Abstract

Purpose: 1) To describe trigger terms that can be used to identify reports of inadequate staffing contributing to medication administration errors, 2) to identify such reports, 3) to compare the degree of harm within incidents with and without those triggers, and 4) to examine the association between the most commonly reported inadequate staffing trigger terms and the incidence of (1) omission errors and (2) 'no harm' terms.

Design and setting: This was a retrospective study using descriptive statistical analysis, text mining and manual analysis of free text descriptions of medication administration related incident reports (n=72,390) reported to the National Reporting and Learning System for England and Wales in 2016.

Methods: Analysis included identifying terms indicating inadequate staffing (manual analysis), followed by text parsing, filtering, and concept linking (SAS® Text Miner tool). IBM SPSS was used to describe the data, compare degree of harm for incidents with and without triggers, and to compare incidence of "omission errors" and "no harm" among the inadequate staffing trigger terms.

Findings: The most effective trigger terms for identifying inadequate staffing were 'short staffing' (n=81), 'workload' (n=80), and 'extremely busy' (n=51). There was significant variation in omission errors across inadequate staffing trigger terms (Fisher's exact test = 44.11, $p<0.001$) with those related to 'workload' most likely to accompany a report of an omission, followed by terms that mention 'staffing' and being 'busy'. Prevalence of 'no harm' did not vary statistically between the trigger terms (Fisher's exact test=11.45, p=0.49), but triggers 'workload', 'staffing level', 'busy night', and 'busy unit' identified incidents with lower levels of 'no harm' than for incidents overall.

Conclusions: Inadequate staffing levels, workload and working in haste may increase the risk of omissions and other types of error, as well as patient harm.

Clinical Relevance: This work lays the groundwork for creating automated text-analytical systems that could analyse incident reports in real time and flag /monitor staffing levels and related medication administration errors.

Keywords: incident report, medication administration, staffing, text mining

Medication administration is a routine nursing practice. However, medication administration errors (MAEs) are common (Keers, Williams, Cooke, & Ashcroft, 2013; McLeod, Barber, & Franklin, 2013). In this study, we use the term 'error' as a synonym for the term 'incident' to represent near misses as well as errors that reach the patient, whether they cause harm or not. Based on previous knowledge, dose omissions are amongst the most common MAE subtypes (Härkänen, Vehviläinen-Julkunen, Murrells, Rafferty, & Franklin, 2018; Keers et al., 2013). Staffing adequacy is one of the factors that may contribute to such missed care and adverse patient outcomes (Kalisch & Lee, 2010) as important nursing tasks are often left undone because of lack of time (Ball et al., 2018; Ausserhofer, et al. 2014; Ball, Murrells, Rafferty, Morrow, & Griffiths P, 2014). Inadequate staffing levels can arise for multiple reasons e.g. cost reductions, sickness absences and inability to fill vacant posts. These factors increase the workload elsewhere in the system, for example, when establishment staff have to supervise agency staff resulting in reduced productivity.

Research on the relationship between nurse staffing and patient outcomes has demonstrated the important role that nurses play in the provision of safe and high-quality care (e.g. Aiken et al., 2014; Brennan, Daly, & Jones, 2013; Coster, Watkins, Norman, 2018; RCN, 2017). Important nursing tasks were more likely to be left undone as the burdens upon staff and workload increase (Aiken et al., 2013, Ball et al., 2014; Ball et al., 2018). This can lead to adverse outcomes and hospital readmissions (Aiken et al., 2014; Ball et al., 2018; Brooks-Carthon, Lasater, Rearden, Holland, & Sloane, 2016; West et al., 2014) and reductions in productivity that places additional burdens on the organisation both operationally and financially. Inadequate resources and staffing that contribute to heavy workload have also been shown to contribute to medication errors (e.g., Berdot et al., 2012; Lawton, Carruthers, Gardner, Wright, & McEachan, 2012; Seynaeve et al., 2011). Nursing work is often demanding and stressful (Kvist et al., 2013). Increased stress lowers job satisfaction, has consequences for healthcare workers' mental and physical health and precipitates burnout and job turnover (Kelly, Runge, & Spencer, 2015). The burden on the remaining staff increases, and the cycle continues with many posts left unfilled particularly amongst registered nurses (RCN, 2017). This is all set against a back-drop of rising demand due to the increasing and aging population.

According the report 'To err is human' published in 1999 by the Institute of Medicine (Kohn, Corrigan, & Donaldson, 2000), one of the key recommendations for learning and decreasing errors was for greater attention to be paid to incident reporting, with the primary purpose of facilitating learning, avoiding the same incidents recurring, and monitoring progress in prevention of errors (Leape, 2002). Nowadays, many health care organisations worldwide gather information on incidents and aggregate into so called incident reports. For example, in England and Wales, the National Reporting & Learning System (NRLS) database on patient safety incidents has captured over 16 million reports (NHS Improvement, 2017) since 2003. The information in incident reports is both structured and unstructured (e.g. free text descriptions of the incidents). Free text information includes valuable information about contextual factors that may contribute to incidents that may remain hidden if solely relying on structured information (Verma & Maiti, 2018). However, manual analysis of free text found in the incident reports is challenging using traditional qualitative text-based analysis methods, as it can include extraneous information. These datasets are also much larger than those normally analysed using qualitative software and novel analytic methods are therefore required.

Text mining brings together multiple techniques from different fields: information retrieval deals with indexing and searching unstructured texts, data mining attempts to discover patterns in structured data, and natural language processing (NLP) analyses and synthesises language and speech (Wachsmuth, 2015). By using text mining it is possible to analyse words, clusters of words, or whole documents to find associations and similarities and also to explore how these entities are related to other variables (Statsoft, 2018). Examples of using text mining in health care include the study of adverse drug reactions using electronic patient records (Warrer, Holme Hansen, Juhl-Jensen, & Aagaard, 2012), automated detection of follow-up appointments (Ruud, Johnson, Liesinger, Grafft, & Naessens, 2010), and extracting detailed structured medication information from free-text prescriptions (Karystianis, Sheppard, Dixon, & Nenadic, 2016). Text mining has been used to study incident report data from other disciplines, for example steel plant incidents (Verma & Maiti, 2018), and for the automated analysis of medical critical incident reports (Denecke, 2016). To our knowledge, apart from our previous pilot study ([redacted]), this is the first time text mining has been used to analyse MAEs and more specifically to investigate how MAE reports relate to staffing factors.

The purpose of this study is to describe trigger terms that can be used to identify reports of inadequate staffing contributing to medication administration errors, to identify such reports, to compare the degree of harm within incidents with and without those triggers, and to examine the association between the most commonly reported inadequate staffing trigger terms and the incidence of (1) omission errors and (2) ‘no harm’ terms. Trigger terms are keywords that act as ‘clues’ to identify specific pre-defined themes derived from the text based data.

Methods

This is a retrospective study using descriptive statistical analysis, text mining and manual analysis of free text descriptions of medication administration related incident reports reported to the NRLS for England and Wales in 2016.

Data collection

The data comprise MAEs reported to the NRLS that occurred between 1 January and 31 December 2016. These data were obtained from NHS Improvement. To be included, incidents needed to involve: 1) medication, 2) administration / supply of a medicine from a clinical area, and 3) have occurred in an acute NHS trust (a healthcare organisation that provides specialist or non-specialist secondary healthcare services within England or Wales; these exclude mental health and long term care settings). For this study, only free text descriptions of the incidents (descriptions of what happened) were used.

Data analysis

The data analysis process included multiple phases (Figure 1). First, staffing-related keywords contributing to MAEs were identified. We used the classification structure described in our pilot study ([redacted]) that manually analysed over a thousand (n=1,012) MAE reports from Finland. In that study, keywords (translated here into English) were divided into eight themes: 1. staffing inadequacy, 2. work overload, 3. number of patients, 4. time-pressure, 5. skill level or mix, 6. nurse ability to conduct the task, 7. distractions & interruptions, and 8. patient-related issues increasing workload. For verification of this classification, a small sample of the NRLSs' medication administration incidents was collected. All incidents that included 'work environment' contributing factors (n=211 of 72,390 reports) were analysed manually to identify keywords that described staffing factors. For this study, only keywords based on both classifications that might be linked to inadequate staffing were chosen as the starting point of the analysis: these were ‘staff’, ‘staffing´, ‘lack’, ‘pressure’, stress´, ´workload´, and ´busy’. (Supplement 1).

The SAS® Enterprise Miner 13.2 Text Miner tool with a ‘bag-of-words method’ was used to count words in the text and to understand how these words relate to each other (summarising and classifying text), rather than using semantic (meaning of words) method. The purpose was to discover themes and concepts within the free text descriptions. The method is described in more detail in a previous pilot study ([redacted]). Data in the form of text (Excel file) was first converted into SAS format for importing into Text Miner where the algorithms would then be applied (Verma & Maiti, 2018). SAS Text Miner automatically processes the data using ‘Text parsing’ that includes tokenisation (breaking text into words / terms), stemming (which reduces words to their stem or root forms), and part-of text tagging (for each word, the algorithm decides whether it is a noun, verb, adjective, adverb, preposition and so on). ‘Text filtering’ is then used to reduce the total number of parsed terms, and check the spellings. The English language was chosen for parsing and for filtering the text. A SAS Text Miner stop list was used (a list of all of the possibly irrelevant words), so some parts of the text that included auxiliary verbs, conjunctions, possessive pronoun, interjections, numbers, participles, prepositions, and pronouns were ignored. Using an interactive filter viewer, synonyms were combined manually. Unwanted terms were excluded (such as most abbreviations), as well as terms occurring in fewer than in ten reports.

Concept linking is a way to find and display other terms that are highly associated with a selected term. The selected term is shown at the centre of a link diagram, and the terms that circle this are those that occur together most often with that central term. (SAS, 2012.) The strength of association between two terms is based on the principle of conditional probability which is, the probability that the term B exists given the term A already exists in the document. Initially, automated concept linking by the SAS Text Miner was verified by comparing the results with a manual analysis. The term “workload” was chosen for this comparison. Concept linking was used to identify highly correlated terms and compared manually against all descriptions that included the term “workload”. Further, concept linking was conducted on other terms that described inadequate staffing level.

The ‘search’ field of the SPSS database including all (n=72,390) incident reports was used to review the free text descriptions and identify trigger terms in the data. Characteristics of the data (trigger/error category /degree of harm) were described using frequencies and percentages (Table 1). Degree of harm was designated by reporters as no harm, low harm [patient(s) required extra observation or minor treatment], moderate harm [short term harm - patient(s) required further treatment, or procedure], severe harm [permanent or long term harm] or death [caused by the Patient Safety Incident], (Table 1). Statistical testing of associations, using Fisher’s Exact tests was confined to the triggers that most commonly reported ‘omissions’ and ‘no harm’. The “no harm” category was chosen for statistical testing as it was only category that existed within all triggers. Incidents with any staffing trigger were then compared with all other incidents to find out if staffing triggers as a group were pointing to higher, lower or a similar risk overall.

Ethics

The research Ethics office of King’s College London gave ethical approval for this study (LRS-17/18-5150) in October 2017.

Results

Characteristics of the data

Data included 72,390 descriptions of medication administration incidents, which comprised 1,257,570 nouns, 781,418 verbs, 226,746 adverbs, 172,527 adjectives, 131,295 noun groups, and 111,156 pronouns. The majority (86.3% n=62,461 incidents) were reported as not causing patient harm. Most common error types were omitted medicine / ingredient (27.4%, n=19,815), other (17.3%, n=12,528), wrong frequency (9.6%, n=6,975), or wrong drug (7.6%, n=5,494) (Table 1).

Identifying triggers describing inadequate staffing level

Workload (including terms 'work load', 'busy workload', and 'high workload') was recorded 114 times in 99 MAE reports. Terms that were most often related to workload based on automated concept linking were: staffing, high, unable, busy, heavy, work, and load. Concept linking of the term 'workload' and expanded links is shown in the appendices (Supplement 2). When findings were compared with the manual analysis of terms closely related to term 'workload', it was found that most terms were identical (Supplement 3).

Further, concept linking of the terms chosen from the preliminary classification and additional terms based on 'workload' revealed connections between those describing staffing inadequacies (Table 2). Utilising this information, triggers (by combining connected words) were chosen for testing. Those triggers were 'poor staffing', 'short staff(ing)', 'lack of staff', 'staffing level', 'staffing workload/workload of staffing', 'workload /work load /busy load /heavy load','busy ward /busy unit/busy staff/busy nurse/ busy colleague/ busy time/ busy shift/ busy night', 'extremely busy', 'workload stress', and 'stress load' (Table 2).

Testing the triggers for identifying inadequate staffing level

The most common trigger was 'short staffing' found in 81 incidents. Of these incidents, 28% were dose omission and most (89%) did not cause patient harm. Other common triggers were 'workload' (n=80), 'extremely busy' (n=59), 'staffing level' (n=35), and 'busy shift' (n=34). For the triggers 'workload' (n=80), 'busy night' (n=8), 'busy unit' (n=6), the percentage of no harm was lower than that found for all incident's (75.0-85.0% vs. 86.3%). Omission errors were more common amongst incidents with documented inadequate staffing triggers than for all incidents combined (with staffing triggers and without), for example “poor staffing” 89.0% [8/9] vs. 27.4% [19,815/72,390] (Table 3).

Associations between triggers and the incidence of omission errors and ‘no harm’

There was significant variation in omission errors across inadequate staffing level trigger terms (Fisher’s exact test = 44.11, $p<0.001$) with those related to workload having the highest percentage of omissions, followed by terms that mention staffing and being busy. The prevalence of ‘no harm’ did not vary statistically between the inadequate staffing trigger terms (Fisher’s exact test=11.45, $p=0.49$) (Table 4).

Discussion

We identified trigger terms associated with reports of inadequate staffing levels that contributed to MAEs. These triggers could be used to study incidents and gain further understanding of inadequate staffing levels and their repercussions. The data used in this study (free text descriptions of 72,390 incidents) contained millions of words and large amounts of extraneous information. Only a limited number of terms describing inadequate staffing levels were found. Data that is classified or structured, however would have been limited in identifying in-depth conditioning factors associated with the occurrence of incidents. Manual categorization of narrative reports can sometimes result in a classification based on a restricted list of categories with a high degree of inconsistency. Furthermore, multiple analysts, and single analysts categorising over time, may classify or group descriptions differently. Additionally, forcing the narrative description into a predetermined and limited number of categories may carry the risk of losing meaningful and relevant factors. (Verma & Maiti, 2018.)

The free text descriptions of incident reports provided by the staff are a rich data source (Verma & Maiti, 2018). We found that omission errors were more common in incident reports that included terms linked to inadequate staffing levels, therefore reports of lack of staff and/or high workload were associated with medications not being administered at the correct time or not at all. In previous studies, it was found that essential nursing care may be left undone due to a lack of time (e.g. Ball et al., 2018; Brooks-Carthon et al., 2016), thus contributing to adverse patient and staff outcomes (Kalisch & Lee, 2010). Administering the wrong drug and/ or at the wrong frequency were amongst the more common types of incident. One possible interpretation is that high workload leads to verification practices as part of medication administration, not being carried out. When compared with all incidents some inadequate staffing level triggers were linked to lower levels of no harm. This link (i.e. more staff and safer care) has been previously found in other studies (e.g. Aiken et al., 2014; Brooks-Carthon et al., 2016; West et al., 2014), which demonstrated insufficient numbers of registered nurses can have life-threatening consequences for patients. When care is left "undone", this places even greater risk on the patient (Ball et al., 2017; RCN, 2017).

Future analysis should consider all other factors that increase nurses' workload, such as inadequate skill-mix, and patient-related factors. Our data were confined to medication administration incidents in acute care but the triggers identified could be tested in other healthcare settings and home care facilities, especially those providing for elderly patients (over 75 years) who are particularly at risk of serious medication administration incidents (Härkänen, et al., 2018). This work lays the groundwork for creating automated text-analytical systems that analyse incident reports in real time and warn managers and staff that staffing levels need adjusting upwards to reduce the occurrence of MAEs. Data from these systems will also identify the circumstances that lead to MAEs, to help inform future intervention studies.

Strengths and limitations

The text mining application was useful for identifying triggers. Its ability to transform qualitative into quantitative and schematic data was effective and the algorithms were helpful for identifying the concept links between terms. In addition, there are now so many records that it is no longer practical, in terms of time and cost, to manually review all the reports (Ruud et al., 2010; Verma & Maiti, 2018). Thus, novel text mining methods need to be employed. The credibility of text mining has already been recognized and tested (Verma & Maiti, 2018). Its accuracy, sensitivity and specificity has proven to be high when compared with manual analysis (Ruud et al., 2010), which was confirmed in our study comparing automated concept linking and manual analysis. Manual analysis was unlikely to be a practical solution for finding triggers because the free text descriptions lack structure and typically have not undergone a process of classification prior to analysis.

The analyses demonstrated in this study required the researchers' to make some subjective decisions, such as identifying and selecting the triggers for testing. It is possible that some have been missed. Similar studies to ours could not be found, so there was no clear guidance to follow. Nevertheless, all analysis phases were conducted methodically utilizing knowledge, processes and procedures from an earlier pilot study which can be applied and adapted for future studies. Combining synonyms were challenging without understanding the original meaning of the word. Many words (for example 'alert') could be either a verb, adjective, noun, or could have multiple meanings, such as the term 'back'. We found that certain words were written multiple ways including some with typing errors, such as ampoule, ampule, ampuole, ampulla. These differences are due to the variations in language usage, so the same meaning can be expressed in different ways (Denecke, 2016).

Incident report data also has some limitations, in particular it suffers from under-reporting which may introduce bias. The quality of the reports may also vary in terms of detail and accuracy. (NHS, 2014.) In addition, the data may have been biased because staff reporting an incident might have attributed the incident to low staffing whilst under-reporting contributing factors that relate to other aspects of inadequate staffing. Finally, SAS Text Miner uses the "bag-of-words" approach which means that documents are represented with a vector that contains the frequency with which each term occurs in each document. Additionally, word order of sentences are ignored. This approach is very effective for short, paragraph-sized documents, but it can lead to a loss of information with longer documents. (SAS, 2012.)

Conclusions

A number of triggers related to inadequate staffing were found in incident reports of MAEs. Omission errors were common in incidents that included inadequate staffing trigger terms, especially with the terms ‘workload’ and being ‘busy’. In addition, the potential risk of patient harm was increased with incident reports that included terms ‘workload’, ‘staffing level’, ‘busy night’, and ‘busy unit’. Although this study did not intend to establish causality, it does provide evidence of potential harm. The degree to which MAEs are associated with verification practices that were omitted or not followed to a high enough standard due to staffing related factors (e.g. heavy demands on a person’s time, high patient acuity) would need to be verified and determined through further research.

The application of text mining to free text reports of medication administration errors is very much in its infancy. This study will hopefully encourage others to pursue similar research that will ultimately lead to safer care and better patient outcomes.

Clinical Resources

NHS Improvement. Analysis of the patient safety incidents reported in England to the National Reporting and Learning System (NRLS) up to June 2017. https://improvement.nhs.uk/resources/national-patient-safety-incident-reports-september-2017/

Royal College of Nursing. Safe and Effective Staffing: Nursing Against the Odds. https://www.rcn.org.uk/professional-development/publications/pub-006415

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