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Development and validation of a data dictionary for a feasibility analysis of emergency department key performance indicators

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ABSTRACT

Objectives: The primary study objective was to describe the development of a data dictionary for a feasibility analysis of 11 emergency department (ED) key performance indicators (KPIs). The secondary objective was to internally validate the data dictionary by measuring the inter-observer agreement between data abstractors at participating study sites.

Methods: A list of data variables based on the minimum data set elements relevant to the KPIs was developed by a panel of emergency medicine (EM) specialists and from the EM literature. A summit involving the relevant stakeholders, including ED frontline staff, a health economist, an ED clinical data manager and a health care informatician, was convened. For the feasibility analysis project, each data abstractor was furnished with a copy of the data dictionary and attended a one-hour training session prior to commencing data abstraction. Data was independently abstracted for each KPI by two abstractors at each of 12 participating EDs. Inter-rater agreement between abstractors was calculated using Cohen's kappa and results were reported using the Landis and Koch criteria.

Results: A data dictionary was developed by creating clear definitions and establishing abstraction instructions for each variable. A total of 43 data variables were included in the study data dictionary: 4 on patient demographics; 19 time variables; 5 outcome variables; 8 ED service and staffing units and 7 medical definitions. A clear definition and a set of data abstraction instructions including data sources were developed for each variable to aid data abstraction during the feasibility analysis. Overall 9,276 ED patient records were used for data abstraction to internally validate the data dictionary. The median Cohen kappa score ranged between 0.56 to 0.81.

Conclusion: There is a continued need to standardize definitions of KPIs for the purpose of comparing ED performance and for research purposes. This is a necessary first step in the implementation of valid and reliable ED performance measures. This study successfully developed an internally valid data dictionary that can be used for day-to-day ED operations and for research purposes.

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1. Introduction

Key performance indicators (KPIs) are frequently used to assist in performance monitoring and can contribute towards performance improvement in the quality of patient care and patient safety [1]. Valid and reliable KPIs rely on the collection of standardized data pertaining to the minimum dataset (MDS) elements, the core data identified as the minimum data required to measure performance using a KPI [1]. There is currently no published standardized, pragmatic data abstraction tool for a feasibility analysis of emergency department (ED) KPIs. This paper focuses on the development of a data dictionary as such a tool.

A data dictionary is defined as a descriptive list of names or variables, definitions, and attributes of data elements to be collected in an information database whose purpose is to ensure consistency of terminology [2]. Data dictionaries are currently used as important tools in data abstraction, information management and database maintenance in clinical research and routine service delivery [3–6]. The potential benefits of a data dictionary for research purposes include improved data quality, improved data integrity, consistency in data use and easier data analysis [7,8]. Furthermore a data dictionary facilitates comparing performance consistently across sites, systems and over time.

Medical professional bodies and healthcare providers are increasingly highlighting the benefits of data dictionaries [1,6,9–13]. The importance of a data dictionary is particularly evident when data collection involves multiple health information systems, service users, clinical conditions, investigations and treatments [6]. No more so is this exemplified than in emergency medicine (EM), a very data-intensive specialty and where EDs are very complex systems [14,15]. Specifically, common definitions of MDS elements can improve the ability to compare ED operations and provide a common language for clinicians, policymakers, healthcare managers and researchers [16].

The importance of a data dictionary becomes evident as ED clinical data are captured in a variety of ways and may be of inconsistent quality [7]. Internationally, there is recognition of the lack of consensus regarding definitions of common ED metrics [16,17]. In Ireland, despite some preliminary work in this area by the national Emergency Medicine Programme (EMP), there is no comprehensive data dictionary for ED operation metrics [18]. This is compounded by the differences in the way different EDs collect data. In common with other jurisdictions, many EDs still have primitive information systems that are often derived from poor quality data elements [19]. Standardization of terminology in a data dictionary can help produce comparable data despite major differences in hospital data collection systems.

The primary aim of this study was to develop a comprehensive data dictionary to use as a data collection tool for a national feasibility analysis of 11 ED KPIs. The secondary aim of the study was to internally validate the data dictionary.

2. Methods

2.1. Ethical approval

Research ethics approval was obtained from the each participant ED's research ethics committee.

2.2. Summit working model

A consensus methodology was used to develop the data dictionary. Eleven ED KPIs (Table 1) were selected a priori by the study team based on the Donabedian framework, the Institute of Medicine's domains of quality framework and an Irish EM consensus study [20–22]. The generation of the data variables started with a review of the relevant published literature [1,16–18]. This was followed by input of expert opinion from the study team, which included EM physicians; health services researchers, a health economist and health care informatics experts.

A previously published summit consensus methodology was employed [16,23]. A one-day multi-disciplinary data dictionary summit was convened on the 7th November 2012 in Dublin, Ireland. Prior to the summit a draft data dictionary with definitions of the relevant MDS elements and potential data element sources was sent to the invited participants. At the summit, the participants were again provided with the draft data dictionary and asked to refine the MDS definitions. Participants debated the key MDS terminology, and reached a consensus on the final version of the data dictionary.

2.3. Participants

Purposive sampling was used to ensure that fourteen appropriate summit participants were invited [24]. The participants included six Consultants (Attendings) in EM, one ED clinical data manager, a health economist, two qualitative research methodologists, one ED clinical nurse manager, a data programmer and a project manager (Table 2). All of the contributions made by the participants were recorded and incorporated into the data dictionary.

The specific eligibility criteria for an invitation to participate in the multi-disciplinary summit were as follows: ED frontline staff (for example, EM physicians, ED clinical nurse managers, ED clerical staff); staff routinely working in a service closely allied to ED service (for example, hospital data managers) and expertise in healthcare informatics, qualitative research methodology, biostatistics and health economics. To ensure that each MDS element was precisely defined, while acknowledging that individual data elements may not be defined in the same way at different study sites, staff members who used the ED data capture system as part of routine service delivery were invited from the twelve participating EDs. Participants representing eight EDs attended. One participant from a ninth ED was unable to attend on the morning of the summit due to logistical reasons. Further invites were sent to the two unrepresented study EDs but failed to secure attendees. The draft data dictionary was sent to the study leads at these two EDs for review after the summit.

2.4. Data dictionary internal validation

The final version of the data dictionary was used for the feasibility analysis study. Two data abstractors in each participating ED performed data collection for the feasibility analysis independently. The data abstractors were hospital staff. Prior to its use, each abstractor was given a copy of the final version of the data dictionary and attended a one-hour training session. A member of the core project team (an EM research fellow) was available at all times to answer any queries from the abstractors regarding the data dictionary.

The abstractors performed a retrospective chart review on two separate occasions (at least two weeks apart) to record the availability of each MDS element on the study database. The availability of each minimum data set element was abstracted four times (twice by each data abstractor). An iterative data cleaning process was conducted to minimize missing data. The study server utilized the International Business Machines (IBM) DB2 database management system and the web interface was provided on BC|CLIN (BC_Platforms, Espoo, Finland).

2.5. Data and statistical analysis

The inter-rater agreement was calculated based on Cohen's kappa (κ) [25]. The completed dataset of the two data abstractors' first data abstraction at each study site from the study database was analyzed using Statistical Package for the Social Sciences (version 22.0, 2013, Armonk, New York, USA). The inter-rater agreement was benchmarked using the Landis and Koch criteria [25,26].

Based on pilot study data, to produce a confidence interval with a width less than 0.50, a sample size of 100 patient records relevant to each of the KPIs being examined was used for data abstraction [27].

Table 1
List of study KPIs.

KPIs	Donabedian	IOM domains of quality
1. Time to analgesia in adult presenting with abdominal pain	Process	Efficient, timely
2. Time to analgesia in children presenting with abdominal pain	Process	Efficient, timely
3. Time to analgesia in children with suspected forearm fractures	Process	Efficient, timely
4. Time to antibiotics in sepsis in adults	Process	Efficient, timely
5. Time to antibiotics in pediatric patients (children) with suspected bacterial meningitis	Process	Efficient, timely
6. Time to first electrocardiogram (ECG) in suspected cardiac chest pain	Process	Efficient, timely
7. Time to brain computed tomography (CT) for patients presenting within 4.5 hours of onset of symptoms consistent with a stroke	Process	Efficient, timely
8. Total ED time	Outcome	Efficient, timely
9. ED attendances with deep vein thrombosis (DVT) that end in hospital admission	Outcome	Patient centered
10. Unplanned ED re-attendance rate within 7 days of original attendance	Outcome	Safe
11. Left before Completion of Treatment Rate (LBCT)	Outcome	Safe

Table 2
Data dictionary summit participants.

	Name	Role	Hospital/ Institution
1	Dr Abel Wakai	EM physician	Beaumont Hospital, Dublin, Ireland.
2	Professor Ronan O'Sullivan	EM physician	University College Cork, Ireland.
3	Dr Jason Carty	EM physician	Kerry General Hospital, County Kerry, Ireland.
4	Dr Patrick Felle	Health care informatician	University College Dublin, Ireland.
5	Dr Maria Brenner	Qualitative research methodologist	University College Dublin, Ireland.
6	Catherine Redican	ED clinical data manager	St James' Hospital, Dublin, Ireland.
7	Sinead Nic An Fhailí	Study project manager	National Children's Research Centre, Dublin, Ireland.
8	Professor Brenda Gannon	Health economist	Centre for Business and Economics of Health, University of Queensland, Australia.
9	Neil Brookes	Data programmer	National Children's Research Centre
10	Professor John Ryan	EM physician	St Vincent's University Hospital, Dublin, Ireland.
11	Dr Eamonn Brazil	EM physician	Mater Misericordiae University Hospital, Dublin, Ireland.
12	Mr Ashraff Butt	EM physician	Cavan General Hospital, Ireland.
13	Norma O'Sullivan	Clinical nurse manager	Cork University Hospital, Ireland.
14	Professor Philip Larkin	Qualitative research methodologist	University College Dublin, Ireland.

3. Results

The agreed version of the data dictionary employed clear MDS definitions and a set of data abstraction instructions. A total of 43 data variables were included in the data dictionary: 4 patient demographic; 19 time-related measures; 5 outcome measures; 8 ED service and staffing units and 7 medical definitions (Appendices A–E).

A number of data inconsistencies were identified at the summit and were highlighted in the data dictionary. The first inconsistent naming conventions pertained to the patient's hospital identifier number. In the absence of a national individual health identifier in Ireland, it became evident during the summit that different EDs use different nomenclature such as medical record number (MRN) or patient chart number. Furthermore, it emerged during the discussion that some EDs ascribe patients' two identifier numbers (an episode number for each ED attendance) and a hospital patient number (such as a MRN) that remains unchanged if there are multiple ED attendances.

A number of examples of inconsistent definitions were highlighted. The most notable pertained to the definition of a pediatric patient. Firstly, in Ireland there is no nationally implemented age cut-off to define ED pediatric patients. During the data dictionary summit discussion, it became apparent that the age cut-off for defining a child in the ED varied, with some EDs defining a child as less than sixteen years old while others as less than fourteen years old. In the data dictionary, a pediatric patient was defined as younger than sixteen years of age and an adult patient as sixteen and older with the proviso that the research fellow would clarify the local definition for each ED. These definitions are consistent with the Irish EMP's definition of ED pediatric and adult patients [18]. Secondly, it was acknowledged that there were inconsistent definitions regarding timestamps such as ED arrival time between EDs and even within an ED between manual data capture (e.g., by a triage nurse) and electronic data capture (e.g., by the ED reception staff electronically registering the patient on ED arrival). To accommodate these inconsistencies, the summit participants defined ED arrival time as the first documentation of the time a patient's presence in the ED is noted on any of the patient's ED electronic or manual clinical records. Thirdly, inconsistencies were noted between definitions for proportion metrics (such as the total number of patients who left before completion of treatment and the total number of ED attendances between EDs). The data dictionary defined and standardized these variables across the participant EDs.

Overall, 9,276 ED patient records were used for data abstraction to internally validate the data dictionary in participant EDs. Data relevant to a KPI was not collected in a study ED if the KPI was not clinically relevant to the ED (for example, a pediatric KPI in an adult-only ED) or if local clinicians advised that it was not logistically practical to obtain data elements relevant to the KPI (Appendix F). 105,982 MDS elements relevant to the 11 KPIs examined were collected and analysed from 9298 ED clinical records. The overall availability of MDS elements for the included KPIs was 74.66% (Fig. 1). The inter-observer agreement between data abstractors was measured using median Cohen kappa scores ranged from 0.56 to 0.81 (Table 3). Variation in the median inter-observer agreements of each study ED across all KPIs is depicted in Fig. 2.

4. Discussion

The primary study objective was to develop a comprehensive data dictionary for a feasibility analysis study of ED KPIs. A summit consensus methodology was used to develop the data dictionary by refining the definitions of the MDS elements relevant to the KPIs being examined and to identify the relevant data sources.

The final version of the data dictionary defined 43 data elements. Its internal validation revealed "moderate" to "almost perfect" inter-observer agreement. The interpretation of source materials and definitions by abstractors is a critical step in the acquisition of accurate data

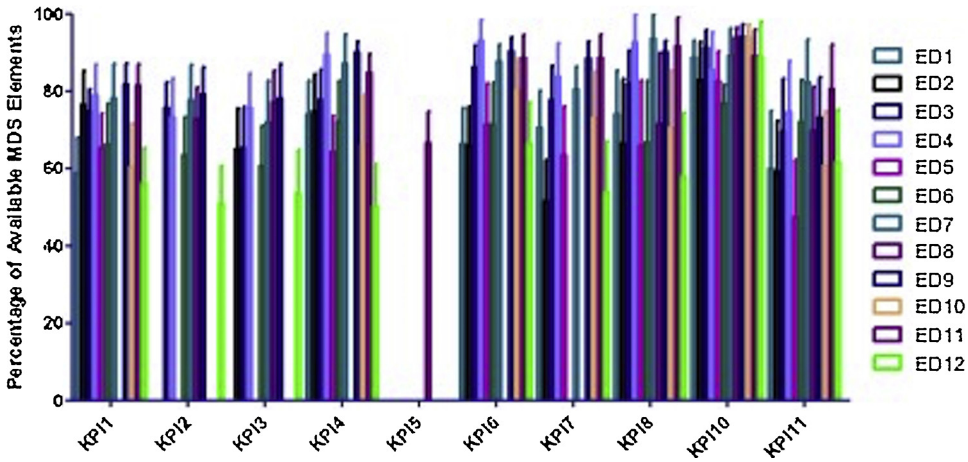

Fig. 1. Percentage of available minimum data set elements for all EDs and KPIs.

[27,28]. The findings of this study highlighted the importance of developing a data dictionary when using data derived from multiple ED databases with different database architecture [7]. Finally, this study describes an effective and efficient methodology of developing a data dictionary for a feasibility analysis of ED KPIs.

This study reveals that approximately a quarter of MDS elements relevant to the KPIs examined are currently absent in Irish ED patient records [29]. This is not surprising given that hitherto there has not been a culture of formally collecting data specifically ED performance monitoring purposes and the reliance on the manual documentation of some of the component MDS elements.

Inter-rater reliability is affected by the fineness of discriminations in the data that collectors must make [30]. This may be due to data abstractors having to review multiple data sources to abstract data. Similarly the variation of data sources across the EDs may account for the wide variability of the ED median inter-rater Cohen kappas.

The methodology for developing the data dictionary was consistent with American Health Information Management Association and the Centers for Disease Control and Prevention guidance [2,7,31]. For example, this data dictionary maps data across all ED systems and complies with Irish ED standards [2]. Our data dictionary is simple, easily managed on tables and accessible [7]. More complex data dictionaries require data management program applications and data mapping methods [5,32].

In the US there are national efforts to develop health industry-wide standards for EM practice and performance metrics. In the US three major ED benchmarking organizations [ED Benchmarking Alliance (EDBA), ED Operations Study Group (EDOSG), and Academy of Academic Administrators of Emergency Medicine (AAAEM)] have met and negotiated a commitment to adopt universal definitions for common ED clinical performance metrics [15]. This impacts performance benchmarking for nearly half of US EDs and it transitions consistency in reporting ED operations metrics from consensus to implementation [15].

There are no EU standards for data dictionary development for health informatics. Countries such as Canada, New Zealand and England recognized that their health information was of variable quality, duplication and fragmented systems, which contributed to cost inefficiencies and poor value for money [33]. An international review found that these jurisdictions harmonized their data sources using a variety of roadmaps, strategies and legislative means [33]. These processes required incremental progress over a long period of time [34].

The objective of this study was to measure the availability of the MDS elements rather than assessing the context of their availability. However, we found that data elements that are routinely captured electronically, such as time and date of ED arrival, were consistently abstracted. This finding suggest that enhanced electronic data capture of MDS elements and a highly functioning EDIS may lead to more consistent data abstraction.

Adoption of electronic health records (EHR) comes with the need to develop common terminology standards to assure semantic interoperability [35]. Data dictionaries form the basis for database organization and semantic interoperability [3]. In the developing world, there has been a challenge with the lack of expertise in dictionary management and policies and procedures required to enable graceful evolution of the dictionary and high quality responsiveness to implementers of the EHR (35).

The findings of this study highlighted many inconsistent definitions

Table 3
Inter-observer kappa scores per KPI.

KPI	Number of participating EDs	Total number of ED patient records	Median κ (range)
1. Time to analgesia in adults presenting with abdominal pain	11	1098	0.74 (0.5 to 0.91)
2. Time to analgesia in children presenting with abdominal pain	7	700	0.8 (0.55 to 0.94)
3. Time to analgesia in children presenting with suspected forearm fractures	8	805	0.81 (0.47 to 0.96)
4.Time to antibiotics in adults presenting with suspected sepsis	11	1096	0.63 (0.16 to 0.91)
5. Time to antibiotics in children presenting with suspected bacterial meningitis	1	100	0.79
6. Time to first electrocardiogram in adults presenting with suspected cardiac chest pain	12	1100	0.56 (0.31 to 0.91)
7. Time to brain computed tomography in adults presenting within 4.5 hours of onset of suspected stroke	9	783	0.7 (0.11 to 0.95)
8. Total ED time	12	1200	0.7 (0.2 to 0.99)
10. Unplanned ED re-attendance rate within 7 days	12	1195	0.71 (0.32 to 0.96)
11. Left before completion of treatment rate	12	1199	0.69 (0.55 to 0.98)
Total number of ED charts reviewed	–	9276	–

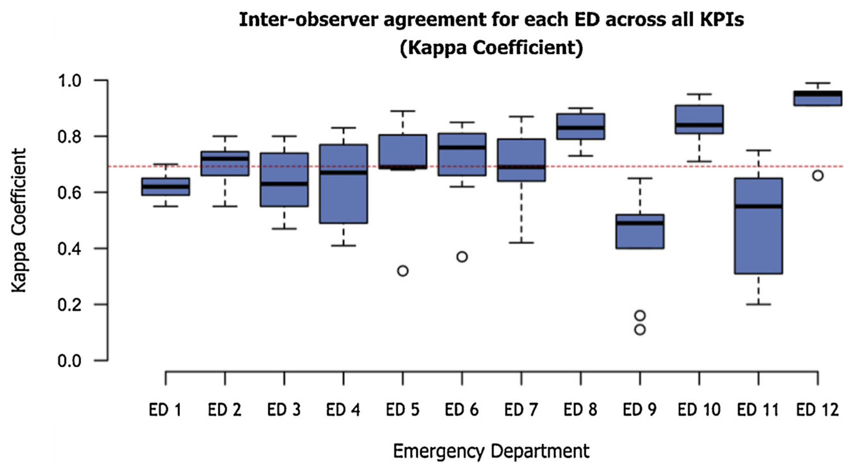

Fig. 2. Inter-observer agreement Cohen's kappa values for each ED across all KPIs.

and inconsistent naming conventions used in recording data in EDs that can lead to data misinterpretation if used for performance monitoring. The use of variable definitions in clinical data and the need to standardize terminology using data dictionaries for research purposes has been identified in studies investigating dementia and childhood pneumonia [8,36]. Indeed one study concluded that librarians are best placed to provide a research data management service [8].

4.1. Strengths

To the best of our knowledge, this is the first study to develop an internally validated data dictionary specifically for a feasibility analysis of ED KPIs. The data dictionary can be used to complement national and international emergency care patient cohort definitions and emergency care activity data [18].

This study took several steps to ensure data integrity was maintained. Firstly, no abstractor started work until they were competent in using the data dictionary. An iterative data cleaning process was conducted to ensure that the data was as complete as possible, reliable and processed in a consistent manner. Our study database managed our data requirements and ensured data integrity and data security. For larger or national data sets, there may be a role for cloud computing to perform massive-scale and complex computing with a focus on data integrity, data quality, privacy, legal and regulatory issues, and governance [37,38].

Secondly, to ensure data collection reproducibility, measuring the inter-observer agreement between the data abstractors validated the outcome data. Whilst there is no "gold standard" method of validating a data dictionary, Lin et al similarly calculated kappa statistics in their data dictionary development [3].

4.2. Limitations

The primary limitation is the development of definitions by consensus in a form of modified Delphi approach [23]. As there are no formal universally agreed guidelines and multiple formats exist for the Delphi approach, there is no consistent method for reporting findings [39,40]. Indeed, there is little evidence to support reliability or reproducibility of Delphi consensus results [41]. Furthermore, concerns regarding validity arise from the perception that it forces consensus [41].

Secondly, it could be argued that the data dictionary summit was limited as there was only representation in person from eight of the twelve study hospitals and possible use of different nomenclature may not have been captured in the data dictionary. Nevertheless, all efforts were made to ensure that the finalized data dictionary was as comprehensive as possible as it was disseminated to representatives of all study EDs for feedback. Thirdly, the reliability of our data dictionary may have been limited by the fact that the variable definitions and abstraction instructions were not available on the study database website thereby limiting interactive data entry [3]. This may not have been a significant factor as the research fellow was available at all times to the abstractors. Fourthly, our study was not designed to investigate the root cause of disagreement between abstractors with respect to individual data elements [3]. However, the data dictionary was deemed acceptable to all abstractors as no significant corrections or clarifications were requested from the research fellow. Fifthly, a data dictionary should be a dynamic document. There should be established change management policies and procedures, and a data quality management process that includes on-going data dictionary maintenance and review [7,35]. Ireland acknowledges that it lags behind other western countries in terms of its data dictionary management expertise but a review by the Irish Health Information and Quality Authority has sought to close the knowledge gap [33].

Lastly, a limitation of our data dictionary is its scope and granularity level. There is always tension as to how dictionaries can meet the diverse needs of the various stakeholders, including clinicians, government and researchers, among others [35]. Standards developers are beginning to recognize and address these concerns [42,43].

5. Conclusion

There is a continued need in emergency medicine to standardize definitions for the purpose of monitoring and comparing ED performance, and also for research purposes. This is a necessary first step in the implementation of valid and reliable ED performance measures. This study successfully developed an internally valid data dictionary that can be used for day-to-day ED operations and for research purposes.

Conflict of interests

Authors declare no conflict of interest.

Authors' contributions

Abel Wakai and Ronan O'Sullivan participated in study conception and design. Abel Wakai participated in acquisition of funding. Abel Wakai, Aileen McCabe, Ronan O'Sullivan, Sinead Nic anFhaili, Maire Brenner, Brenda Gannon, John Ryan and Ashraf Butt participated in acquisition of the data. Aileen McCabe and Abel Wakai participated in analysis and interpretation of the data and drafting of the manuscript.

All authors participated in critical revision of the manuscript for important intellectual content.

Summary points

What was already known on the topic?

- A data dictionary is defined as a descriptive list of names or variables, definitions, and attributes of data elements to be collected in an information database whose purpose is to ensure consistency of terminology.
- Data dictionaries are currently used as important tools in data abstraction, information management and database maintenance in clinical research and routine service delivery.

What this study added to our knowledge?

- This study describes the development of an internally validated data dictionary specifically for a feasibility analysis of ED KPIs.
- A data dictionary facilitates abstracting data consistently across sites, systems and over time.
- This study highlights inconsistent definitions and inconsistent naming conventions used in recording data in EDs can lead to data misinterpretation if used for performance monitoring.

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