1. Capturing personal health information in the EHR changes the way sensitive data is stored and utilised, and data protection and security need to be considered.
2. Changing the way HCPs capture and utilise patient information with the introduction of an EHR will require change management which will likely include strong leadership, education and support.
3. Ongoing review of the clinical information captured within the EHR is required to optimise the EHR interface and data collection methods, improve effectiveness and efficiency, and ensure clinical data is being captured as intended (i.e., no workarounds).

EHR clinical data types:

4. The EHR will likely need to allow input of unstructured, structured, coded and semi-structured data types to accommodate different clinical scenarios and secondary uses of data.
5. Determining which data type options are required for the components of the EHR template in each clinical scenario should consider:
    - Existence of or need for national EHR templates.
    - Category of data being collected *(e.g., demographics, assessment, diagnosis, problem list, social history, psychosocial, history of presenting complaint, outcome measure, investigation results, medications, progress notes).*
    - Purpose of data collection *(e.g., clinical decision-making, monitoring patient's condition, trigger an alert, autofill a report, medico-legal, research, policy making).*
    - Minimum dataset required to ensure clinical information collected remains individualised for patient-centred care and is interdisciplinary.
    - Minimum dataset required for secondary purposes such as CDS and data retrieval for analytics and reporting.
    - End-user workflows and downstream effects of using each data type.
    - End-user involvement in decisions to ensure templates meet their needs.
6. Standardised terminologies (e.g., SNOMED-CT) should be identified nationally and utilised where possible and appropriate to promote the collection of consistent data which has a common meaning and value to all HCPs.
7. Selection of the most appropriate standardised terminologies should be decided prior to EHR design and require consideration of the available evidence to support its use, stakeholder involvement, availability of mapping to other terminologies and licence fees.
8. Whilst reference and aggregation terminologies will likely be decided by policy makers and impact on the EHR design team rather than end-users, interface terminologies utilised at point-of-care may necessitate end-user training and involvement.
9. To optimise EHR use, changes to EHR data fields will likely occur on an ongoing basis but with each change to how data is captured, a comprehensive testing process of the downstream effects on other workflows (including national workflows) and population of data fields is required.

EHR Data Entry Methods:

10. Although this report focused on data entry by HCPs, data entry by patients themselves should also be considered in the future.
11. Irrespective of other data entry methods offered, all end-users should be competent in personal entry and where required, basic computer literacy training should be provided.

12. Adjunct devices (e.g., wearable) should meet certain data quality, provenance and interoperability standards as well as clinical validation prior to integration with the EHR to ensure integrated devices can effectively 'talk' to the EHR and only share clinically relevant, valid and reliable data with the EHR.
13. Whilst vendors may provide a list of adjunct devices which can be integrated with the EHR they supplied, middleware may also be provided to enable interoperability between adjunct devices and the EHR.
14. Importing data from adjunct devices requires a unique patient identifier as well as an episode of care identifier, to ensure the data is imported into the correct patient record and correct location within the record.
15. All data imported using content importing technology should be verified and interpreted by the HCP prior to committing the data to the EHR.
16. If the copy-and-paste function is enabled within the EHR, the copied information should be clearly identifiable and attributed to its original source.
17. Use of the auto-fill function within the EHR requires analysis of workflows and review of the downstream effects of automatically populating data fields from other locations in the EHR.
18. Unlike personal entry, SR technology and clinical scribes require additional resourcing (i.e., finance, time, staff) outside of the basic EHR package and a cost-benefits analysis of implementing these in each clinical setting would be required.
19. As SR and clinical scribes reduce time spent by HCPs navigating the EHR, this could risk HCPs missing critical patient information documented in the EHR as well as HCPs not being able to provide input on EHR system enhancement and appropriateness of data fields within the EHR.
20. Although potentially critical errors have occurred with use of SR, significant advances in technology and natural language processing may result in improvements in the accuracy of SR in the future.
21. End-users may use a combination of data entry methods depending on the specific clinical encounter and setting (e.g., SR for long narrative notes and personal entry for an admission checklist).

1 Introduction

1.1 Electronic Health Record in the Irish Context

The digital maturity of the health service in Ireland varies across healthcare organisations and paper-based medical charts remain in use in most public acute and community services. Although perhaps lagging behind other countries such as the United Kingdom (UK), Denmark and the United States (US), some progress has been made to embed technology within the Irish healthcare infrastructure including:

- National Integrated Medical Imaging System (NIMIS) [20]
- Lighthouse Projects [21]
- Maternal and Newborn Clinical Management System (MN-CMS) [22]
- Individual Health Identifiers (IHI) Act 2014 [23]
- National HealthLink Project [24]
- EPR Project (Project Oak) at St. James' Hospital

Other eHealth projects currently under development in Ireland include:

- National Medical Laboratory Information System (MedLIS) [25]
- Cancer Care eHealth Programme (previously MOCIS) [26]
- ePharmacy Programme [27]
- National Electronic Health Record (EHR) Programme [2]

According to the Sláintecare Implementation Plan Report, the Electronic Health Record (EHR) is the cornerstone of this eHealth Strategy and it has been identified by the Health Service Executive (HSE) National Directors and Clinical Leaders as the key capability requirement of the future delivery of integrated healthcare [1, 6]. An EHR will provide a longitudinal record of information regarding the health status of a subject of care which follows them from one practice or specialist to the next, in computer processible form [7, 8]. This will differ to the Electronic Patient Record (EPR) (or Electronic Medical Record (EMR)) which provides a longitudinal record of health information within a single institution [7]. As the HSE embarks on delivering the EHR, three national projects have been established (Fig. 2).

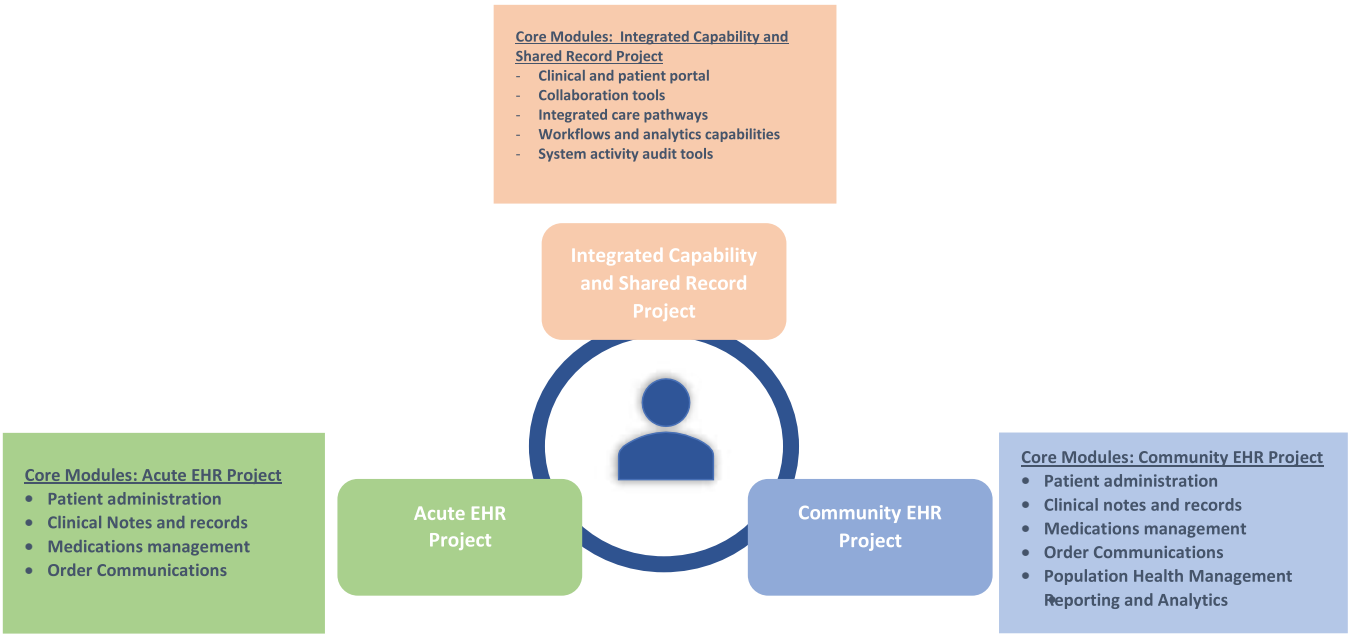


Figure 2. National EHR Programme Projects in Ireland

These projects aim to create a future healthcare environment that is information rich, supports improvements in care and makes a step change in the availability of patient information across the various organisations within the remit of the HSE [28]. Whilst, the Acute and Community Projects aim to deliver a patient-centred, clinically driven and integrated EHR to the secondary and primary care services respectively, the Shared Record Project will aggregate patient data from disparate healthcare organisations' IT systems into a single patient-centric record. The IHI National Register will enable the aggregation of a patient's data to this shared record and improve healthcare professional (HCP) access to patient health records and enhance their capability to coordinate, plan and manage patient care across healthcare settings [29]. In the future, making information from the shared record appropriately available to patients and carers in the form of a patient portal will enable self-care and improved collaboration with patients and carers [29]. These patient portals usually comprise of health information documented and managed by the HCP which is relevant to the patient (e.g., medications, appointments) [30]. Personal Health Records (PHRs) have also been utilised internationally and are usually patient-held (as opposed to managed by the healthcare organisation) and comprise of information from the shared record as well as information generated by the patient themselves or an integrated device (e.g., wearable) [7, 31, 32].

1.2 Clinical Documentation

Clinical documentation is one of several core modules of the Acute and Community EHR Projects and it is the module with which HCPs will interact with every day, constituting the largest change to their daily practice. Clinical documentation provides a record to track a patient's condition and communicate findings and thoughts to other members of the healthcare team [18, 19]. Clinical records are legal documents which contain sensitive personal information summarising the assessment of the person's physical, psychological and social well-being, and whenever necessary, the views and observations of family members in relation to that assessment, evidence of decision-making and care delivery and evaluation of the care provided [4, 5]. This may include clinical notes from outpatient visits, inpatient admissions and discharges, personal correspondence related to clinical matters, laboratory results, imaging records (e.g., X-ray), photographs, videos, audio-recording and consent forms [5, 33]. Overtime, the requirements of clinical documentation have expanded beyond monitoring patient care, to include administrative and managerial decision-making, clinical audit, evaluation and reflection on current practice, research to evaluate clinical improvements and provide the necessary factual base for responding to complaints and clinical negligence claims [5, 18, 34].

Traditional paper-based clinical documentation presents many challenges and inefficient work processes including: illegible hand-written notes; poor flagging of crucial information (e.g. allergies); missing information or missing charts; and delays in medical care due to lack of access to necessary information at point-of-care [35, 36]. These issues also carry a financial cost including labour and time required to search for paper charts, space requirement to store paper charts and duplication in work due to lack of access to patient information at point-of-care [5, 35, 37]. Transferring to electronic clinical documentation will improve readability and accessibility of health records as well as freeing up hospital space. Additionally, it will enable HCPs to spend more time with patients, enhance intradisciplinary and interdisciplinary communication, and facilitate convenient data retrieval [35, 36].

1.3 Capturing and utilising clinical information in the EHR

Implementation of an EHR expands the capacity of information systems to capture, use and exchange these sensitive personal data [38]. This enables multiple benefits including more timely access to health information which reduces duplication in work, improved end-user efficiencies and enables retrieval of pertinent information (e.g., patients on a specific medication) and aggregation of large data sets to enable service development and new potential for research [1, 13, 16, 17]. Additionally, the EHR can improve patient safety and quality of care with flagging of crucial information (e.g., allergies), standardisation of workflows and use of clinical decision support (CDS) software [17]. CDS matches the characteristics of an individual patient to a computerised clinical knowledge base, and patient-specific assessments or recommendations are then presented to the clinician to aid decision-making [39]. However, the increased access to information and opportunities to utilise data also brings new concerns regarding data privacy, security and ethics [10, 12-14, 40-49]. Such concerns need to be addressed with a fully developed and implemented information governance framework ensuring robust privacy policies [14, 41], physical and technical security elements [50] and additional safeguards such as role-based access control and regular audits of user access [51].

Other concerns related to the implementation of an EHR include changes to the workflows or practices of the individual HCPs [12, 47, 52, 53]. Whilst automating the habitual paper-based processes with the EHR would limit changes to end-user workflows, this paper-on-glass clinical information system would not be a fully functional EHR as it would not enable the exchange of information with other systems and across organisations. Similarly, scanning of paper documents into the clinical information system limits the secondary use and sharing of data, as well as being difficult to navigate unless the scanned files are indexed [39, 54]. Therefore, scanning of documents into an EHR is usually limited to initial data migration from paper to digital, mail correspondence and where data collection is too costly or inefficient to capture electronically [55]. Whilst ensuring all clinical information is accessible during the transformation from paper to digital is extremely important [41], in addition to scanned files being difficult to navigate and identify critical information on, it is costly and time consuming to scan entire paper medical charts onto the EHR [39, 54]. Other data migration options include transferring a minimal core clinical data set from the paper chart into the EHR, but staff must be aware that prior to a certain date the record is not electronic and processes for accessing paper charts also need to be available [54].

Although most off-the-shelf EHR systems will come with a library of templates for different specialities and HCP disciplines, the EHR will need to be adapted to meet the needs of the healthcare organisation and end-users, as well as ensuring the EHR realises its potential benefits [41, 43, 44, 52]. Implementation of an EHR provides a unique opportunity to update current non-standardised practices, embed best practice standards and identify any inefficiencies and safety issues [39, 52, 53, 56, 57]. However, the selected structure of the clinical record is very important as it will have profound effects on the way the HCP entering or reading the notes thinks about the patient [58]. Additionally, to enable adjunct functions such as CDS and data retrieval, the clinical information will need to be captured in a recognisable and computer processable format [43, 46] and to facilitate interoperability, some standardisation of clinical documentation will need to occur [59, 60]. With the increase in use and development of information computer technology (ICT) in healthcare, methods of clinical data entry onto the EHR by HCPs are constantly evolving. It is unlikely that a single documentation template or method of entry will be fit-for-purpose for a clinician in every scenario, and therefore, the advantages and disadvantages of each method should be considered within each clinical context [59].

2 Literature Review and Expert Consultation

2.1 Aims

An initial scoping review of the literature and consultations with the Advisory Group were undertaken to examine the breadth of literature on clinical documentation in EHR systems. This initial review identified that clinical data in a text format were captured using several data types and entry methods by HCPs within EHRs. The types of clinical data identified were: (i) Unstructured; (ii) Structured; (iii) Coded; and (iv) Semi-structured. The methods of data entry in the EHR identified were classified as: (i) Personal entry; (ii) Content Importing Technology; (iii) Speech Recognition; and (iv) Clinical Scribes. Therefore, the aim of the more in-depth literature review was to identify the advantages and disadvantages of each of the different types of clinical data and data entry methods within EHRs.

2.2 Methods

2.2.1 Search Strategy

A large number of search terms to describe *"Electronic Health Record"* as well as each of the data types: *"unstructured", "structured", "coded"* and *"semi-structured"*; and data entry methods *"personal entry", "content importing technology", "speech recognition",* and *"clinical scribes"* were identified from previous systematic reviews [13, 41, 45, 61-66], additional literature [67], subject headings from selected reference search engines, and via consultation with experienced information technologists, researchers, HCPs and a liaison librarian at the Health Sciences Library, UCD. The search terms identified have been outlined in the Appendix. *"Electronic Health Record"* search terms were then combined using Boolean Operators with search terms related to each of the data types and data entry methods, and these searches were employed across nine databases: PubMed, CINAHL, Scopus, Embase, Web of Science, IEEE Xplore, ACM Digital Library, ProQuest and Cochrane. Grey literature (i.e., materials not formally published by peer-reviewed journals), such as reports and conference proceedings, were also searched. These grey literature sources included: international Health Informatics Societies; the World Health Organisation (WHO); European e-health network; Kings Fund, KLAS; Gartner; ProQuest thesis and dissertations; and Lenus.

2.2.2 Identification of Studies and Data Extraction

Titles and abstracts of the identified studies were screened. Inclusion criteria included all study types published in the English language which discussed and/or evaluated clinical data types or clinical data entry methods in the EHR. Data were extracted from the studies in relation to the country of origin, setting, population, advantages and disadvantages.

2.2.3 Advisory Group Consultation

The clinical data types and data entry methods identified during the initial scope of the literature were reviewed and expanded upon by the Advisory Group who had extensive experience in implementing large scale IT projects. Following several consultations with the Advisory Group, consensus regarding the key considerations for clinical data types and data entry methods was agreed and these were outlined in the executive summary of this report.

3 EHR Clinical Data Types

3.1 Unstructured Data

Unstructured text refers to free or narrative text generated using a single window (i.e., similar to a word processing programme) which is often included in clinical notes, surgical records, medical reports or discharge summaries [68-70]. Unstructured free text entry of clinical data allows freedom of speech and expressivity [70, 71], which facilitates documentation of complex presentations or impressions of a diagnosis which do not fit into predictable templates or quantifiable values [33, 72]. It is also a critical factor in assisting management decisions and reflecting the training and perspective of the professional recording the data [36, 71]. Free text is often preferred and valued by HCPs due to its familiarity, speed and ease-of-use [33, 71, 73]. For the reader, narrative text provides a greater and more comprehensive understanding of the patient compared with highly-structured data [33, 71]. However, narrative text often contains large amounts of text, much of which may be redundant, which can obscure key information [74, 75]. Due to its unstructured format, it can also lead to omission of important information [71, 76] and makes it difficult to effectively retrieve and use information for preventive care, disease management and quality improvement purposes [73]. These challenges may also be amplified where *copy-and-paste* or some *autofill* functions are utilised to duplicate unstructured narrative data from one note into the new current note [76, 77] *(See Section 4.4 Content Importing Technology)*.

Many of the intended benefits of EHR systems such as clinical decision support (CDS) and automatic pull of data from one section of the EHR to another (e.g., Smart Form*)*, require automatic processing of clinical information which necessitates the use of controlled vocabulary as opposed to free text. Therefore, whilst free text may be more familiar to end-users [33, 71, 78-80], it limits the extent and reliability to which computers can interpret and re-use the data [71, 81, 82]. Conversion of free text into a structured format can be a time-consuming and difficult task [60] and thus, development of automated mechanisms for interpreting free text is of utmost importance [69]. Artificial intelligence (AI) such as natural language processing (NLP) is a promising method for data extraction and retrieval from unstructured text [33, 83]. AI could be used by the HCP at the time of data entry to identify key terms from unstructured text [84] or for secondary purposes (e.g., data retrieval for audits). However at present, challenges exist with the portability of NLP systems between clinical settings and its ability to recognise improper grammatical use, misspellings, local dialects, short phrases (e.g., BID) and clinical shorthand (e.g., D2M) [33, 69, 85, 86]. Overall, whilst unstructured data facilitates more comprehensive and flexible clinical documentation, it also comes with many challenges to optimising EHR use which could affect patient safety and HCP productivity.

3.2 Structured Data

Structured data entry at the point-of-care, as opposed to post hoc structuring using NLP discussed above, includes: (1) Inputting data into structured forms/templates which divide components of the note into different sections (e.g., history of presenting illness); and (2) Selecting options from drop-down lists, tick boxes or radio buttons [33, 66, 87, 88]. Structured documentation templates often lend themselves to less complicated patient presentations [19, 68], computerised provider order entry (CPOE) system [36, 89], registry forms, research forms dates [90], social information, biological data measures and biological investigation results [69, 70]. Whereas check boxes, radio buttons and drop down lists suit aspects which have limited options [33, 68, 69] such as yes/no and patient-reported outcome measures [91, 92]. Until large scale NLP can accurately produce structured data from dictated and free text reports, structured data entry will be an essential input method to enable data retrieval for reports and analytics as well as CDS software [68].

For the author, entering data into structured templates in the EHR can reduce data omission, as checklists can act as 'memory joggers' to assist HCPs to comply with best practice [14, 33, 68, 71, 93, 94]. Additionally, structured data facilitates automated population of data fields (i.e., autofill*)* from other sections of the EHR (e.g., problem lists) [68, 69, 71] and from EHR-integrated devices [95], improving overall efficiency in clinical documentation as well as reducing errors in the transfer of data between systems [96]. Additionally, for the reader, structured templates are easier to read and locate information, whilst administrative staff benefit from the ability to easily aggregate and retrieve structured data [80]. However, whilst end-user efficiency may be improved when taking into account secondary uses of clinical data such as content importing technology, entering structured data at point-of-care requires more effort on the part of the end-user [33, 71, 78-80] and can negatively affect system usability [12, 14, 43]. It also imposes restrictions on clinicians in terms of how they document [66, 81] and how they critically think and make decisions, which can risk the depersonalisation of healthcare [13, 94] and the incorrect identification of patients as having a certain condition due to lack of room for ambiguity [71, 72].

To negate these risks, the American College of Physicians (ACP) have recommended that the EHR system does not mandate end-users to check a box if not appropriate and that structured templates should never replace the clinical narrative [18]. Unprecedented challenges have also been identified with structuring and standardising certain types of data such as psychosocial and emotional information, and whilst their importance is recognised, according to the literature, the best format for recording these data needs to be explored further [91]. It is recommended that the design of structured templates involves a multi-disciplinary task force, workflow analysis (including downstream effects) and ongoing evaluation and comparisons of pre and post templates [97]. Fundamental to any discussion of structured documentation is patient care [87], as well as recognition of the minimum dataset which needs to be collected to support patient care [98]. Additionally, whilst structure needs to be balanced with flexibility, developers should be mindful that the addition of too many options within the structured template could result in no meaningful data being collected [33]. Even after following this process, a structured template will not suit every patient presentation, especially the more complicated patients [87]. Therefore, personalisation which enables end-users to customise how data is input and viewed is recommended to allow some flexibility and improve end-user satisfaction with structured templates [99-101].

3.3 Coded Data

Clinical information can often be tacit, context-bound, and ambiguous [102], and without a 'shared tongue', communication between HCPs can be significantly impaired [103]. Therefore, standardised terminologies have been developed which are associated with codes and represent defined aspects of clinical practice [104-106]. For example, traditionally several terms are utilised to describe high cholesterol but with standardised terminologies everyone uses the same term, and these are mapped to a code (e.g., ICD-10 code E78.0 represents Hypercholesterolemia). This multiples the benefits of structured data, as definitions are understood and synonyms can be aggregated (e.g., heart attack, myocardial infarct and MI) [87]. Additional benefits include:

1. Improved data quality [103, 105, 107, 108].
2. Terminology understood by all HCPs across organisations and geographical boundaries (irrespective of language) [103, 105, 107, 108].
3. Patients benefit from HCPs utilising same term across clinical documentation to describe their condition [103].
4. Improved quality of care [103].
5. Semantic interoperability between systems [105, 107, 108].
6. Accurate and comprehensive searches to identify patients requiring follow-up or changes to treatment based on revised guidelines [103, 105, 107, 108].
7. Monitoring of treatment effectiveness, patterns and trends [66, 87, 94].
8. Use of CDS software [66, 87, 94].
9. Additional research opportunities [103, 105, 107, 108].

Whilst many standardised terminologies have been developed, no single terminology has been accepted as a universal standard [109]. Three different types of coding sets have been discussed in the literature:

Aggregation Terminologies (or Administrative Code Sets): Enable classification of concepts using simple hierarchy relationships for administrative purposes such as reimbursement [104, 106, 107]. As these codes were designed to either group diagnoses and procedures or to contain broad categories with administrative technical terms, aggregation terminologies can be restrictive and prevent concepts from having multiple parents [104]. Where HCPs are forced to use these code sets to capture clinical data, there is potential for inaccuracies and loss of the clinical intent [104, 106]. Currently the Irish health system principally uses the aggregation terminology *International Classification of Diseases and related health problems, tenth revision Australian Modification (ICD-10-AM)*, to classify and report activity in respect of inpatient and day cases in the Hospital In-Patient Enquiry (HIPE) system [105, 107]. Other aggregation terminologies include *International Classification of Primary Care (ICPC), Read version 2* and *Office of Population Censuses and Surveys Classification of Interventions and Procedures (OPCS-4).*

Reference Terminologies (or Clinical Code Sets): Enable more sensitive and specific terms to be collected as they are concept-based and controlled clinical terminologies which maintain a common reference point in healthcare [106]. Unlike aggregation terminologies, reference terminologies facilitate the combination of concepts (i.e., post-coordination) to create a more detailed or complex concept from a simple one [104, 109]. For example, the following terms may coexist: chest pain, substernal chest pain and crushing substernal chest pain. Reference terminologies are less restrictive, considered more usable and meaningful for HCPs, reduce time spent searching for terms and enable use of CDS software as well as aggregation of data [106, 109, 110]. Reference terminologies utilised at point-of-care

include the *Systematized Nomenclature of Medicine - Clinical Terms* (SNOMED-CT) which capture all clinical notes including allergies, vitals, past history, family history, symptoms, clinical findings and diagnosis and has been recommended for use in Ireland by the Health Information and Quality Authority (HIQA) [107]; the *Logical Observation Identifiers Names and Codes* (LOINC) which captures laboratory and clinical observations; and *RxNorm* which captures medication names [106, 107, 111]. To balance the more usable reference terminology with the more rigorous aggregation terminologies which may be needed for national audits or reimbursement, reference terminologies can be mapped to an aggregation terminology (e.g., ICD-10) [112].

Interface Terminology: To capture more granularity and clinical intent in the documentation, a third type of standardised terminology has been developed referred to as interface terminologies [106]. These interface terminologies are often discipline-specific (e.g., *International Classification for Nursing Practice* [ICNP]; *Nursing Interventions Classification* [NIC]; O*maha System; Nursing Outcomes Classification* [NOC]; *Nutrition Care Process Terminology* (NCPT))[112, 113], institution-specific [114] or speciality-specific [103]. Whilst large-scale reference terminologies attempt to represent every possible entity, interface terminologies reduce the need for post-coordination (e.g., combination of "acute" and "pain") as they represent the common terms utilised in the specific practice its employed in [106, 114, 115]. Additionally, this decreases time spent searching for codes and facilitates documentation of more comprehensive, accurate and relevant clinical information [106, 114, 115]. Interface terminologies can be also be used to gain a deeper understanding of care approaches during evaluations, as well as having potential to improve patient outcomes [94, 112, 116, 117]. Therefore, interface terminologies are important for problem lists [106] and these can then be mapped to the reference and aggregation terminologies where required [106, 112, 118].

Overall, use of standardised terminologies within the EHR provide several benefits to end-users, patients, healthcare organisations and policy makers, and it is likely that more than one type of terminology will be required in the EHR to facilitate both administrative and clinical purposes. Decisions regarding the selection of these terminologies should be made prior to EHR design as otherwise adaptations to the terminology in the EHR is expensive and labour-intensive [103]. Each of these terminologies will come with a license fee and mapping of terminologies to one another will need to be maintained by the software developer, third-party vendor or the individual healthcare organisation [81, 112, 119]. Where end-users are selecting a standardised term from a list, they may not be aware that they are using coded data, however, if end-users are incorporating an interface terminology into an unstructured note, training of end-users in the terminology may be required [103, 120, 121]. Searching for the correct code to match a patient's diagnosis from a list can also be time-consuming, which affects system usability [66]. Therefore, EHR systems should support shortcuts such as searching mechanisms where end-users can enter a keyword or phrase to find the relevant code, display of the most frequently selected codes (for the given user) at the top of the list, i.e., 'favourites' [87] and/or use of NLP techniques to suggest appropriate codes and expression, as well as enabling end-users to input free text [111, 122]. AI algorithms can also be utilised to identify standardised terminologies from unstructured notes and produce the matching code, but this comes with additional cost and the validity and reliability of such software should be assessed, especially if being utilised for CDS systems [123]. Additionally, codes do not always easily accommodate for diagnostic uncertainty [83] and are not always sensitive and specific to the condition in question (e.g., depression could present symptomatically as insomnia, fatigue, malaise) [124].

3.4 Semi-structured Data

Unstructured, structured and coded data do not have to be mutually exclusive and hybrid model known as semi-structured data has been recommended in the literature [87, 88]. Most EHRs allow end-users to enter both narrative free text and structured data onto a template [83]. In this way, structured and/or coded data, which is amenable to computer processing, is input and facilitates the secondary use of the clinical data, whilst free-form boxes at the end of notes allow additional context or further clinically-relevant information can be added [76, 87, 103]. Additionally, within the structured elements of the EHR, options to input narrative data are often provided where end-users cannot find an appropriate structured concept or code [33]. However, this can risk end-users overusing the free text box rather than searching for the appropriate code and thus, end-users need to understand the benefits of using coded and structured data in combination with unstructured data. Overall, semi-structured clinical data combines the benefits associated with the flexibility of unstructured data with the downstream benefits of using coded and structured data.

3.5 Key findings: EHR Clinical Data Types

No one type of clinical data will accommodate the documentation of every clinical scenario and/or secondary use of the data and thus, it is likely that a combination of those will be utilised [59]. In determining the most appropriate type of data or combination of data types, the advantages and disadvantages of each should be considered (Table 1), as well as the workflows and downstream effects of capturing data in this format.

Table 1. Summary of clinical data types in the electronic health record

	Unstructured	Structured	Coded	Semi-structured
Definition	Free or narrative text.	Templates divided into defined sections, checklists, drop-down lists or radio buttons.	Standardised terminologies with defined terms associated with codes.	Combination of unstructured, structured and coded data.
Advantages	• Flexible. • Easy-to-use. • Can be faster to enter. • More comprehensive.	• Easier to read and navigate • Prompts HCP to ask questions. • Enables autofill function. • More comprehensive searches and data retrieval.	• Consistent meaning and value associated with terms. • Facilitates: ○ Interoperability ○ Data retrieval ○ CDS ○ Autofill	Allows some flexibility whilst retaining the benefits associated with structured and coded data.
Disadvantages	• Risk of large amounts of text obscuring key information. • Risk of omission of information. • Difficult to retrieve specific information. • Difficult for computer to process.	• Restrictive for HCPs. • Can be more time-consuming to enter. • Risk of losing individualised patient information capture.	• Restrictive for HCPs. • Can be more time-consuming to search for codes. • Costs associated with licence fees and maintenance.	Risk of overuse of free text form as opposed to searching for appropriate code/structured element.
Recommended uses	Where a clinical presentation does not lend itself to a predefined template.	CPOE, birth date, biological data measure or biological investigation results, limited possible answers (yes/no) etc..	Diagnostic codes, laboratory results, procedure codes etc..	Where HCP may need to expand on the coded and structured data using free text.

4 EHR Data Entry Methods

4.1 Personal Entry

Personal entry, for the purpose of this report, refers to the HCP manually inputting clinical data into the EHR themselves using the keyboard, mouse, stylus or touch screens. All EHR systems will accommodate personal entry of clinical data but the type of data may impact on the data entry device selected. For logging long unstructured clinical data, HCPs reportedly prefer to use a keyboard and mouse at a stationary computer [125, 126] compared to a touch screen tablet [127, 128]. Conversely, according to the literature, there is greater adoption of touch screen tablets amongst HCPs for documenting structured clinical data such as checklists [125]. Use of personal entry enables the end-user to benefit from the cognitive resources within the EHR such as structured templates which can prompt questions and CDS which assists with clinical decision-making [68]. Disadvantages of personal entry include the time-consuming nature of typing long narrative notes [125, 126]. Personal entry also requires end-users to have basic computing and keyboard skills which has been a substantial barrier to EHR adoption amongst end-users [14, 41, 44]. Additionally, manually entering data during the patient encounter can negatively impact on the patient-clinician communication as it reduces eye-contact [72, 73, 129].

To improve the efficiency of entering clinical information onto the EHR, alternative methods have been developed which include speech recognition (SR) and clinical scribes, which are discussed in further detail below. However, according to a KLAS report, end-users with access to personal entry only, were more satisfied with an EHR overall compared to those with access to SR or a clinical scribe [130]. Additionally, whilst errors in clinical documentation do occur with personal entry in the EHR, these were reportedly fewer and less critical when compared to SR-related errors [131]. Technology is constantly evolving but at present, personal entry facilitates the most accurate use of structured templates, coded data, autofill and CDS [131, 132]. Additionally, even where clinical scribes are employed to enter clinical data, the HCP needs to be able to manually enter clinical information themselves as they may need to train the clinical scribe in use of the EHR or they may not always have access to the scribe. Therefore, irrespective of the availability of other data entry methods, all end-users need to be competent in entering data using personal entry onto the EHR and this requires training and front-line support [41, 133]. Additionally, to facilitate use of personal entry, the EHR system should be intuitive and simple to use [12, 14, 42, 44, 47, 61, 134] and computing skills of end-users should be assessed [135] with basic computer literacy training should be provided to those requiring it [41, 133].

4.2 Content importing technology

Rather than the end-user personally transferring data from one system or data field to another, which can be an inefficient and error-prone process [90], EHR software allows for information to be moved from one part of a patient's record into another section (e.g., auto-fill or copy-and-paste) or from another device or cloud technology into the EHR (e.g., EHR-integrated medical devices or bar-coding) [77]. Whilst obvious benefits to content importing technology exist including improved user efficiency and data accuracy, there are also risks associated with populating EHR fields with existing data which may have been inputted by an unattributed source. The advantages and disadvantages of content importing technology identified in the literature are discussed in further detail below.

4.2.1 Copy-and-paste

EHR systems may facilitate end-users to copy text, images or other data from one location to another using the keyboard command *Ctrl-C* followed by *Ctrl-V* and this function is referred to as *copy-and-paste* [63, 77, 136]. For the purpose of this report, the following section will focus on the *copy-and-paste* of text only as opposed to images. Attributions of the original note including author, source and date/time of creation may be lost in the copied note or if this information is embedded within the copied information, it usually isn't apparent to the average reader [77]. Copying of clinical notes from one day to another or from another clinician's notes (e.g., doctor coping excerpts from nursing notes) and modifying it accordingly, aims to save clinician time by allowing for information, that does not readily change, to be easily transferred [137, 138]. It can also improve usability by allowing end-users to insert test results from another system or page (e.g., laboratory results), which may not be easily accessed when composing the note [36, 63].

The *copy-and-paste* function may reduce transcription errors when re-typing complex information and produce more complete documentation, especially for patients with multiple and complex problems [63, 138]. This improves continuity of care and decision-making, while also reducing the risk of neglecting important issues [63, 138]. However, overuse of *copy-and-paste* can promote long, poorly organised and less accurate notes due to inclusion of redundant, potentially outdated or inconsistent information, referred to as 'note bloat' [63, 136]. These lengthy duplicated notes can obscure critical information, reduce credibility in notes, cloud critical thinking, limit proper coding and rob the chart of its narrative flow and function [13, 77, 138]. This affects clinical decision-making and may create more queries and work for clinicians to determine if information is correct [13, 77, 138]. Another risk discussed in the literature is referred to as 'cloned documentation' which refers to the repetitive pattern of identical or nearly identical notes recorded over the course of an individual patient's illness or among patients with similar conditions [77].

A recent systematic review identified that 66-90% of doctors used the *copy-and-paste* function in the EHR, and 78% use it "almost always" or "most of the time" for inpatient documentation [63]. Another study reported that progress notes contained double the amount of copied information compared to new manually-entered information [139]. Whilst *copy-and-paste* facilitates speed of clinical documentation, this is not the same as efficiency [140], and copied notes which include inaccuracies or are from an unknown source may have implications for patient safety [141]. Both clinical and non-clinical harm to patients have occurred as a result of *copy-and-paste*, including contribution to diagnostic errors [63, 142] and outdated problem lists discussed with patients resulting in reduced patient confidence in clinicians [63]. There is also a risk of pasting information into the wrong patient chart or pasting an incorrect block of text.

The *copy-and-paste* function can be disabled by vendors to mitigate these safety risks, but this won't eliminate the above challenges completely and there are benefits to *copy-and-paste* use within the EHR. Therefore, recommendations have been made in the literature to promote best practice with the use of *copy-and-paste* including:

- Copied data copied should be essential and pertinent to the clinical encounter and should be reviewed or updated meticulously [63].
- End-user acknowledges legal responsibility for verifying the accuracy of all information included in their note and ensures it reflects the patient's current clinical status and plan of care [63, 140, 143, 144].
- Attributions of copied text should be acknowledged (including date, time and original author) and functionalities can be developed to allow easy identification of copied material e.g., font colour, highlighting copied text or toggles to view new and/or copied information [63, 144].
- Documentation standards should be developed to provide clarity regarding proper use of *copy-and-paste* including information which is permissible to copy and consequences for violation of policies [63, 144] (e.g., prohibition of copying information from one patient's record to another's and copying notes of an unlicensed individual such as students [140]).
- Organisations should provide education and feedback related to use of *copy-and-paste* which align to their policies (e.g., use of audits to provide timely feedback to users regarding proper and improper use) [63, 77].

4.2.2 Autofill

To improve clinical documentation efficiency in the EHR, functions can be configured to automatically draw data from one location in the EHR and insert it in another location, and this function has been termed *autofill* in this report [77]. Some examples of autofill identified in the literature included:

Copy-note-forward: Duplicates unstructured narrative data from one note into the new current note of the same patient which can then be edited by the HCP. Attribution of the original source of the data is usually available to the reader [68, 76, 77].

Dot-phrase: End-user inserts a short phrase preceded by a full-stop into the text field and this expands into either a generic phrase which is the same for all patients (e.g., .bp could expand to blood pressure) or a phrase pulled from a specific patient's chart (e.g., .age could expand to 80 years of age) [145, 146].

Smart Form or Template: Pulls data from the patient's chart into a pre-defined template (e.g., discharge letter) [146-148].

An additional benefit of using *autofill functions* such as *dot-phrases* within progress notes is that should this text be copied into a new note using the *copy-and-paste* or *copy-note-forward* functions, any changes to the data linked to the *dot-phrase* (e.g., medication list) will be imported in the new copied note [149]. However, importation of inaccurate or out-dated data which are not corrected could greatly compromise patient safety and outcomes [76] and increases risk of 'note-bloat' [149, 150]. According to the American College of Physicians (ACP), there are potential benefits to *autofill* functions such as *copy-note-forward,* however misuse of these documentation techniques can be to the detriment of clinical data accuracy, high-quality care and patient safety [18]. Similar to *copy-and-paste,* all data copied from another section of the EHR needs to be verified and this is the responsibility of the author of the note [151]. Access to and training on use of *autofill* shortcuts could improve end-user efficiency with clinical documentation, however, end-users should be aware of the risks of over-use of such functions and the need to verify data.

4.2.3 Bar-code scanning

According to the literature, bar-code scanning is being utilised for a variety of purposes within healthcare organisations including to track patient wristbands throughout the hospital [57], document operating room equipment utilised (e.g., sponges and implants) [79], to ensure the correct patient for blood transfusions [152] and for medication administration documentation and safety [153]. Barcode medication administration (BMCA) includes the automated documentation of medication in the electronic medication administration record and therefore, will be the main focus of this report [153]. As well as reducing transcription errors and nursing documentation time with the automated documentation of medications and time administered [153], BCMA also aims to improve patient safety by ensuring right patient, right dose, right drug, right time and right route, via scanning both the patient's wristband and the medication to be administered [154].

Utilisation of BCMA has reduced medication administration errors by up to 50% including adverse drug events (ADEs) which can lead to patient harm as well as increased hospital length of stay and costs [153, 155, 156]. However, even in the best systems errors will inevitably occur and the biggest failure of BCMA has been bar codes not scanning or products missing barcodes [157]. Whilst future developments in this field may include 2-dimensional bar codes (i.e., QR or quick response) and/or radio-frequency identification [158] (which may be especially useful in operating rooms [79]), literature recommendations to reduce bar-code related workarounds and/or errors include:

- Mandatory application of linear bar codes to all products by pharmaceutical companies [159].
- Regular system updates with new medications or brands [153, 158, 160, 161].
- Printing equipment specifications such as regular cleaning to ensure printing of clear bar codes [153, 158, 160, 161].
- Adequate infrastructure which meet defined standards (e.g., bar code charger at each nursing station) [161, 162].

Bar code-related issues and changes to traditional work processes increase the steps involved for nurses and the potential distractions which results in less time for nurses to explain medications to patients [153]. This results in workarounds such as scanning the medication in the medication room instead of at the bedside, which negate the 'right patient' safeguards of the BCMA [163, 164]. To reduce workarounds, best practice workflows should be identified and end-users should be trained on and aware of the benefits of the new workflow [165, 166], which will help foster a culture of patient safety [167]. However, ongoing evaluation of these workflows are required and in some circumstances overriding of the BCMA workflow should be permitted [161].

Introduction of electronic prescribing including BCMA, has been recommended by the European Association of Hospital Pharmacists [168], but not all departments may be appropriate for BCMA systems. For example, emergency departments often require more verbal orders due to medical emergencies [169]. According to the literature, phased implementation starting with a small department which will benefit most from BCMA introduction (i.e., high risk of ADEs) is recommended, but transferring of patients between units with and without BCMA must be monitored closely [166]. Taking both implementation and maintenance costs into account, BCMA systems are said to be cost effective within 1-4 years of implementation [156]. However, cost savings will depend on hospital size, availability of infrastructure and number and cost of ADEs prior to implementation [170], as well as the success of implementation and engagement of staff. With development of policies which ensure patient safety and successful implementation, BCMA systems could promote safe, efficient and cost-effective medication administration and transcription.

4.2.4 EHR-Integrated devices

Commercially-available devices have been integrated with EHR systems to automatically or semi-automatically (i.e., with clinician approval) capture patient-generated health data which are recorded by or gathered directly from patients [95]. These data may have traditionally been collected and documented by a clinician at point-of-care (e.g., blood pressure, heart rate, patient questionnaires) [171-178] or could include relevant longitudinal data measured remotely (e.g., glucometers, wearables) [177, 179-181]. The advances in sensor technology and wearables has enabled remote monitoring outside of traditional hospital settings [179]. This allows HCPs to focus on patient care rather than transcribing values during outpatient appointments [182] and has the potential to augment and transform healthcare [179]. To enable integration, the medical device must have the ability to share data with the EHR using open language such as HL7 [183] or using middleware which is software that can integrate with both the EHR and the specific device [95, 175, 180].

The automatic documentation in the EHR of data previously input by HCPs has been shown to improve data quality (i.e., accuracy and completeness), reduce the steps and time required by HCPs to enter this data, and promote the availability of real-time data for clinical decision-making [171-176]. This can be especially useful in high demand settings such as the ED where its reported that without automated documentation, HCPs often initially write findings on paper and transfer the information to the EHR at a later time [171]. It may also be valuable in scenarios where collection of longitudinal and continuous data is beneficial for decision-making such as intensive care [171] or for certain chronic conditions (e.g., diabetes, asthma) [177, 180, 184]. Benefits for patient care have also been reported such as improved patient safety with devices such as intravenous (IV) medication administration which uses readings documented in the EHR to recommend a medication dosage, usually based on best practice guidelines [175, 176]. Additionally, home-monitoring devices reportedly improve patient-initiated communication with HCPs, patient self-management and more accurate assessments of health status [95, 177, 184]. However, further research on the benefits of integrated devices within the EHR for patient-centred care is required [171-173], as well as how they should be effectively, efficiently and safely incorporated within clinical workflows and displayed within the EHR [95].

Potential safety risks associated with EHR-integrated devices include lack of interpretation of the automated documentation [171] and patients expecting clinicians to review their remotely-generated data in real-time rather than patients self-monitoring for abnormalities [95, 180]. Whilst there is potential for integrated devices to send notifications of concerning trends and outlier values to the HCP via the EHR, this results in an increased workload for the HCP, in addition to the already time-consuming set-up of devices [95, 177]. The volume of data collected by the EHR-integrated device may also present challenges for the EHR to manage and the HCP to interpret [181]. Use of integrated devices, especially those within the home, require a patient to possess compatible technology or the healthcare organisation to purchase this equipment [177, 185] and if middleware is required, this increases the complexity as three systems are in use [177]. To reduce the risk of overwhelming HCPs, AI could be applied to these devices in the future to provide clinically useful patient summaries [179].

These devices have potential to move healthcare in the direction of true patient-centeredness but they bring changes to work processes once integrated [95, 179]. The downstream effects on workflows of implementing any software or hardware need to be analysed and planned [52]. For example, automated documentation of vital signs needs to be signed by a HCP who is responsible for interpreting and ensuring accuracy of the data [151]. Where additional clinical information is being provided (e.g., longitudinal blood glucose levels), clinical involvement in the design and purchase of such devices is required to ensure the information being made available is clinically useful and will inform practice [53] and not result in information overload for HCPs [177]. To ensure HCPs and patients can trust the

information provided to inform their clinical decisions, any device integrated with the EHR needs to meet certain regulatory standards and clinical validation [95, 172, 179, 185]. Devices which may be integrated with the EHR should all be assessed for interoperability, safety, efficiency, efficacy, accuracy and security [175]. To be fully interoperable with the EHR the use of a patient identifier (e.g., IHI) is required to ensure data generated is entered into correct patient record and for the correct episode of care, otherwise, their introduction will risk fragmentation, duplication and inefficiency of care delivery [179]. Overall, integration of devices with the EHR has potential to improve patient care and accessibility of patient data for clinical decision-making but there are several considerations to ensure patient safety.

4.3 Speech Recognition

Speech recognition (SR) is a technology which translates spoken word into text or executes verbal demands in the EHR (e.g., opening/closing window or screen, selecting from a drop-down menu, or authentication of an individual) [64, 131, 186]. Despite the wide availability of SR technology utilised to execute demands, this has received little formal evaluation in the literature [187] and dictation will be the focus of this report. SR to transcribe clinical information differs from traditional digital dictation, as the software transcribes the clinical information rather than an individual. This technology presents a valuable tool for clinical documentation which allows the clinicians to focus on patient interactions and care rather than the computer screen, and according to the literature, may have a major impact in primary care, outpatients and the emergency department (ED) [179]. Across the literature, SR technology has most commonly been utilised to generate radiology reports both internationally and in Ireland [64, 188], and it can be an ideal mechanism for logging long notes in certain disciplines and specialities [87, 187, 189]. Additionally, it can be utilised for structured data templates [190]. Two forms of SR for dictating notes were discussed in the literature, namely Front-end and Back-end.

Front-end speech recognition: Technology which dictates spoken word of the HCP directly into the EHR in real-time which the HCP can review and edit as the text is dictated [59, 132, 191]. Correcting of errors in real-time helps the program to 'learn' and improve accuracy levels but this can be time-consuming during a patient encounter and potentially tether the HCP to a specific workstation which recognises their voice [189].

Back-end speech recognition: Dialog is recorded, passed through a recognition engine and the dictated text is sent back to the HCP or a medical transcriptionist for verification before being committed to the EHR [59, 132, 191]. Unlike front-end, back-end SR is not transcribed in real-time and thus, clinical information can be dictated using hand-held mobile devices [186] and may provide additional quality control if a medical transcriptionist reviews the note [131, 190].

According to the literature, SR technology has reduced report turn-around time by 50-95.8% [64, 190], even when using back-end SR [191], making clinical documentation more readily available to all healthcare teams [192]. The Topol Report estimated that use of SR would save 400,000 hours of ED consultation time, one million hours for outpatients and 5.7million hours for GPs annually [179]. However, although these figures were conservatively taken, these data were solely based on the perceived time-savings reported by HCPs and was published by the supplier of the SR [193]. Additionally, whilst time savings and increased productivity levels have been noted [194], a recent systematic review reported that use of SR was more time-consuming than personal entry [130]. Contributions to these inconclusive findings may be related to the use of various SR technologies produced by different

companies [190] and the accuracy of the SR which HCPs must spend time correcting especially during the early stages of software conditioning [187].

Errors occur with use of both SR and personal entry, however, SR-related errors have reportedly been more critical to patient safety [131, 190, 195]. For example, critical errors have included insertion of "grown mass" instead of a "groin mass" [132] and a full-stop instead of "period" referring to menstrual cycle [196]. However, whilst time should be spent by the HCP correcting these errors, it has been shown that HCPs did not always thoroughly review the dictations before committing them to the EHR [68, 132]. Unacceptable error rates have led to slow uptake of SR technology in healthcare [179], as well as the subsequent impact of errors on downstream systems such as auto-fill and CDS systems. On the other hand, unlike errors created by personal entry, SR-related errors are often systemic across the system (e.g., SR dictating 'period' as '.') and thus, once one error is identified, these can easily be identified across the system and corrected. As technology evolves, the accuracy of SR technology will improve [131] but it is also influenced by:

- Time spent conditioning the system to the HCP's voice and correcting errors during the early implementation phase [190, 197].
- Quality of the sound hardware and medical terminology dictionary programmed into the system [190, 197].
- Dialect and accent of the HCP [130].
- Environment and background noise [130] (e.g., ED is a natural fit for SR but may be nosier and contain more distractions during SR use [192]).

The evidence regarding cost effectiveness of installing SR technology within the EHR is inconclusive, likely due to the variances in products and settings [64, 131, 190]. However, some financial benefits have been noted including being a cheaper alternative to clinical scribes [59]. Cost analysis in each setting should however include consideration of the following costs: software, hardware (i.e., hand-held digital recorder versus computers compatible with SR vendor product), installation, maintenance, transcriptionist (if utilised), end-user training and support, and time required to train the software [131, 189]. Additional benefits associated with SR include a reduction in time spent by doctors looking at a computer screen during a patient appointment compared to personal entry [197] and the storage of a voice file should it be required for verification purposes, unlike use of scribes [59]. However, according to a KLAS report, reduced interaction with the EHR as a consequence of using SR technology resulted in overall lower levels of end-user satisfaction with the EHR [130]. This could negatively impact on patient care due to reduced use of the available cognitive resources within the EHR for problem solving and recall (e.g., structured templates) [68]. Use of SR could also result in longer narrative text with the potential to impact on clinical decisions and obscure critical clinical information [131].

Although the evidence presented in relation to SR technologies is variable regarding its benefits, the underlying technology used to recognise and process speech within SR systems is evolving dramatically and at a faster rate than with HCPs' skills with keyboard and mouse documentation [131, 132]. SR technologies have great potential for use with a variety of tasks such as order entry, alert management and patient handoffs [131] and are being combined with advanced NLP and AI to provide HCPs with tools to identify obvious errors and coded terms to enable use of CDS [87, 187].

4.4 Clinical Scribes

In the United States (US), difficult-to-use and time-consuming EHR systems which required accurate entry of multiple codes for billing purposes, led to the introduction of clinical scribes, also known as medical or physician scribes, across emergency departments in the 1970s [65, 198]. To reduce the burden of clinical documentation and allow HCPs to spend more time with patients, these scribes enter the clinical information as verbally-stated by the HCP, who later reviews and signs off on the notes after the patient encounter [187, 199]. Additionally the scribe may assist the HCP to navigate the EHR, provide clerical support and track availability of results [199, 200]. More recently, demands on public emergency departments in Australia and Canada, who have similar health systems to Ireland, have led to the creation of clinical scribe roles [201] and in the US, these roles have expanded to other settings such as primary care [202, 203]. Scribes are reportedly often students pursing a medical or nursing career and have been trained in medical terminology and commonly encountered disease presentations using a combination of text books, e-learning, classroom and direct supervision [198, 200, 204-207]. Employing students as scribes could expose them to additional learning experiences, however, the benefits of this have not been demonstrated in the literature, and a large staff turnover is likely if employing students [208].

According to the literature, scribes produce accurate and comprehensive records, while decreasing burn-out and increasing productivity of HCPs, and both patients and HCPs have been satisfied with this new role [201, 203]. However, the competency and capability of the individual scribe will impact on whether these positive findings are transferable to other settings [198, 199, 209]. Additionally, much of this research has been conducted in the US where 'physician burnout' has been high due to pressures of comprehensive billable coding for insurance companies [210]. However, a recent multi-centre randomised controlled trial (RCT) in Australia demonstrated that scribes in the ED increased the number of patients seen by doctors, reduced the length of stay in ED for patients and was cost effective despite training costs but these benefits were variable across hospitals [204]. This RCT also identified an error rate by the scribes of 1 in every 300 consultations, mainly related to selection of the incorrect patient for ordering investigations [204]. Whilst all these errors were identified by the doctor or the scribe themselves, concerns regarding patient safety and legal and governance issues have been raised regarding expansion of clinical scribe roles beyond documentation to ordering investigations [200, 203].

A recent report by KLAS which compared doctors with and without access to a scribe stated that no benefits were noted by those with access and in fact, those with access were marginally less satisfied with the EHR overall [130]. This is likely due to them spending less time interacting with the EHR system, similar to the finding in relation to SR [130]. Whilst use of both clinical scribes and SR reduce the clinical documentation burden on HCPs, clinical scribes do provide an added quality control of accurately transcribing clinical information in an unstructured, structured, coded or semi-structured format in real-time. However, this is reportedly more expensive than SR [59]. Advances in NLP and AI however, have potential to combine the benefits of clinical scribes and SR with the development of what is known as a digital scribe but to date, this has not been trialled in a clinical setting [187].

4.5 Key Findings: EHR Data Entry Methods

The four methods of data entry discussed above are not mutually exclusive and it is likely that a combination of those methods will be utilised across healthcare systems. The advantages and disadvantages of each method should be considered for each setting and a summary of these are provided in Table 2.

Table 2. Summary of data entry methods of text in the electronic health record

	Personal Entry	Content Importing Technology	Speech Recognition (SR)	Clinical Scribes
Definition	HCP manually inputs data using the keyboard and mouse, stylus or touch screen.	Automatically or semi-automatically transfers clinical data from one data field or system to another (e.g., copy-and-paste, autofill, barcode scanning, EHR-integrated devices).	Technology which translates spoken word into text.	Individuals employed to transcribe clinical data verbally state by the HCP in real-time.
Advantages	• Fewer and less critical errors compared to SR. • Facilitates entry of all data types. • End-user benefits from prompts provided by CDS and structured templates.	• Can reduce transcription errors and documentation time. • Improves availability of data in real-time. • Improves patient safety when utilised with medication administration.	• Reduces report turnaround times • Reduces time spent by HCP looking at a computer screen during patient encounter.	• May increase HCP productivity. • Some evidence to support cost-effectiveness. • Can facilitate HCP to spend more time with patients.
Disadvantages	• Can be time-consuming. • Requires good typing skills. • May have negative impact on patient-clinician communication.	Risk of: • Information overload and note-bloat. • Imported data not being attributed to a source or interpreted. • HCP distrust of imported data.	• High upfront costs • Risk of critical patient safety errors. • Ambient noise, accents and interruptions affect SR accuracy. • HCP spends less time navigating EHR - lower EHR satisfaction/missing critical patient information.	• Costs associated with recruitment, salaries and training. • Governance policies, legal issues and patient consent concerns. • HCP spends less time navigating EHR - lower EHR satisfaction/missing critical patient information.
Key considerations	Typing skills of end-users should be assessed and basic computer training should be provided where needed.	• Imported data should be reviewed, interpreted, attributed to the original source and verified by the author. • Only data essential and pertinent to the clinical encounter should be imported. • Integrated devices should be quality approved. • Certain settings will benefit more from integrated devices than others	• SR technology constantly evolving. • Quality of SR dependent on many variables e.g., environment, vendor. • Needs to be conditioned to voice and environment. • HCP should review transcribed notes prior to committing them to EHR. • SR effect on downstream functions e.g., autofill.	• Majority of research conducted in US where 'physician burn-out' attributed burden of inputting billable codes for insurance companies. • Scribes require training and there may be large staff turnover.

5. Conclusion

This report identified the different clinical data types and methods of data entry in the EHR (Fig. 3) as well as the advantages and disadvantages associated with each according to the international literature and consultation with the Advisory Group. Whilst this report provided an overview of the literature available at time of the search, technology and healthcare are constantly evolving and a more in-depth evaluation of each type of data and method of entry should be conducted prior to implementation. These data types and methods are not mutually exclusive and no one method will accommodate every clinical scenario and need, therefore it is likely that a combination of these will be utilised [59]. In conclusion, this report highlights that there are advantages and disadvantages to capturing data using each of the identified data types and data entry methods. Therefore, each healthcare organisation should consider these in relation to the needs of their specific organisation and wider health service, as well the HCPs and patients.

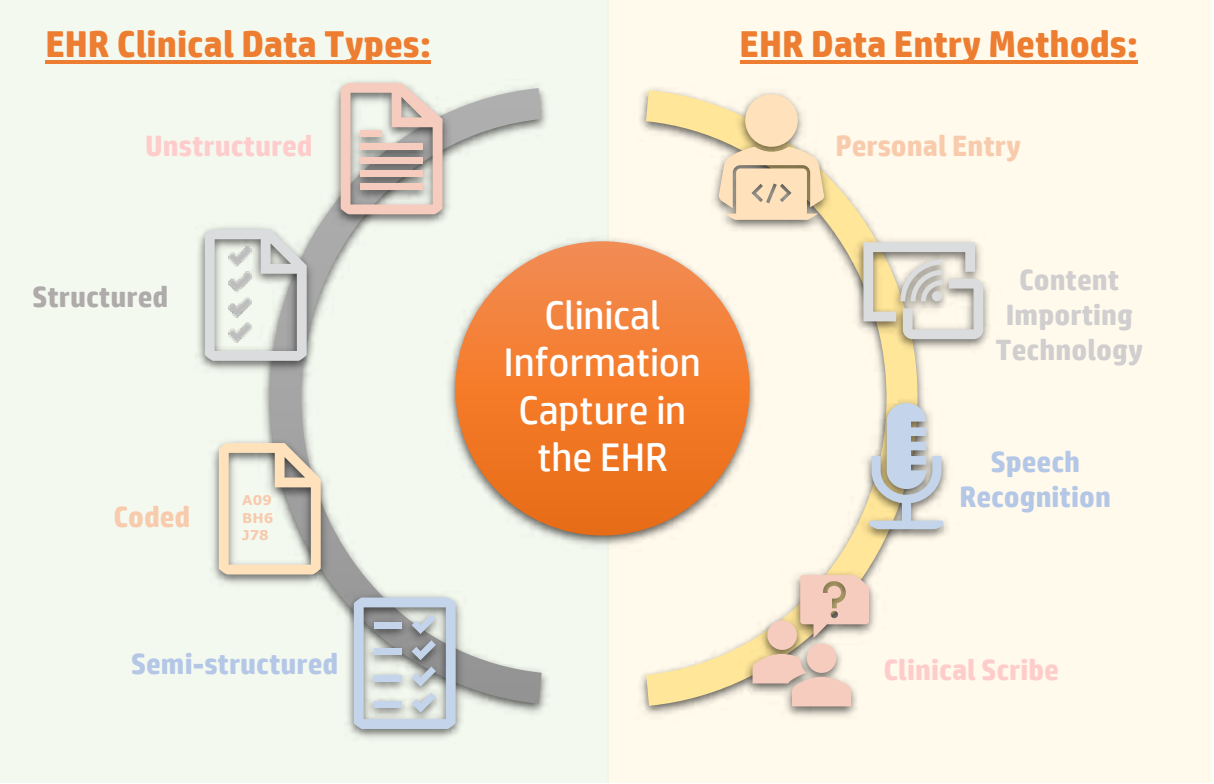


Figure 3. Clinical data types (text) and data entry methods utilised in an EHR identified via the literature review and consultation with the Advisory Group

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Appendix

Search Terms

Electronic Health Record		Data Types	Personal Entry	Content Importing Technology	Speech Recognition	Clinical Scribe
Electronic Health Record*	*Electronic health record*	Cod*	Personal Entry	Content importing	Voice recognition	Scribe
Electronic Healthcare Record*	*Electronic health records*	Encod*	Manual Entry	technology	Speech recognition	Medical scribe
Electronic patient record*	*Electronic medical record*	Structur*		Auto-fill	*Voice Recognition*	Physician scribe
Computeri?ed health record*	*Computerized medical*	Documentat*		Autofill	*Systems*	Clinical scribe
Electronic medical record*	*records*	Teminolog*		Copy-and-paste		Transcriptionist
Online health record*	*Automated medical records*	Syntax*		Automated		
Digital health record*	*Medical Order Entry Systems*	Vocabulary		Automatic		
Computeri?ed medical record*	*Electronic Order Entry*	Narrat*		Pre-populate*		
Electronic Medical Record	*Computerized provider order*	Natural Language		Populate*		
Automated medical records	*entry*	Free text		Template		
Electronic Record System*	*Health Information Systems*	Data Entry		Smart-phrase		
Clinical Information system*	*Medical records system,*	Diagnosis related group*		Smart phrase		
Electronic Health Record System*	*Computerized*	Medical subject		Smart set		
Medical Information System	*Electronic health record*	headings		Health Information Exchange		
Computeri?ed medical systems	*system*	icd		Health Care Information		
Clinical data repositor*	*Medical information system*	SNOMED		Exchange		
Health Records System*	*Patient Portals*	MeSH		Medical record linkage"		
Medical Records System*	*Health Information*	Language*		Interoperable		
Health information system*	*Interoperability*	Ontolog*		Interoperability		
Hospital information system*	*Data interoperability*	Systemati?ed		Integrat*		
Electronic prescribing	*Interoperability*	Nomenclature		Bar code		
eprescri* OR e-prescri*	*Health Information Exchange*	Record*		Bar codes		
Electronic pharmaceutical record	*Medical Record Linkage*	Summary		Bar coding		
Electronic Order Entry	EHR	Chart		Barcoding		
Computerized ordering	PHR	Metadata		Automatic data processing		
Medical Order Entry System*	EHCR	Form*				
Drug Information System	EPR	Template				
Order comm*	EMR	Clinical data				
Computeri?ed Physician Order Management	CIS	Data collection				
Computeri?ed Provider Order Entry	EHRS	Clinical notes				
Computeri?ed Provider Order Management	DIS	Kardex				
Computeri?ed Physician Order Entry	CPOM	Patient histor*				
Personal health record*	CPOE	History taking				
Patient health record*	EPR	Clerking				
Patient portal*	EHRS	Note capture				
Shared care record*		Note taking				
Summary care record*		Patient interview*				
Patient data repositor*		Reason for encounter				

Note: Italicised terms relate to subject headings which were exploded in the relevant databases; *, truncation i.e., locating all terms that begin with the given string of text; ?, wildcard, i.e., replaces one character within the word; Boolean operator "AND" was used to conduct searches for ["Electronic health record" AND "Data Types"], ["Electronic health record" AND "Speech Recognition"], ["Electronic health record" AND "Clinical Scribe"], and ["Electronic health record" AND "Content Importing Technology"].

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