Chapter 7
Nursing Documentation in Digital Solutions

Loretto Grogan, Angela Reed, and Orna Fennelly

Abstract Information plays a vital role in the nursing process. The information aggregated by registered nurses in a wide range of records across the breadth of practice underpins and can bring about services that will support global populations into the next decade and beyond.

Nurse leaders need to be able to translate, synthesise, interpret and manage that information into measurable outcomes. The impact of knowledgeable and enthusiastic Executive Nurses who provide and develop informatics leadership is essential to build both the art and science of nursing into the next decade.

In terms of how nursing data is captured and structured to effectively do that, no one type of clinical data will accommodate the spectrum of nursing and midwifery practice for every scenario but in determining the most appropriate type of data or combination of data types, the advantages and disadvantages of each should be considered, as well as the workflows and downstream effects of capturing data.

Much work has been completed in the last 20 years to advance thinking around the use of nursing Standardised Terminologies. The findings from the identified studies cited demonstrate benefits of using Standardised Terminologies although it is difficult to determine whether STs impact directly on patient outcomes or the time efficiency of end-users. The careful implementation, education and support of nurses and midwives to utilise STs as well as a well-designed, user-friendly EHCR system contributes to its use and the benefits derived.

Electronic Supplementary Material The online version of this chapter (https://doi.org/10.1007/978-3-030-58740-6_7) contains supplementary material, which is available to authorized users.

L. Grogan (✉)
Health Service Executive, Dublin 8, Ireland

Five Country Nursing and Midwifery Digital Leadership Group, Belfast, Ireland
e-mail: loretto.grogan1@hse.ie

A. Reed
Northern Ireland Practice and Education Council for Nursing and Midwifery, Belfast, UK

Five Country Nursing and Midwifery Digital Leadership Group, Belfast, UK

O. Fennelly
ICHEC, Irish Centre for High-End Computing, Dublin, Ireland

P. Hussey, M. A. Kennedy (eds.), *Introduction to Nursing Informatics*, Health Informatics, https://doi.org/10.1007/978-3-030-58740-6_7

Keywords Nursing documentation · Nursing data · Nursing practice · Nursing leadership · Data collection · Clinical information capture · Data types · Structured data · Unstructured data · Coded data · Semi-structured data · Standardised terminologies

Overview
This chapter is presented in two sections.

The first section sets a professional context for nursing documentation, the impact of nursing data and the nursing imperative for efficient and appropriate processes for current and future data collection including the impact of dynamic knowledgeable and nursing leadership to leverage appropriate data collection.

The second section discusses capturing nursing data. It focuses on clinical data types namely unstructured data, structured data, coded data and semi-structured data, their application and the advantages and disadvantages of each type. Standardised nursing terminologies and their impact on practice are also discussed.

Learning Objectives for the Chapter

Section 1—To gain an understanding of:

1. The imperative for and impact of effective professional record keeping practice in nursing.
2. The importance of nursing data to underpin and bring about services that will support global populations into the next decade and beyond.
3. The impact of Executive Nurses who provide and develop leadership in the informatics area of practice in their organisations for digital practice and the knowledge age.

Section 2—To gain an understanding of:

1. Clinical data types namely unstructured data, structured data, coded data and semi-structured data.
2. The application of clinical data types and the advantages and disadvantages of each type.
3. Standardised Nursing Terminologies and their impact on practice.

7.1 Recording and Evidencing Nursing Practice

In their study of innovation across 152 differing health systems globally, Braithwaite et al. (Braithwaite et al. 2018), identified five principles for optimising future health and social care underpinned by four success factors. Across those elements, digital

practice and the meaningful use of data were significant levers for change including: development of sustainable systems; digital innovation; and recognition of the need to situate models of care as near to the person's own home or community; underpinned by: evaluative activity using appropriate measures (Braithwaite et al. 2016); transformation of data into information and then intelligence to continually create an evidence base (Braithwaite et al. 2018); authentic collaboration between multiple stakeholders; and person-centredness (Braithwaite et al. 2017). Nursing is well placed to leverage the future service change required that will support global populations into the next decade and beyond. The levers and success factors for change identified by Braithwaite et al. (Braithwaite et al. 2018) should be the stimulus for nursing leadership to renew and redouble focus on meaningful use of data, efficient digital practice and interoperability across systems and places of care, recognising appropriate evaluative activity, across global health economies.

7.2 The Nursing Imperative

In this global context and that of nursing practice in the twenty-first century, where services are under increasing pressure (Kelly et al. 2016), populations are rising with predicted large numbers of over 65 year olds many living with complex comorbidities and associated conditions of ageing (Amalberti et al. 2016), the profession is evolving, to take on a broader scope of practice, improving the quality and person centric nature of models of care (Kennedy and Moen 2017). The largest percentage of the professional healthcare workforce nursing occupies 50% of the total headcount for many countries (World Health Organisation 2016a). Simultaneously, there is a wealth of evidence demonstrating the impact of registered nurses on healthcare outcomes for populations across a range of roles (Dick et al. 2017; Griffiths et al. 2016). Working across programmes of care and service delivery environments, the need for high quality information from this significant section of the health care workforce is an imperative to drive future change harnessed through the professions' ability to collect data at the point of care.

The imperative for registered nurses to make accurate records of their interactions with staff and people, regardless of where they work, falls under a number of obligations within statutory, regulatory and contractual frameworks, and not least the requirement to evidence the professional impact and quality of their daily work. More usually, advice and guidance across organisations emanate from local policy and standards set by national or regional bodies, which have led to a range of views often differing in emphasis, rather than a clear national strategy to nursing and midwifery data.

Like many nursing and midwifery regulatory bodies globally, those in the United Kingdom (UK) and Ireland make explicit reference to the necessity for high quality professional records in their codes of practice (Nursing and Midwifery Council 2018; Nursing and Midwifery Board Ireland 2014) drawing attention to the need for timely, accurate record keeping that demonstrates decision making and service provision to populations. Whilst it is well discussed that accurate and complete records

providing a detailed account of a person's journey through health and social care services can protect both patient and registrant (Prideaux 2011), a common cause of legal claim arises from a breakdown in communication between health professionals particularly related to incomplete or inadequate records (Wood 2010). Evidence exists of variance of the quality of nursing information reflected in records (Saranto et al. 2014); incomplete records demonstrating a lack of information on the effect of nursing measures (Jeffries et al. 2012) and considerable deficiencies in quality of information (Gomes et al. 2019). Additionally, studies have demonstrated that when staffing issues impact on a care environment, documentation of nursing care is one of the safety critical activities which is often missed (Thomas-Hawkins et al. 2020; Ball et al. 2018). 'Good' records put the patient at the centre of care, demonstrate clinical decision-making and goals of care, allow audit of practice, support quality improvement and evidence co-production, safety and efficacy over time.

7.3 The Information Future of Nursing Practice

Increasingly nurses are being invited to expand their scope of practice in service models, to purportedly enable a holistic response to evolving needs, rurality of populations and Social Determinants of Health (SDH) (Mason et al. 2015; Nelson-Brantley et al. 2018). Whilst the nursing profession is often well placed to implement new models of service delivery, a change in ways of working is required to engage with the increasing complexity of care for populations and impact of SDH (Mason et al. 2015). Enhanced ways of working for nurses to match future service models linked to demographic trends include: promoting population health literacy (McMurray et al. 2018); greater use of technologies and Electronic Health Care Records (EHCRs) with advanced coordination of multi-professions across care settings (Zaworsky and Bower 2016; Erikson et al. 2017); and collaborative partnership with service users and their families to negotiate individualised person-centred outcomes. Whilst such service models obviously require investment to maximise the shift in demand from populations through development of the profession to support them (Leahy-Warren et al. 2017), early findings from global nursing exemplars have demonstrated positive outcomes such as reduction of hospital admissions, improved experience of care and cost reductions (McMurray et al. 2018; Maeung et al. 2013). In these practice prototypes, meaningful real-time data has been identified as a crucial enabler for efficient services to make best use of available nursing time (McMurray et al. 2018).

Evidence on the impact of documenting in EHCRs in terms of contribution to sustainability and efficacy of global health services varies, ranging from positively preventing hospitalisations (Burnel 2018) to reported 'weak empirical evidence in relation to increasing efficiency and improving medical care' (Bolous-Rødje 2019, p. 3). Furthermore, the necessary integration across organisational boundaries to communicate and share data seamlessly has not been achieved (Fitzpatrick and Ellingsen 2013). These issues are of particular importance when considering the

intention to focus efforts on providing future nursing practice models, co-producing plans of care and supporting individuals in their own homes (Braithwaite et al. 2018), as movement of data across primary, secondary and community locations will be required to facilitate nursing and other members of professional teams. Accessible, reliable integrated systems are essential to the success of maximising digital nursing record keeping practice across organisations. Inefficient design and technical issues have been evidenced to impact on care delivery (Staggers et al. 2018), where nurses struggle to access systems to input relevant data across organisational boundaries and buildings. Poorly designed technology that fails to capture the essence of nursing practice and decision making, along with systems wrought with technical issues have been demonstrated to frustrate nurses, who will resort to printing documents to manually include information (Staggers et al. 2011). All too often, design flaws arise from the simple translation of paper documents into digital forms, rather than investment in system designs that map nursing workflows, capture nursing decision making through appropriate terminologies and enable point of care nursing data entry.

In addition, undoubtedly, as person-centred approaches evolve along with a focus on co-production, the use of citizen portals linking to EHCRS will increase, as populations become more digitally enabled across health economies. The sparse evaluative evidence on the efficacy of citizen portals demonstrates the value of a mixed approach model of both professional and digital contact (Zanaboni et al. 2018) and as the profession with the highest level of constancy with populations (All Party Parliamentary Group on Global Health (APPG) 2016), nursing has undoubtedly the greatest opportunity to influence the uptake and therefore utility of this digital partnership, therefore unlocking the potential of new approaches to health outcomes for populations, including those underpinned by self-care.

7.4 Evidencing Impact and Supporting Nursing Practice

The importance of evidencing the impact of registered nurses on population health outcomes, given the opportunity from the breadth and scale of the workforce, should be a driver for a strengthened professional focus in a world that is increasingly digitally driven and data saturated. Nurses, as the largest regulated profession with continuous contact with the public to impact on population health (All Party Parliamentary Group on Global Health (APPG) 2016) generate the greatest volume of healthcare data (Englebright and Caspers 2016). It is imperative, therefore, that this data is meaningfully structured and captured (Hussey et al. 2015), for the purposes of analysis and sharing (Ricciardi and Boccia 2017), evidencing and assuring the contribution of nursing.

The development of the emerging discipline of nurse informaticians has been growing on a global scale over the last 30 years (Liu et al. 2015), if somewhat driven by interested enthusiasts rather than a determined workforce decision to value and grow such roles. This piecemeal development of the discipline appears

counterintuitive, the digital knowledge and skills of the nursing workforce, including those required to meaningfully use and evaluate information, evidently requiring a focus for investment in the current global context of services to create a workforce that is appropriately equipped to expertly handle their own professional data.

Big data capabilities from EHCRs can now provide healthcare organisations with information that enables understanding and evaluation of care decisions, processes and outcomes. Founds (Founds 2018) welcoming the big data era, asserted that the individualised and public facing ethos of nursing practice positioned the profession well to adopt and promote this future enabler for sustainable service models. This in turn can help quantify the nursing contribution, underpinning evidence-informed practice with real-time data (Reid Ponte et al. 2016). Sadly, EHCRs can sometimes include scant data describing nursing interventions and outcomes, failing to adequately describe critical decision making. Learning over the years of implementation would suggest there is a danger in trying to compare nurse and physician use of an EHCR to apply the same terminologies (Rogers et al. 2013). Evidence demonstrates that the 'checklist' medical system of recording within current EHCRs does not always capture relevant nursing information, leading to a lack of nursing narrative, particularly around psychosocial needs, often devoid of critical data on the performance of the largest professional workforce (Green and Thomas 2008).

Current data capture processes globally have varying degrees of efficacy to realise the future potential of the profession. Much of the vast volumes of nursing data captured, even when in digital format, are not structured or coded in a standardised way to allow linkages to be made across data elements (Khokar et al. 2017). There is also recognition that nurses spend considerable amounts of time recording high volumes of data of questionable utility (Lodhi et al. 2016; Leary et al. 2017). Great possibilities exist through the wealth of information gathered via the constancy of nursing including the potential to monitor real-time nursing assessments, interventions, processes and outcomes across care continuums (Welton and Harper 2016). Coupled with the opportunity to connect with and gather health data from populations through wearable technologies, cloud computing, smartphone mobile technologies and social media (Lokuge et al. 2018), there has never been such an era of opportunity to study and evaluate linkages to create knowledge for the purposes of improvement of professional practice, Personalised Medicine and population health outcomes (Higgins et al. 2018). This presents unprecedented prospects to advance the scientific knowledge and discover new opportunities for emphasis on aspects of nursing practice that effect improved predicted outcomes of care (Lodhi et al. 2016). The reality however is that adoption is slow, systems not fully understood (Gee et al. 2012) and funding to support development hard won, mainly due to the risk of failure which has been significant in the past within the United Kingdom (UK) (Campion Awaad et al. 2014). Barriers to technology adoption and therefore meaningful use include: misconceptions about evidence based practice; lack of leadership support; lack of time and mentorship; poor information literacy; and challenges with financial investment (Fulton et al. 2014).

7.5 Leading Digital Transformation of Nursing Information Practice

Some of the challenges to adoption could be positively leveraged through the influence and voice of nursing leadership globally, particularly those in executive roles. Whilst Kennedy-Page and Simpson (Kennedy-Page and Simpson 2016) asserted: 'Big data has the potential to elucidate the phenomena of nursing' (p. 272), other authors are more cautious in their prediction, understanding that it is dependent on strategic nursing leaders to recognise this potential and provide the necessary leadership for digital innovation to enhance nursing and develop an appropriately skilled and future facing workforce that includes the competence to manage information in an increasingly digital world (Jaimet 2016). Worryingly, the evidence suggests a lack of digital competence for nurse leaders in executive positions (Simpson 2013; Remus 2016). Those executive nurses who understand the value in providing and developing leadership in this area of practice in their organisations however, positively impact professional development processes for digital practice and the knowledge age (Remus 2016; Clarke and Mitchell 2014). Understanding and representing the experience of nurses, ensuring that technology appropriately captures, rather than impairing, burdening or eroding critical thinking and practice, is a new and important area of competence for executive nurses (Burkosi 2019).

Linking executive responsibilities, Kennedy-Page and Simpson (Simpson 2013) asserted that a critical component of the Executive Nurse leadership role is the meaningful capture and use of nursing data to drive quality practices across organisations. This included ability to transform raw data into information and then subsequently knowledge that could underpin the 'art and science of nursing practice' (Simpson 2013, p. 271). It is imperative, therefore, that executive nurses lead the development of nursing capabilities to capture, mine, collate and study data leading to relevant knowledge emerging directly in real-time rather than that gathered retrospectively (Khokar et al. 2017; Westra et al. 2017), including awareness of high volume data machine learning processes for predictive outcomes modelling (Obermeyer and Emanuel 2016). A critical future step for executive nurses is to push beyond current acceptance of physician-led EHCR design to data capture (Byrne 2012; Kerfoot 2015) reframing the purpose of nursing data collection from a focus on the legal and regulatory responsibilities to an opportunity to exponentially increase underpinning knowledge, advancing quality and the scientific practice of nursing (Kennedy-Page and Simpson 2016).

Key Points of Learning

1. Nursing is well placed to leverage the future change required to bring about services that will support global populations into the next decade and beyond.
2. Occupying 50% of the professional healthcare workforce globally, the need for high quality information is an imperative to drive future change harnessed through the professions' ability to collect data at the point of care.
3. Effective record keeping practice puts the patient at the centre of care, demonstrates clinical decision-making and goals of care, allows audit of practice, sup-

ports quality improvement and evidences co-production, safety and efficacy over time.
4. Future facing service prototypes have identified meaningful real-time data as a crucial enabler for efficient services to make best use of available nursing time.
5. The digital knowledge and skills of the nursing workforce, including those required to meaningfully use and evaluate information, requires a focus for investment to create a workforce that is appropriately equipped to expertly handle data.
6. Generating the greatest volume of healthcare data, it is imperative that nursing data is meaningfully structured and captured for the purposes of analysis and sharing evidencing and assuring the contribution of nursing.
7. Executive nurses who understand the value in providing and developing leadership in the informatics area of practice in their organisations, positively impact professional development processes for digital practice and the knowledge age.

7.6 Capturing Nursing Data in a Digital Environment

Development and implementation of Electronic Health Care Records (EHCRs) and other information technology (IT) offers tremendous opportunities to enhance nursing practice and capacity to capture and utilise patients' clinical information to improve healthcare. 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 planning and new potential for research (Department of Health 2017; Nguyen et al. 2014; Kouroubali and Katehakis 2019; HIMSS 2019).

These benefits are extended via adjunct technologies such as clinical decision support (CDS) software and the Internet of Things (IoT) which respectively match patient clinical information with a computerised knowledge base to provide recommendations to the healthcare professional (HCP) and provide more comprehensive and accurate patient-generated information to the EHCR (Gartner 2019).

Access to more clinical data does not necessitate higher quality data and patient care, and we need to consider what are best practices to drive value from an EHCR as well as the adjunct technologies (Gartner 2019). At the same time, we must retain the overarching aim of capturing clinical information which is to track a patient's condition and communicate this to other members of the nursing and midwifery team in addition to the wider healthcare team to inform clinical decision-making (Kuhn et al. 2015; Mehta et al. 2016).

With nurses and midwives being responsible for a large amount of the data being entered into the EHCR or other digital systems it is vital that that nursing data is represented in a shareable manner which preserves its complexity, context and richness of patient care. These data can usually be entered in an unstructured, structured, coded or semi-structured format (HSE 2019).

7.7 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 (Linder et al. 2012; Helgheim et al. 2019; Lardon et al. 2015). Unstructured free text entry of clinical data allows freedom of speech and expressivity (Lardon et al. 2015; Johnson et al. 2008), which facilitates documentation of complex presentations or impressions of a diagnosis which do not fit into predictable templates or quantifiable values (Rosenbloom et al. 2011; Crampton et al. 2016). It is also a critical factor in assisting management decisions and reflecting the training and perspective of the professional recording the data (Johnson et al. 2008; Siegler and Adelman 2009). Free text is often preferred and valued by HCPs due to its familiarity, speed and ease-of-use (Johnson et al. 2008; Rosenbloom et al. 2011; Shachak et al. 2013). For the reader, narrative text provides a greater and more comprehensive understanding of the patient compared with highly-structured data (Johnson et al. 2008; Rosenbloom et al. 2011). However, narrative text often contains large amounts of text, much of which may be redundant, which can obscure key information (Wrenn et al. 2010; Huang et al. 2018). Due to its unstructured format, it can also lead to omission of important information (Johnson et al. 2008; Wilbanks et al. 2018) and makes it difficult to effectively retrieve and use information for preventive care, disease management and quality improvement purposes (Shachak et al. 2013). 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 (Wilbanks et al. 2018; Weis and Levy 2014).

Many of the intended benefits of EHCR systems such as clinical decision support (CDS) and automatic pull of data from one section of the EHCR 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 (Lardon et al. 2015; Weis and Levy 2014; Bush et al. 2017; Campion et al. 2014; Joukes et al. 2018), it limits the extent and reliability to which computers can interpret and re-use the data (Johnson et al. 2008; Kalra 2006; Joukes et al. 2019). Conversion of free text into a structured format can be a time-consuming and difficult task (Kreimeyer et al. 2017) and thus, development of automated mechanisms for interpreting free text is of utmost importance (Helgheim et al. 2019). Artificial intelligence (AI) such as natural language processing (NLP) is a promising method for data extraction and retrieval from unstructured text (Rosenbloom et al. 2011; Ford et al. 2016). AI could be used by the HCP at the time of data entry to identify key terms from unstructured text and formulate structured text from it (Loui and Hollinshead 2016), 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) (Rosenbloom et al. 2011; Helgheim et al. 2019; Sohn et al. 2017;

Pomares-Quimbaya et al. 2019). Overall, whilst unstructured data facilitates more comprehensive and flexible clinical documentation, it also comes with many challenges to optimising EHCR use which could affect patient safety and HCP productivity.

7.8 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 (Rosenbloom et al. 2011; Vuokko et al. 2017; California Healthcare Group 2010; Murray and Berberian 2011). Structured documentation templates often lend themselves to less complicated patient presentations (Mehta et al. 2016; Linder et al. 2012), computerised provider order entry (CPOE) systems (Siegler and Adelman 2009; Seidling and Bates 2016), registry forms, research forms dates (Krumm et al. 2014), social information, biological data measures and biological investigation results (Lardon et al. 2015; Helgheim et al. 2019). Whereas check boxes, radio buttons and drop down lists suit aspects which have limited options (Rosenbloom et al. 2011; Kreimeyer et al. 2017; Murray and Berberian 2011) such as yes/no and patient-reported outcome measures (Busack et al. 2016; Zhang et al. 2019). 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 (Linder et al. 2012).

For the author, entering data into structured templates in the EHCR can reduce data omission, as checklists can act as 'memory joggers' to assist HCPs to comply with best practice (Johnson et al. 2008; Rosenbloom et al. 2011; Linder et al. 2012; O'Donnell et al. 2018; Lorenzetti et al. 2018; Saranto et al. 2014). Additionally, structured data facilitates automated population of data fields (i.e., autofill) from other sections of the EHCR (Johnson et al. 2008; Helgheim et al. 2019; Linder et al. 2012) and from EHCR-integrated devices (Plastiras and O'Sullivan 2018) (e.g., bar code medication administration), improving overall efficiency in clinical documentation as well as reducing errors in the transfer of data between systems (Lawrence et al. 2018). 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 (Joukes et al. 2018). However, whilst end-user efficiency may be improved when taking into account secondary uses of clinical data such as content importing technology (e.g., SmartForms), entering structured data at point-of-care requires more effort on the part of the end-user (Johnson et al. 2008; Rosenbloom et al. 2011; Bush et al. 2017; Campion et al.

2014; Joukes et al. 2018) and can negatively affect system usability (O'Donnell et al. 2018; Ajami and Bagheri-Tadi 2013; Kruse et al. 2016). It also imposes restrictions on HCPs in terms of how they document (Kalra 2006; Vuokko et al. 2017) and how they critically think and make decisions, which can risk the depersonalisation of healthcare (Nguyen et al. 2014; Saranto et al. 2014) and the incorrect identification of patients as having a certain condition due to lack of room for ambiguity (Johnson et al. 2008; Crampton et al. 2016).

To negate these risks, it has been recommended that the EHCR system does not mandate end-users to check a box if not appropriate, and that structured templates should never replace the clinical narrative (Kuhn et al. 2015). 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 (Busack et al. 2016). 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 (Cao et al. 2017). Fundamental to any discussion of structured documentation is patient care (California Healthcare Group 2010), as well as recognition of the minimum dataset which needs to be collected to support patient care (Hakonsen et al. 2019). 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 (Rosenbloom et al. 2011). Even after following this process, a structured template will not suit every patient presentation, especially the more complicated patients (California Healthcare Group 2010). 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 (Parent 2017; KLAS 2018; Hine et al. 2008).

7.9 Coded Data

Clinical information can often be tacit, context-bound, and ambiguous (Ben-Zion et al. 2014), and without a 'shared tongue', communication between HCPs can be significantly impaired (Sundling and Kurtycz 2019). Therefore, standardised terminologies (STs) have been developed which are associated with codes and represent defined aspects of clinical practice (Williams et al. 2017; World Health Organisation 2016b; Bronnert et al. 2012). For example, traditionally several terms are utilised to describe high cholesterol but with STs 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) (California Healthcare Group 2010). Additional benefits include:

1. Improved data quality (Sundling and Kurtycz 2019; World Health Organisation 2016b; Health Information and Quality Authority (HIQA) 2014; SNOMED International 2017).
2. Terminology understood by all HCPs across organisations and geographical boundaries (irrespective of language) (Sundling and Kurtycz 2019; World Health Organisation 2016b; Health Information and Quality Authority (HIQA) 2014; SNOMED International 2017).
3. Patients benefit from HCPs utilising same term across clinical documentation to describe their condition (Sundling and Kurtycz 2019).
4. Improved quality of care (Sundling and Kurtycz 2019).
5. Semantic interoperability between information systems (Cao et al. 2017; Health Information and Quality Authority (HIQA) 2014; SNOMED International 2017).
6. Accurate and comprehensive searches to identify patients requiring follow-up or changes to treatment based on revised guidelines (Sundling and Kurtycz 2019; World Health Organisation 2016b; Health Information and Quality Authority (HIQA) 2014; SNOMED International 2017).
7. Monitoring of treatment effectiveness, patterns and trends (Vuokko et al. 2017; California Healthcare Group 2010; Saranto et al. 2014).
8. Use of CDS software (Vuokko et al. 2017; California Healthcare Group 2010; Saranto et al. 2014).
9. Additional research opportunities (Sundling and Kurtycz 2019; World Health Organisation 2016b; Health Information and Quality Authority (HIQA) 2014; SNOMED International 2017).

Whilst many STs have been developed, no single terminology has been accepted as a universal standard (Rosenbloom et al. 2006). Three different types of coding sets exist:

7.9.1 Aggregation Terminologies (or Administrative Code Sets)

Enable classification of concepts using simple hierarchy relationships for administrative purposes such as reimbursement (Williams et al. 2017; Bronnert et al. 2012; Health Information and Quality Authority (HIQA) 2014). 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 (Williams et al. 2017). Where HCPs are forced to use these code sets to capture clinical data, there is potential for inaccuracies and loss of the clinical intent (Williams et al. 2017; Bronnert et al. 2012). Examples of aggregation terminologies include International Classification of Diseases and related health problems (ICD), International Classification of Primary Care (ICPC), Read Codes and Office of Population Censuses and Surveys Classification of Interventions and Procedures (OPCS).

7.9.2 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 (Bronnert et al. 2012). 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 (Williams et al. 2017; Rosenbloom et al. 2006). 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 (Bronnert et al. 2012; Rosenbloom et al. 2006; van der Kooija et al. 2006). 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; the Logical Observation Identifiers Names and Codes (LOINC) which captures laboratory and clinical observations; and RxNorm which captures medication names (Bronnert et al. 2012; Health Information and Quality Authority (HIQA) 2014; SNOMED International 2019). 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 (The Office of the National Coordinator for Health Information Technology 2017).

7.9.3 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 (Bronnert et al. 2012). These interface terminologies are often discipline-specific such as standardised nursing terminologies (The Office of the National Coordinator for Health Information Technology 2017; Vivanti et al. 2018), institution-specific (Rosenbloom et al. 2013) or speciality-specific (Sundling and Kurtycz 2019). 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 (Bronnert et al. 2012; Rosenbloom et al. 2013; Berger 2013). Additionally, this decreases time spent searching for codes and facilitates documentation of more comprehensive, accurate and relevant clinical information (Bronnert et al. 2012; Rosenbloom et al. 2013; Berger 2013). 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 (Saranto et al. 2014; The Office of the National Coordinator for Health Information Technology

2017; Macieira et al. 2017; Tayyib et al. 2015). Therefore, interface terminologies are important for problem lists (Bronnert et al. 2012) and these can then be mapped to the reference and aggregation terminologies where required for health information exchange, administrative or secondary use (Bronnert et al. 2012; The Office of the National Coordinator for Health Information Technology 2017; Westra et al. 2008).

7.10 Standardised Terminologies in Nursing Practice

Since the 1970s, there has been a concerted effort to promote STs within nursing and midwifery practice (Hardiker 2011) with the pioneering of the first standardised nursing language or terminology NANDA International (NANDA-I), formerly known as North American Nursing Diagnosis Association (Jones et al. 2010; Oreofe and Oyenike 2018). These standardised nursing terminologies commonly systematically group, define and encode nursing care as nursing diagnoses, interventions and outcomes (Kieft et al. 2018; Warren et al. 2015; Hellesø 2006; Bernhart-Just et al. 2010) and link nursing diagnoses with evidenced-based interventions and outcomes (Clancy et al. 2006). This is seen as the pathway for making the nursing process more useable and visible (Oreofe and Oyenike 2018) which promotes good communication, provides the basis for care planning and identification of patient problems (Dykes et al. 2009) and improves data quality for research and service development planning (da Costa and da Costa Linch 2018).

The American Nurses Association (ANA) have approved twelve terminology sets that support nursing practice for use within the ECHR which includes both nursing-specific and multi-disciplinary terminologies (Table 7.1) (Gencbas et al.

Table 7.1 American Nurses Association (ANA)-approved terminology sets

Standardised terminology	Content
Nursing outcomes classification (NOC)	Nursing outcomes
NANDA-I	Nursing diagnoses
Nursing intervention classification (NIC)	Nursing interventions
Clinical care classification (CCC) system	Nursing diagnoses, interventions, outcome ratings
Perioperative nursing data set (PNDS)	Perioperative nursing diagnoses, interventions, outcomes
Omaha system	Nursing diagnoses, interventions, outcomes ratings
International classification for nursing practice (ICNP®)	Nursing diagnoses, interventions, outcome
Nursing minimum data set (NMDS)	Nursing clinical data elements
Logical observation identifiers names and codes (LOINC®)	Assessments, outcomes
ABC codes	Billing codes
Systematized nomenclature of medicine-clinical terms (SNOMED-CT®)	Diagnoses, interventions, outcomes, findings

2018; The Office of the National Coordinator for Health Information Technology 2017). Additionally, a recent review commissioned by the Five Country Nursing and Midwifery Digital Leadership Group identified that in addition to the STs outlined in Table 7.1, nurses and midwives have also used locally-controlled and other medical and/or multi-disciplinary STs (Fennelly et al. 2020). These STs are in utilisation across at least 26 different countries (Fennelly et al. 2020) but although both the UK and Ireland have adopted the use of SNOMED-CT (Health Information and Quality Authority (HIQA) 2014; Sheerin 2003; Arnot-Smith and Smith 2010), their utilisation of nursing-specific STs has been more sporadic (Sheerin 2003; Murphy et al. 2018).

Initially, the deployment of STs in nursing and midwifery practice has been uncoordinated with little convergence towards a unified nursing language system that can be integrated within the wider health-care language arena (Cho and Park 2006). It is now acknowledged that these STs need to be integrated and understood within the broader healthcare system to support interoperability and data continuity across community and acute settings (Oreofe and Oyenike 2018; Martin et al. 2011; Kim et al. 2014). However, many of the nursing-specific STs have been developed, utilised and evaluated in a specific clinical setting such as the Omaha System and CCC in primary care, and the ICNP and PNDS in secondary care (Fennelly et al. 2020). Consideration, therefore, needs to be given to the advantages and disadvantages of a large comprehensive multi-disciplinary ST versus a discipline or institution-specific ST, and the purpose of using the ST. Although the multi-disciplinary ST may facilitate communication between professions and settings (Jukes et al. 2012), searching for the correct code to match a patient's diagnosis from a long list can also be time-consuming (Vuokko et al. 2017). Whereas nursing-specific STs offer more granularity, help to distinguish nursing care (Estrada and Dunn 2012) and enable the linkage of nursing diagnoses with evidence-based interventions which have potential to improve clinical decision-making skills (Wuryanto et al. 2017) and patient care (Zhang et al. 2018). However, they may not always fully comprehensive of the nursing and midwifery care provided (Cho and Park 2006) and have, at times, resulted in the availability of too many terms representing the same patient presentation (i.e., content duplication) (Morais et al. 2015; Monsen et al. 2011). Therefore, irrespective of the type of ST being used, its applicability, validity and reliability should be considered for the specific context it is being implemented in. Otherwise, it could jeopardise patient care and safety as well not as driving the full potential of using the ST.

Although the type and content of the ST is important, its implementation also drives its success. A usable ECHR interface in which the ST is searched or enters influences the use and acceptability of the ST amongst nurses and midwives (Cho and Park 2003; Hariyati et al. 2016). An interface which supports shortcuts such as searching mechanisms, display of the most frequently selected codes (for the given user) at the top of the list, i.e., 'favourites' (California Healthcare Group 2010) and/or use of NLP techniques to suggest appropriate codes and expression (SNOMED International 2019; Hodge and Narus 2018) have been recommended. Additionally, when the ST is being used within a unstructured template compared to a drop down list, the education of nurses to use the ST has been shown to impact on the quality

of the nursing documentation (Müller-Staub et al. 2007, 2008; Müller-Staub 2009). Although STs have been shown to facilitate retrieval and aggregation of data from clinical records and health information exchange (Tastan et al. 2014; Topaz et al. 2014), this also depended on the reporting and analytical capabilities built into the ECHR system and the format and file types used (Westra et al. 2010).

Overall, use of STs or coded data within the EHCR 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 EHCR to facilitate both administrative and clinical purposes. Decisions regarding the selection of these STs should be made prior to EHCR design as otherwise adaptations to the terminology in the EHCR are expensive and labour-intensive (Sundling and Kurtycz 2019). Each of these terminologies will come with a license fee and mapping of terminologies to one another will need to be maintained as changes and updates are made to the ST by the software developer, third-party vendor or the individual healthcare organisation (Kalra 2006; The Office of the National Coordinator for Health Information Technology 2017; Houser et al. 2013).

7.11 Semi-structured Data

Use of STs do not always easily accommodate for diagnostic uncertainty (Ford et al. 2016) and are not always sensitive and specific to the condition in question (e.g., depression could present symptomatically as insomnia, fatigue, malaise) (McBrien et al. 2018). Therefore, the option to enter free text in conjunction with the ST is often allowed within the ECHR (Ford et al. 2016) to allow additional context or further clinically-relevant information to be added (Wilbanks et al. 2018; California Healthcare Group 2010; Sundling and Kurtycz 2019). This hybrid model of unstructured, structured and coded data is known as semi-structured data (California Healthcare Group 2010; Murray and Berberian 2011). Additionally, within the structured elements of the EHCR, options to input narrative data are often provided where end-users cannot find an appropriate structured concept or code (Rosenbloom et al. 2011). 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.

7.12 Key Findings for Nursing on Clinical Data Types

No one type of clinical data will accommodate nursing and midwifery 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 (Arrendale 2018). In determining the

Table 7.2 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 definitions which are associated with codes	Combination of unstructured, structured and coded data
Advantages	• Flexible • Easy-to-use • Fast • 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	• Large amounts of text obscuring key information • 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	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

Source: HSE (HSE 2019)

most appropriate type of data or combination of data types, the advantages and disadvantages of each should be considered (Table 7.2), as well as the workflows and downstream effects of capturing data in this format.

Key Points of Learning

1. With nurses and midwives being responsible for a large amount of the data being entered into the EHCR or other digital systems it is vital that that nursing data is represented in a shareable manner which preserves its complexity, context and richness of patient care. These data can usually be entered in an unstructured, structured, coded or semi-structured format.

2. No one type of clinical data will accommodate nursing and midwifery 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
3. In determining the most appropriate type of data or combination of data types, the advantages and disadvantages of each should be considered as well as the workflows and downstream effects of capturing data in this format.
4. Use of Standardised Terminologies or coded data within the EHCR 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 EHCR to facilitate both administrative and clinical purposes.
5. There has been a concerted effort to promote Standardised Terminologies within nursing and midwifery practice. These standardised nursing terminologies commonly systematically group, define and encode nursing care as nursing diagnoses, interventions and outcomes and link nursing diagnoses with evidenced-based interventions and outcomes
6. Decisions regarding the selection of these STs should be made prior to EHCR design as otherwise adaptations to the terminology in the EHCR are expensive and labour-intensive

Review Questions

Questions

1. Describe what you consider to be the core requirements for delivery of good records in nursing care documentation?

   Answer

   'Good' records put the patient at the centre of care, demonstrate clinical decision-making and goals of care, allow audit of practice, support quality improvement and evidence co-production, safety and efficacy over time.

2. What do you consider to be the key barriers to technology adoption in your area of clinical practice?
3. Do they reflect all, one or some of the key barriers listed in this chapter. Select one of the barriers from the list of items below and expand using supporting evidence.

   (a) Misconceptions about evidence based practice;
   (b) Lack of leadership support;
   (c) Lack of time and mentorship;
   (d) Poor information literacy;
   (e) Challenges with financial investment

   Ref https://indiana.pure.elsevier.com/en/publications/faculty-and-organizational-characteristics-associated-with-inform
4. This chapter explains the importance of representing nursing data in EHCRs or other digital systems in a shareable manner which preserves its complexity, context and richness of patient care. Discuss the different types and formats of data that can usually be entered in an EHCR.

Answer

EHCR data can usually be entered in an unstructured, structured, coded or semi-structured format. We briefly provide some of the key points from the chapter on the different type of data formats.

Unstructured text refers to free or narrative text generated using a single window. Unstructured free text entry of clinical data allows freedom of speech and expressivity, which facilitates documentation of complex presentations or impressions of a diagnosis which do not fit into predictable templates or quantifiable values. However, narrative text often contains large amounts of text, much of which may be redundant, which can obscure key information. Due to its unstructured format, it can also lead to omission of important information and makes it difficult to effectively retrieve and use information for preventive care, disease management and quality improvement purposes.

Structured data entry at the point-of-care, as opposed to post hoc structuring using Natural Language Processing (NLP), 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. Structured documentation templates often lend themselves to less complicated patient presentations, computerised provider order entry (CPOE) systems, registry forms, research forms dates, social information, biological data measures and biological investigation results. For the author, entering data into structured templates in the EHCR can reduce data omission, as checklists can act as 'memory joggers' to assist HCPs to comply with best practice. It also imposes restrictions on HCPs in terms of how they document and how they critically think and make decisions, which can risk the depersonalisation of healthcare and the incorrect identification of patients as having a certain condition due to lack of room for ambiguity.

Coded data and standardised terminologies (STs) have been developed which are associated with codes and represent defined aspects of clinical practice. For example, traditionally several terms are utilised to describe high cholesterol but with STs 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).

A semi structured hybrid model of unstructured, structured and coded data is known as semi-structured data. Additionally, within the structured elements of the EHCR, options to input narrative data are often provided where end-users cannot find an appropriate structured concept or code. 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.

Glossary

ABC Billing Codes
CCC Clinical Care Classification
CDS Clinical Decision Support
EHCR Electronic Health Care Record
HCP Health Care Professional
ICD International Classification of Diseases
ICNP International Classification for Nursing Practice
ICPC International Classification of Primary Care
IoT Internet of Things
LOINC Logical Observation Identifiers Names and Codes
NANDA North American Nursing Diagnosis Association
NANDA I North American Nursing Diagnosis Association International
NIC Nursing Intervention Classification
NLP Natural Language Processing
NOC Nursing Outcome Classification
OPCS Office of Population Censuses and Surveys Classification of Interventions and Procedures
PNDS Peri Operative Nursing Dataset
SDH Social Determinants of Health
SNOMED CT Systematized Nomenclature of Medicine—Clinical Terms
ST Standardised Terminologies

References

Ajami S, Bagheri-Tadi T. Barriers for adopting electronic health records (EHRs) by physicians. Acta Inform Med. 2013;21(2):129–34.

All Party Parliamentary Group on Global Health (APPG). Triple Impact. How developing nursing will improve health, promote gender equality and support economic growth. APPG. 2016. https://www.who.int/hrh/com-heeg/digital-APPG_triple-impact.pdf.

Amalberti R, Nicklin W, Braithwaite J. Preparing national health systems to cope with the impending tsunami of ageing and its associated complexities: towards more sustainable health care. Int J Qual Health Care. 2016;28(3):412–4.

Arnot-Smith J, Smith AF. Patient safety incidents involving neuromuscular blockade: analysis of the UK National Reporting and Learning System data from 2006 to 2008. Anaesthesia. 2010;65(11):1106–13.

Arrendale D. Transcription trends: self-documentation challenges. For The Record. 2018;30(8):28.

Ball JE, Bruynell L, Aiken LH, Sermeus W, Sloane DM, Raffert AM, et al. Post-operative mortality, missed care and nurse staffing in nine countries: a cross-sectional study. Int J Nurs Stud. 2018;78(Feb):10–5.

Ben-Zion R, Pliskin N, Fink L. Critical success factors for adoption of electronic health record systems: literature review and prescriptive analysis. Inf Syst Manag. 2014;31(4):296–312.

Berger M. Classification, diagnosis and datasets: towards an approach for clinical psychology services and electronic records. British Pscyhological Society (BPS). 2013.

Bernhart-Just A, Lassen B, Schwendimann R. Representing the nursing process with nursing terminologies in electronic medical record systems: a Swiss approach. Comput Inform Nurs. 2010;28(6):345–52.
Bolous-Rødje N. Tactics for constructing visions about electronic health records (EHRs). CJC. 2019;44:1–22.
Braithwaite J, Matsuyama Y, Mannion R, Johnson J, Bates DW, Hughes C. How to do better health reform: a snapshot of change and improvement initiatives in the health systems of 30 countries. Int J Qual Health Care. 2016;28(6):843–6.
Braithwaite J, Mannion R, Matsuyama Y, Shekelle P, Whittaker S, Al-Adawi S. Accomplishing reform: successful case studies drawn from the health systems of 60 countries. Int J Qual Health Care. 2017;29(6):880–6.
Braithwaite J, Mannion R, Matsuyama Y, Shekelle PG, Whittaker S, Al-Adawi S. Healthcare systems: future predictions for global care. Florida: CRS Press; 2018.
Bronnert J, Masarie C, Naeymi-Rad F, Rose E, Aldin G. Problem-centered care delivery: how Interface terminology makes standardized health information possible. J AHIMA. 2012;83(7):30–5.
Burkosi V. Nursing leadership in the fully digital practice realm. Nurs Leadersh. 2019;32(SI):9–15.
Burnel P. The introduction of electronic medical records in France: more progress during the second attempt. Health Policy. 2018;122:937–40.
Busack C, Daskalakis C, Rosen P. Physician and parent perspectives on psychosocial and emotional data entry in the electronic medical record in a pediatric setting. J Patient Exp. 2016;3(1):10–6.
Bush RA, Kuelbs C, Ryu J, Jiang W, Chiang G. Structured data entry in the electronic medical record: perspectives of pediatric specialty physicians and surgeons. J Med Syst. 2017;41(5):75.
Byrne MD. Informatics competence in the EHR era. J Perianesth Nurs. 2012;27(1):42–5.
California Healthcare Group. Clinical documentation: EHR deployment techniques. 2010.
Campion Awaad O, Hayton A, Smith L, Vuaran M. The national programme for IT in the NHS: a case history. MPhil Public Policy 2014, University of Cambridge. 2014. https://www.cl.cam.ac.uk/~rja14/Papers/npfit-mpp-2014-case-history.pdf.
Campion T, Johnson S, Paxton E, Mushlin A, Sedrakyan A. Implementing unique device identification in electronic health record systems: organizational, workflow, and technological challenges. Med Care. 2014;52(1):26–31.
Cao J, Farmer R, Carry PM, Goodfellow M, Gerhardt DC, Scott F, et al. Standardized note templates improve electronic medical record documentation of neurovascular examinations for pediatric supracondylar humeral fractures. JB JS Open Access. 2017;2(4):e0027.
Cho I, Park HA. Development and evaluation of a terminology-based electronic nursing record system. J Biomed Inform. 2003;36(4-5):304–12.
Cho I, Park HA. Evaluation of the expressiveness of an ICNP-based nursing data dictionary in a computerized nursing record system. J Am Med Inform Assoc. 2006;13(4):456–64.
Clancy TR, Delaney CW, Morrison B, Gunn JK. The benefits of standardized nursing languages in complex adaptive systems such as hospitals. J Nurs Adm. 2006;36(9):426–34.
Clarke JS, Mitchell MB. The CNE-CNIO partnership: improving patient care through technology. Nurse Lead. 2014;12(1):52–64.
da Costa C, da Costa Linch G. Implementation of electronic records related to nursing diagnoses. Int J Nurs Knowl. 2018;31(1):50–8.
Crampton NH, Reis S, Shachak A. Computers in the clinical encounter: a scoping review and thematic analysis. J Am Med Inform Assoc. 2016;23(3):654–65.
Department of Health. Sláintecare implementation strategy. Dublin, Ireland; 2017.
Dick TK, Patrician PA, Loan LA. The value of nursing care: a concept analysis. Nurs Forum. 2017;52(4):357–65.
Dykes PC, Kim HE, Goldsmith DM, Choi J, Esumi K, Goldberg HS. The adequacy of ICNP version 1.0 as a representational model for electronic nursing assessment documentation. J Am Med Inform Assoc. 2009;16(2):238–46.

Englebright J, Caspers B. The role of the chief nurse executive in the big data revolution. Nurse Lead. 2016;14(4):280–4.
Erikson CE, Pittman P, LaFrance A, Chapman S. Alternative payment models lead to strategic care coordination workforce investments. Nurs Outlook. 2017;65(6):737–45.
Estrada NA, Dunn CR. Standardized nursing diagnoses in an electronic health record: nursing survey results. Int J Nurs Knowl. 2012;23(2):86–95.
Fennelly O, Grogan L, Reed A, Hardiker N. Representing what we do as nurses and midwives – terminologies and standardised languages: systematic literature review and key considerations. Awating publication. 2020;
Fitzpatrick G, Ellingsen G. A review of 25 years of CSCW research in healthcare: contributions, challenges and future agendas. CSCW. 2013;22(4–6):609–65. https://doi.org/10.1007/s10606-012-9168-0.
Ford E, Carroll JA, Smith HE, Scott D, Cassell JA. Extracting information from the text of electronic medical records to improve case detection: a systematic review. J Am Med Inform Assoc. 2016;23(5):1007–15.
Founds S. Systems biology for nursing in the era of big data and precision health. Nurs Outlook. 2018;66:283–92.
Fulton CR, Meek JA, Hinton Walker P. Faculty and organisational characteristics associated with informatics/health information technology adoption in DNP programs. J Prof Nursing. 2014;30(4):292–9.
Gartner. Healthcare EHR and digital care delivery optimization primer for 2019. 2019.
Gee PM, Greenwood DA, Kim KK, Perez SL, Staggers N, De Von HA. Exploration of the e-patient phenomenon in nursing informatics. Nurs Outlook. 2012;60:E9–E16.
Gencbas D, Bebis H, Cicek H. Evaluation of the efficiency of the nursing care plan applied using NANDA, NOC, and NIC linkages to elderly women with incontinence living in a nursing home: a randomized controlled study. Int J Nurs Knowl. 2018;29(4):217–26.
Gomes PAR, Farah BF, Rocha RS, Friedrich DBC, Dutra HS. Electronic citizen record: an instrument for nursing care. Rev Fund Care Online. 2019;11(5):1226–35.
Green SD, Thomas JD. Interdisciplinary collaboration and the electronic medical record. Paediatr Nurs. 2008;34(3):225–40.
Griffiths P, Ball JE, Drennan J, Dall'Ora C, Jones J, Maruotti A, et al. Nurse staffing and patient outcomes: strengths and limitations of the evidence to inform policy and practice. A review and discussion paper based on evidence reviewed for the National Institute for Health and Care Excellence Safe Staffing guideline development. Int J Nurs Stud. 2016;63:213–25.
Hakonsen SJ, Pedersen PU, Bygholm A, Peters MD, Bjerrum M. Speaking the same language: development of a nutrition minimum data set for healthcare professionals in primary healthcare. Health Informatics J. 2019;26(1):248–63. https://doi.org/10.1177/1460458218824707.
Hardiker N. Developing standardised terminologies to support nursing practice. Boston: Jones and Bartlett Publishers LLC; 2011.
Hariyati RTS, Yani A, Eryando T, Hasibuan Z, Milanti A. The effectiveness and efficiency of nursing care documentation using the SIMPRO model. Int J Nurs Knowl. 2016;27(3):136–42.
Health Information and Quality Authority (HIQA). Recommendations regarding the adoption of SNOMED Clinical Terms as the Clinical Terminology for Ireland. Ireland; 2014.
Helgheim BI, Maia R, Ferreira JC, Martins AL. Merging data diversity of clinical medical records to improve effectiveness. Int J Environ Res Public Health. 2019;16(5):769.
Hellesø R. Information handling in the nursing discharge note. J Clin Nurs. 2006;15:11–21.
Higgins M, Simpson RL, Johnson WG. What about big data and nursing? Am Nurse Today. 2018;13(5):29–31.
HIMSS. Improving patient safety outcomes with health IT. 2019. https://www.himss.org/case-studies-improving-patient-safety-through-health-it.
Hine N, Petersen F, Pluke M, Sund T, editors. Standardization work on personalized eHealth systems. 30th Annual International IEEE EMBS Conference 2008; Vancouver, British Columbia, Canada.

Hodge CM, Narus SP. Electronic problem lists: a thematic analysis of a systematic literature review to identify aspects critical to success. J Am Med Inform Assoc. 2018;25(5):603–13.
Houser S, Morgan D, Clements K, Hart-Hester S. Assessing the planning and implementation strategies for the ICD-10-CM/PCS coding transition in Alabama hospital. Perspect Health Inf Manag. 2013;10:1a.
HSE. Clinical information capture in the electronic health record: literature review and key considerations. 2019. https://www.ehealthireland.ie/Strategic-Programmes/Electronic-Health-Record-EHR-/Information-Resources/Clinical-Information-Capture-in-the-EHR-Literature-Review-and-Key-Considerations.pdf.
Huang A, Hribar M, Goldstein I, Henriksen B, Lin W, Chiang M. Clinical documentation in electronic health record systems: analysis of similarity in progress notes from consecutive outpatient ophthalmology encounters. AMIA Annu Symp Proc. 2018;2018:1310–8.
Hussey P, Adams E, Shaffer FA. Nursing informatics and leadership, an essential competency for a global priority. Nurse Lead. 2015;13(5):52–7.
Jaimet K. Technology, demographics and new models of care: ready to embrace the future? Can Nurse. 2016;112(3):20–1.
Jeffries D, Johnson M, Nicholls D. Nursing documentation: how meaning is obscured by fragmentary language. Nurs Outlook. 2012;59(6):e6–e12.
Johnson SB, Bakken S, Dine D, Hyun S, Mendonca E, Morrison F, et al. An electronic health record based on structured narrative. J Am Med Inform Assoc. 2008;15(1):54–64.
Jones D, Lunney M, Keenan G, Moorhead S. Standardized nursing languages: essential for the nursing workforce. Annu Rev Nurs Res. 2010;28:253–94.
Joukes E, Cornet R, de Bruijne MC, de Keizer NF, Abu-Hanna A. Development and validation of a model for the adoption of structured and standardised data recording among healthcare professionals. BMC Med Inform Decis Mak. 2018;18(1):54.
Joukes E, de Keizer NF, de Bruijne MC, Abu-Hanna A, Cornet R. Impact of electronic versus paper-based recording before EHR implementation on health care professionals' perceptions of EHR use, data quality, and data reuse. Appl Clin Inform. 2019;10(2):199–209.
Jukes S, Cichero JA, Haines T, Wilson C, Paul K, O'Rourke M. Evaluation of the uptake of the Australian standardized terminology and definitions for texture modified foods and fluids. Int J Speech Lang Pathol. 2012;14(3):214–25.
Kalra D. Electronic health record standards. IMIA Yearbook of Medical Informatics. 2006;45:S136–44.
Kelly D, Lankshear A, Jones A. Stress and resilience in a post-Francis world – a qualitative study of executive nurse directors. J Adv Nurs. 2016;72(12):3160–8.
Kennedy MA, Moen A. Nurse leadership and informatics competencies: shaping transformation of professional practice. Forecasting informatics competencies for nurses in the future of connected health. Stud Health Technol Inform. 2017;232:197–206.
Kennedy-Page C, Simpson RL. Nurse leader challenges in data transparency: eyes to the future. Nurse Lead. 2016;14:271–4.
Kerfoot KM. Intelligently managed data: achieving excellence in nursing care. Nurs Econ. 2015;33(6):342–3.
Khokar A, Lodhi MK, Yao Y, Ansari R, Keenan G, Wilkie DJ. Framework for mining and analysis of standardized nursing care plan data. West J Nurs Res. 2017;39(1):20–41.
Kieft R, Vreeke EM, de Groot EM, de Graaf-Waar HI, van Gool CH, Koster N, et al. Mapping the Dutch SNOMED CT subset to Omaha system, NANDA international and international classification of functioning, disability and health. Int J Med Inform. 2018;111:77–82.
Kim TY, Hardiker N, Coenen A. Inter-terminology mapping of nursing problems. J Biomed Inform. 2014;49:213–20.
KLAS. Improving the EHR experience through personalization: Impact report. UK; 2018.
van der Kooija J, Goossena W, Goossen-Baremansa A, de Jong-Fintelmana M, van Beeka L. Using SNOMED CT codes for coding information in electronic health records for stroke patients. Stud Health Technol Inform. 2006;124:815–23.

Kouroubali A, Katehakis DG. The new European interoperability framework as a facilitator of digital transformation for citizen empowerment. J Biomed Inform. 2019;94, 103166

Kreimeyer K, Foster M, Pandey A, Arya N, Halford G, Jones SF, et al. Natural language processing systems for capturing and standardizing unstructured clinical information: a systematic review. J Biomed Inform. 2017;73:14–29.

Krumm R, Semjonow A, Tio J, Duhme H, Burkle T, Haier J, et al. The need for harmonized structured documentation and chances of secondary use - results of a systematic analysis with automated form comparison for prostate and breast cancer. J Biomed Inform. 2014;51:86–99.

Kruse CS, Kristof C, Jones B, Mitchell E, Martinez A. Barriers to electronic health record adoption: a systematic literature review. J Med Syst. 2016;40(12):252.

Kuhn T, Basch P, Barr M, Yackel T, Medical Informatics Committee of the American College of Physicians. Clinical documentation in the 21st century: executive summary of a policy position paper from the American College of Physicians. Ann Intern Med. 2015;162(4):301–3.

Lardon J, Asfari A, Souvignet J, Trombert-Paviot B, Bousquet C. Improvement of diagnosis coding by analysing EHR and using rule engine: application to the chronic kidney disease. Stud Health Technol Inform. 2015;210:120–4.

Lawrence JE, Cundall-Curry D, Stewart ME, Fountain DM, Gooding CR. The use of an electronic health record system reduces errors in the National Hip Fracture Database. Age Ageing. 2018;48(2):285–90.

Leahy-Warren P, Mulcahy H, Benefield L, Bradley C, Coffey A, Donohoe A, et al. Conceptualising a model to guide nursing and midwifery in the community guided by an evidence review. BMC Nurs. 2017;16:1–13.

Leary A, Tomai B, Swift A, Woodword A, Hurst K. Nurse staffing levels and outcomes – mining the UK national data sets for insight. Int J Health Care Qual Assur. 2017;30(3):235–47.

Linder JA, Schnipper JL, Middleton B. Method of electronic health record documentation and quality of primary care. J Am Med Inform Assoc. 2012;19(6):1019–24.

Liu CH, Lee TT, Mills ME. The experience if informatics nurses in Taiwan. J Prof Nurs. 2015;31(2):158–64.

Lodhi KM, Ansari R, Yao Y, Keenan GM, Wilkie DJ, Khokhar A. A framework to predict outcome for cancer patients using data from a nursing EHR. IEEE International Conference on Big Data. 2016:3387–95.

Lokuge S, Sedera D, Grover V, Xu D. Organizational readiness for digital innovation: development and empirical calibration of a construct. Inf Manag. 2018:1–17. https://doi.org/10.1016/j.im.2018.09.001.

Lorenzetti DL, Quan H, Lucyk K, Cunningham C, Hennessy D, Jiang J, et al. Strategies for improving physician documentation in the emergency department: a systematic review. BMC Emerg Med. 2018;18(1):36.

Loui RP, Hollinshead A. Efficient population of structured data forms for medical records using syntactic constraints and intermediate text. 2016 IEEE International Conference on Healthcare Informatics (ICHI), 2016. p. 317.

Macieira T, Smith M, Davis N, Yao Y, Wilkie D, Dunn Lopez K, et al. Evidence of progress in making nursing practice visible using standardized nursing data: a systematic review. AMIA Annu Symp Proc. 2017:1205–14.

Maeung D, Davis D, Tomcavage J, Graf T, Procopio K. Improving patient experience by transforming primary care: evidence from Geisinger's patient-centred medical homes. Pop Health Manag. 2013;16(3):157–63.

Martin KS, Monsen KA, Bowles KH. The Omaha system and meaningful use: applications for practice, education, and research. Comput Inform Nurs. 2011;29(1):52–8.

Mason DJ, Jones DA, Roy C, Sullivan CG, Woods LJ. Commonalities of nurse-designed models of health care. Nurs Outlook. 2015;63(5):540–53.

McBrien KA, Souri S, Symonds NE, Rouhi A, Lethebe BC, Williamson TS, et al. Identification of validated case definitions for medical conditions used in primary care electronic medical record databases: a systematic review. J Am Med Inform Assoc. 2018;25(11):1567–78.

McMurray A, Ward L, Johnson K, Yang L, Connor M. The primary health care nurse of the future: preliminary evaluation of the nurse navigator role in integrated care. Collegian. 2018;25:517–24.
Mehta R, Radhakrishnan NS, Warring CD, Jain A, Fuentes J, Dolganiuc A, et al. The use of evidence-based, problem-oriented templates as a clinical decision support in an inpatient electronic health record system. Appl Clin Inform. 2016;7(3):790–802.
Monsen K, Melton-Meaux G, Timm J, Westra B, Kerr M, Raman N, et al. An empiric analysis of Omaha system targets. Appl Clin Inform. 2011;2(3):317–30.
Morais SC, da Nobrega MM, de Carvalho EC. Convergence, divergence and diagnostic accuracy in the light of two nursing terminologies. Rev Bras Enferm. 2015;68(6):1086–92.
Müller-Staub M. Preparing nurses to use standardized nursing language in the electronic health record. Stud Health Technol Inform. 2009;146:337–41.
Müller-Staub M, Needham I, Odenbreit M, Lavin MA, van Achterberg T. Improved quality of nursing documentation: results of a nursing diagnoses, interventions, and outcomes implementation study. Int J Nurs Terminol Classif. 2007;18(1):5–17.
Müller-Staub M, Needham I, Odenbreit M, Lavin MA, van Achterberg T. Implementing nursing diagnostics effectively: cluster randomized trial. Journal of Advanced Nursing (Wiley-Blackwell). 2008;63(3):291–301.
Murphy S, Mc Mullin R, Brennan S, Meehan TC. Exploring implementation of the careful nursing philosophy and professional practice model© in hospital-based practice. J Nurs Manag. 2018;26(3):263–73.
Murray T, Berberian L. The importance of structured data elements in EHRs: Computer World; 2011.
Nelson-Brantley HV, Ford D, Miller KL, Bott MJ. Nurse executives leading change to improve critical access hospital outcomes: a literature review with research-informed recommendations. Online J Rural Nurs Health Care. 2018;18(1):148–79.
Nguyen L, Bellucci E, Nguyen LT. Electronic health records implementation: an evaluation of information system impact and contingency factors. Int J Med Inform. 2014;83(11):779–96.
Nursing and Midwifery Board Ireland. Code of professional conduct and ethics. Dublin: NMBI; 2014.
Nursing and Midwifery Council. The Code: Professional standards of practice and behaviour for nurses, midwives and nursing associates. London: NMC; 2018.
Obermeyer Z, Emanuel EJ. Predicting the future – big data, machine learning, and clinical medicine. N Engl J Med. 2016;375(13):1216–9.
O'Donnell A, Kaner E, Shaw C, Haighton C. Primary care physicians' attitudes to the adoption of electronic medical records: a systematic review and evidence synthesis using the clinical adoption framework. BMC Med Inform Decis Mak. 2018;18(1):101.
Oreofe A, Oyenike A. Transforming practice through nursing innovative patient centered care: standardized nursing languages. Int J Caring Sci. 2018;11(2):1319–22.
Parent C. How EHRs can give time back to docs. Health Management Technology. 2017.
Plastiras P, O'Sullivan D. Exchanging personal health data with electronic health records: a standardized information model for patient generated health data and observations of daily living. Int J Med Inform. 2018;120:116–25.
Pomares-Quimbaya A, Kreuzthaler M, Schulz S. Current approaches to identify sections within clinical narratives from electronic health records: a systematic review. BMC Med Res Methodol. 2019;19(1):155.
Prideaux A. Issues in nursing documentation and record-keeping practice. Br J Nurs. 2011;20(22):1450.
Reid Ponte P, Somerville JG, Adams JM. Assuring the capture of standardized nursing data: a call to action for chief nursing officers. Int J Nurs Knowl. 2016;27(3):127–8.
Remus S. The big data revolution: opportunities for chief nurse executives. Nurs Leadersh. 2016;28(4):18–28.
Ricciardi W, Boccia S. New challenges of public health: bringing the future of personalised healthcare into focus. Eur J Pub Health. 2017;27(4):36–9.

Rogers ML, Sockolow PS, Bowles KH, Hand KE, George J. Use of a human factors approach to uncover informatics needs of nurses in documentation of care. Int J of Med Inform. 2013;82:1068–74.
Rosenbloom ST, Miller RA, Johnson KB, Elkin PL, Brown SH. Interface terminologies: facilitating direct entry of clinical data into electronic health record systems. J Am Med Inform Assoc. 2006;13(3):277–88.
Rosenbloom ST, Denny JC, Xu H, Lorenzi N, Stead WW, Johnson KB. Data from clinical notes: a perspective on the tension between structure and flexible documentation. J Am Med Inform Assoc. 2011;18(2):181–6.
Rosenbloom ST, Miller RA, Adams P, Madani S, Khan N, Shultz EK. Implementing an interface terminology for structured clinical documentation. J Am Med Inform Assoc. 2013;20(e1):e178–82.
Saranto K, Kinnunen UM, Kivekas E, Lappalainen AM, Liljamo P, Rajalahti E, Hyppönen H. Impacts of structuring nursing records: a systematic review. Scand J Caring Sci. 2014;28(4):629–47.
Seidling H, Bates D. Evaluating the impact of health IT on medication safety. Stud Health Technol Inform. 2016;222:195–205.
Shachak A, Montgomery C, Dow R, Barnsley J, Tu K, Jadad AR, et al. End-user support for primary care electronic medical records: a qualitative case study of users' needs, expectations and realities. Health Syst (Basingstoke). 2013;2(3):198–212.
Sheerin F. NANDA and NIC: mediators to describe Irish intellectual disability nursing. Int J Nurs Terminol Classif. 2003;14:22.
Siegler EL, Adelman R. Copy and paste: a remediable hazard of electronic health records. Am J Med. 2009;122(6):495–6.
Simpson RL. Chief nurse executives need contemporary informatics competencies. Nurs Econ. 2013;31(6):277–88.
SNOMED International. SNOMED CT starter guide. 2017.
SNOMED International. SNOMED International: leading healthcare terminology worldwide 2019. http://www.snomed.org/.
Sohn S, Wang Y, Wi CI, Krusemark EA, Ryu E, Ali MH, et al. Clinical documentation variations and NLP system portability: a case study in asthma birth cohorts across institutions. J Am Med Inform Assoc. 2017;25(3):353–9.
Staggers N, Clark L, Blaz JW, Kasandoy S. Nurses' information management and use of electronic tools during acute care handoffs. West J Nurs Res. 2011;34(2):153–73.
Staggers N, Elias BL, Makar E, Alexander GL. The imperative of solving nurses' usability problems with health information technology. J Nurs Adm. 2018;48(4):191–6.
Sundling KE, Kurtycz DFI. Standardized terminology systems in cytopathology. Diagn Cytopathol. 2019;47(1):53–63.
Tastan S, Linch GC, Keenan GM, Stifter J, McKinney D, Fahey L, et al. Evidence for the existing American Nurses Association-recognized standardized nursing terminologies: a systematic review. Int J Nurs Stud. 2014;51(8):1160–70.
Tayyib N, Coyer F, Lewis PA. A two-arm cluster randomized control trial to determine the effectiveness of a pressure ulcer prevention bundle for critically ill patients. J Nurs Scholarsh. 2015;47(3):237–47.
The Office of the National Coordinator for Health Information Technology. Standard nursing terminologies: a landscape analysis. 2017.
Thomas-Hawkins C, Flynn L, Dillon J. Registered nurse staffing, workload and nursing care left undone, and their relationships to patient safety in hemodialysis units. Neph Nurs J. 2020;47(2):133–42.
Topaz M, Golfenshtein N, Bowles KH. The Omaha system: a systematic review of the recent literature. J Am Med Inform Assoc. 2014;21(1):163–70.

Vivanti A, Lewis J, O'Sullivan TA. The nutrition care process terminology: changes in perceptions, attitudes, knowledge and implementation amongst Australian dietitians after three years. Nutr Diet. 2018;75(1):87–97.
Vuokko R, Makela-Bengs P, Hypponen H, Lindqvist M, Doupi P. Impacts of structuring the electronic health record: results of a systematic literature review from the perspective of secondary use of patient data. Int J Med Inform. 2017;97:293–303.
Warren JJ, Matney SA, Foster ED, Auld VA, Roy SL. Toward interoperability: a new resource to support nursing terminology standards. Comput Inform Nurs. 2015;33(12):515–9.
Weis JM, Levy PC. Copy, paste, and cloned notes in electronic health records. Chest. 2014;145(3):632–8.
Welton JM, Harper EM. Measuring nursing care value. Nurs Econ. 2016;34(1):7–14.
Westra BL, Delaney CW, Konicek D, Keenan G. Nursing standards to support the electronic health record. Nurs Outlook. 2008;56(5):258–66.e1.
Westra BL, Oancea C, Savik K, Marek KD. The feasibility of integrating the Omaha system data across home care agencies and vendors. Comput Inform Nurs. 2010;28(3):162–71.
Westra B, Sylvia M, Weinfurter EF, Pruinelli L, Park J-I, Dodd D, et al. Big data science: a literature review of nursing research exemplars. Nurs Outlook. 2017;65:549–61.
Wilbanks BA, Berner ES, Alexander GL, Azuero A, Patrician PA, Moss JA. The effect of data-entry template design and anesthesia provider workload on documentation accuracy, documentation efficiency, and user-satisfaction. Int J Med Inform. 2018;118:29–35.
Williams R, Kontopantelis E, Buchan I, Peek N. Clinical code set engineering for reusing EHR data for research: a review. J Biomed Inform. 2017;70:1–13.
Wood S. Effective record-keeping. Pract Nurse. 2010;39(4):20–3.
World Health Organisation. Global strategic directions for strengthening nursing and midwifery 2016–2020. Geneva, WHO. 2016a.
World Health Organisation. International statistical classification of diseases and related health problems 10th revision (ICD-10)-WHO version. 2016b.
Wrenn JO, Stein DM, Bakken S, Stetson PD. Quantifying clinical narrative redundancy in an electronic health record. J Am Med Inform Assoc. 2010;17(1):49–53.
Wuryanto E, Rahayu GR, Emilia O, Harsono, APR O. Application of an outcome present test-peer learning model to improve clinical reasoning of nursing students in the intensive care unit. Ann Trop Med Public Health. 2017;10(3):657–63.
Zanaboni P, Ngangue P, Mbemba GIC, Schopf TR, Bergmo TS, Gagnon MP. Methods to evaluate the effects of internet-based digital health interventions for citizens: systematic review of reviews. J Med Internet Res. 2018;20(6):e10202. https://doi.org/10.2196/10202.
Zaworsky D, Bower K. Care coordination: using the present to transform the future. Nurse Lead. 2016;2016:324–8.
Zhang P, Xing FM, Li CZ, Wang FL, Zhang XL. Effects of a nurse-led transitional care programme on readmission, self-efficacy to implement health-promoting behaviours, functional status and life quality among Chinese patients with coronary artery disease: a randomised controlled trial. J Clin Nurs. 2018;27(5-6):969–79.
Zhang R, Burgess ER, Reddy MC, Rothrock NE, Bhatt S, Rasmussen LV, et al. Provider perspectives on the integration of patient-reported outcomes in an electronic health record. JAMIA Open. 2019;2(1):73–80.