An Exploratory Study of Quality-related Events Reported by Community Pharmacies in the United Kingdom: Applying Association Rule Mining

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LIST OF ABBREVIATIONS USED

ADRs	Adverse Drug reactions.
AI	Artificial Intelligence.
ARM	Association Rule Mining.
BMJ	British Medical Journal.
FDA	Food & Drug Administration.
GP	General Practitioner.
IM	Interestingness Measures.
MURs	Medicine Use Reviews.
NHS	National Health Service.
NPSA	National Patient Safety Agency.
NRLS	Nation Reporting and Learning System.
QUM	Quality Use of Medicines.
US	United States.
UK	United Kingdom.

WHO World Health Organization.

ABSTRACT

Errors in healthcare systems can cost resources and sometimes lives. Studying errors in healthcare can help to improve service quality. This study aims to explore the prevalent patterns in medication errors in UK's community pharmacies by using error data voluntarily reported from 859 community pharmacies to incident management system managed by Pharmapod Inc. from 2015 to 2018. The primary output of the study is three sets of association rules that can characterize the relationship of error-factors, error-categories, and event-types. The sample data of 72733 events of medication errors were analyzed using association rule mining. Three sets of strong rules are identified, including six strong rules from error-factors to event-type, nine strong rules from error-categories to event-type, and twenty-two strong rules from the combination of error-factor and error-category to event-type. The implications of the findings are discussed with the literature.

Keywords: medication errors, UK, association rule mining, data mining, accuracy, data completeness.

CHAPTER 1 INTRODUCTION

1.1 Background

Healthcare services are provided worldwide to people to improve their health and quality of life. Healthcare services should be safe and accessible globally so that they promote well-being. Medical workers work hard to provide high-quality healthcare services. However, these services could accidentally result in harmful events, even though their service quality was high (World Health Organisation, 2016, p. 1).

There are various medical errors that result in harmful events during the provision of healthcare service. Wen (2013) presents types of medical errors as follows. First, *wrong diagnosis error* that causes a delay in treatments. Second, *unnecessary treatments error* that causes hazardous incidents. For example, the son of advocate Patty Skolnik received an unnecessary brain surgery that paralyzed him for two years and then resulted in death. Third, the risk of diseases from *injurious procedures errors* in the medical industry. For example, dyes used in a medical procedure like C.T. scans can cause a risk of cancer and kidney failures. Fourth, *medication error* caused by missing the medication or wrong prescription is another error from the medical industry. Fifth, *never-events errors* meaning these errors should not have happened, but they did. For example, scissors left inside the body after an operation are fatal. Sixth, *uncoordinated care* of a patient in hospital taken by an on-call doctor and several specialists who write notes on the chart never coordinating among themselves can result in a harmful event, such as two prescribed medications interfering with each other. *Uncoordinated care errors* between doctors and nurses can also cause harmful events. Seventh, infections gained from the *hospital error* like infectious

urinary catheters can also cause harmful events. Eighth, accidents from *medical devices error* like breaking off a pacemaker's wires can cause harmful events.

Additionally, *missed alert signs errors* like missing low blood pressure can worsen the conditions. Finally, *returning to the hospital again error* because the treatment was not adequate, and the hospital discharged the person before they were ready. Of all these medical errors, this study focuses on medication errors.

The United States (US) National Coordinating Council for medication error Reporting and Prevention defines medication error as: "any preventable event that may cause or lead to inappropriate medication use or patient harm while the medication is in the control of the health care professional, patient, or consumer" (US FDA, 2019). Such events in community pharmacies may be related to dispensing an incorrect medication, incorrect doses, and incorrect directions. The medication error events in community pharmacies may also be related to new prescriptions and may occur during the pharmacist final check stage and during the data entry phase of the initial processing of the prescription and may also occur due shortage of staff (Pervanas et al., 2015, p. 72).

Understanding the magnitude and the nature of the harm caused by medication errors is very important because millions of people use healthcare services daily, for example, general practice, community pharmacies, etc. (World Health Organisation, 2016, p. 16). Approximately 98000 people die every year due to medical errors. This number is higher than the number of people that die from road accidents, breast cancer, AIDS, and workplace accidents (Institute of Medicine et al., 2000, pp. 1–3). There are 237 million medication errors occur in the National Health Service (NHS) in England per year. Of the 237 million

errors reported, 3 out of 4 errors are harmless. Preventing 1 out of 4 harmful error can prevent hundreds of deaths (University of Manchester, 2018).

In some cases, medication errors can be fatal. For instance, Mary Scheuerman, age 85, died two weeks after she started taking the wrong medication. The pharmacy had given her a potent chemotherapy drug in place of the antidepressant her doctor had prescribed (Gabler, 2020). Medication errors incur cost of 40 billion dollars each year in the US (Tariq et al., 2020).

According to Wolf and Hughes (2008), in their book , 90% of the medication errors can be prevented. These potential harmful events can be reduced to fewer avoidable illnesses or hospitalizations. To overcome such accidents, we should understand the causes of medication errors (World Health Organisation, 2016, p. 1–3). Therefore, reporting of medication errors becomes a fundamental principle. Reporting of harmless errors, and near-miss events, can be used to prevent medication errors (Wolf & Hughes, 2008). In the UK, pharmacies must record the medication errors in an incident management log and send these to the National Reporting and Learning Service (NRLS) since 2005 (Pharmaceutical Services Negotiating Committee, n.d.).

Non-medical industries like aviation developed an incident reporting system by concentrating on near-miss reporting (Barach, 2000, p. 759). Industry started providing legal support to staff if they voluntarily submitted an error report within ten days of the occurrence of the error. Industry was using confidentiality over anonymity to increase the responsibility of reporting during near-miss reporting as it is easy to report more near-miss events without fear (Barach, 2000, p. 763). Increased reporting of near-miss events improves learning as near-miss events are just like adverse events with slightly different

conditions (Barach, 2000, p. 759). Benefits of non-punitive and protected error reporting system includes higher instances for accurate quantitative analysis, fewer barriers to data collection, less liability. Patterns in the errors can be used to study and improve the customer safety (Barach, 2000, p. 759). Such industries have made reporting easy, right, and complete, so that the undesirable outcomes of the events can be reduced (Barach, 2000, p. 763).

Errors can be reported through various mechanisms. Verbal reports and paper-based incident reports are the conventional methods of error reporting. These data collection methods can be used to investigate the nature and magnitude of the problem. Modern techniques like automated detection of errors include Web-based forms or adapted standard spreadsheets involve data collection or learning management systems that are useful for identifying patterns in the system (Wolf & Hughes, 2008). Learning management systems are software applications for administering, documenting, tracking, reporting, or learning and development programs (Wikipedia contributors, 2020c). These modern techniques of data collection require huge database to store the data. Extracting useful information from such big databases can be difficult as well. Data mining techniques helps in obtaining useful information from huge databases (McCabe, Adomavicius, Johnson PE &et al, 2008). Data mining results could help make data-driven decisions to reduce medication errors incidence (new medication error cases, (NIMH » What Is Prevalence?, 2017)) and improve patient safety.

In community pharmacy domain quality-related events (QREs) are defined as medication error events that reached patient as well as events that were caught in the community pharmacy before it could reach patient (Boyle et al., 2014, p. 442). Reporting

QREs helps in identifying root causes and presents an opportunity for patient safety improvement and reduce medication error incidence. Reporting using modern techniques can be done to a learning system from a third-party vendor or national database (Boyle et al., 2014, p. 442). According to WHO reporting systems should enhance patient safety, must be safe and anonymous to avoid blame culture, provide an opportunity for data analysis and recommendations for changes (Ho et al., 2010, p. 18). One such learning system that community pharmacies in UK use is Pharmapod Inc.

Pharmapod Inc. is a cloud-based incident management service provider for community pharmacies, hospitals, and long-term care to report medication errors (Pharmapod Ltd, 2020). Community pharmacies can use data from the Pharmapod Inc. system to detect patterns and behavior of medication errors. Most of the literature review available today is strengthened around secondary care institutions(hospitals) and not much information is available about the epidemiology and classification of errors in community pharmacies in UK. This study also bridges the gap between the small-scale studies of community pharmacies as this study is for a period of four years and uses incident management system for reporting errors where most of the previous incident studies have reported data to a paper-based error reporting system. Lack of information on the likely associations between reported error-factor and error-categories of medication events in the existing literature promoted this research idea. Associations between contributary factors and medication error event-type is the major contribution of the study to the existing literature. The next section explains the specific objectives of the study.

1.2 Objectives of the study

The key objective of current study is to identify the potential prevalent pattern of medication errors (within existing cases/events, (NIMH » What Is Prevalence? 2017)) within the community pharmacies using error-data reported to Pharmapod system. Identifying patterns will help in managing the risks of medication errors. Risk management involves identifying risks, evaluate their impacts and make strategies to reduce or eliminate the risk (Nyatyowa, 2018). Specifically, the current study attempts to investigate associations within the contributory error-factors, error-categories, and event-types. Thirty-seven strong association rules helped discover the likelihood of influence of error-factors and error-categories on event-type. For example, *Competence deficiency/training* error-factor, *wrong quantity selected* error-category can contribute to a near-miss event-type with 89% probability. These results will help the community pharmacies to make data driven decisions to reduce medication error incidence. Thus, the study's overall goal was to expand the community pharmacies' knowledge base concerning medication errors and enhance their professional development support.

1.3 Methods and findings

The quantitative descriptive analyses were conducted to identify prevalent patterns in the data extracted from Pharmapod Inc. The exploratory data analysis approach in statistics outlines the characteristics of data (Wikipedia contributors, 2020b). Exploratory analysis of archived data from the Pharmapod database used statistical functions of counting, sorting, reorganizing, grouping, counting, etc. The sample of 72733 cases over a period of four years. Association rule mining (ARM) can help uncover associative relations

in the data (Rai, 2019). Apriori, an ARM algorithm was used to identify associations between the categorical data like error-factor, error-category, and event-type. For example, Policy/procedures not followed e.g., double checking factor can contribute to a near-miss event-type with 80% likelihood. The dataset of the study is focused on community pharmacies in the UK that use the Pharmapod Inc. system for error reporting. The data is available from 2015 to 2018. The data did not categorize the Pharmacy roles into pharmacists, technicians, interns, pharmacy assistants, etc. For this purpose, we say the staff working at the pharmacy stations was involved in the incident.

1.4 Organization of the thesis

This study consists of five chapters. Chapter 1 includes the study background, objectives of the study and methods and findings. Chapter 2 presents a literature review on classification, causes and costs of medication errors, sociotechnical factors related to medication errors, impact of workload and job satisfaction on medication errors, attitudes of healthcare professionals and barriers to reporting medication errors, ethical obligations for healthcare professionals when errors occur and automated technologies for medication errors. Chapter 3 describes the methodology used for the research study. It also includes the dataset, research design, data preparation, and data analysis used in the study. Chapter 4 presents the results of the research study. Finally, Chapter 5 provides discussion, limitation, and implications of the study. Chapter 6 presents the conclusion and future research of the study.

CHAPTER 2 LITERATURE REVIEW

Medication errors pose a global challenge. This chapter presents the classification, causes. It also explains impact of socio-technical factors on medication errors in pharmaceutical environment. Impact of workload and job satisfaction on medication errors are discussed in this chapter as well. There are also potential barriers to medication error reporting. The chapter discusses the attitude of healthcare professionals towards medication errors and their ethical obligations once the error occurs. The end of the section elaborates automation to detect and reduce medication errors. At the end we discuss the impacts and cost of medication errors.

2.1 Classification and causes of medication errors

Investigating medication errors can help classify and identify the causes of medication errors. There are various ways to classify medication errors. Some studies classify errors based on whether *the error was harmful or not.* This method of classification has a drawback since serious harm is rare. A large and sensitive sample of population will be needed to classify the errors efficiently based on damage. So, a careful analysis of the system may provide a robust network of classification of errors (Ferner, 2012).

They can also be classified based on *where the error occurs* in the workflow process. The stages where error could occur are ordering/prescribing, documenting, transcribing, dispensing, administration, or monitoring stage (Tariq et al., 2020). Classification of medication errors can also be based on error-category. For example, *wrong medication, wrong frequency*, or *wrong patient* (World Health Organization, 2016, p. 4). A medication

error can also be classified by whether the error occurred while *planning workflow processes incorrectly* (knowledge-based or rule-based errors or mistakes) (Ferner, 2012). Or by *executing the correct planned operations poorly* (action-based errors, known as "slips," or memory-based errors, known as "lapses") (Aronson, 2009, p. 603). An example for memory-based error would be forgetting that the patient is allergic to penicillin and still giving them penicillin (Aronson, 2009). Any approach taken to classify the medication error will depend on the medical organization.

There are various *causes* of medication errors. *Lack of experience and training as well as poor communication* between healthcare professionals and patients is one of the contributing factors. Other factors connected to patients can be *literacy and language barriers.* There are other factors relating to *work setting characteristics* such as workload pressure, interruptions, distractions, and no standardized protocols which also contribute to medication errors. Factors associated with *medicines* such as naming/labeling of medication and other repetitive tasks also contribute to medication errors (World Health Organization, 2016, p. 7).

2.2 Sociotechnical factors related to medication errors

A study defines Socio-technical factors as relations between the "technical", "social elements" and organizational settings of a pharmaceutical work environment. Technical factors include workload and staffing, social factors include pharmacist's relationship with healthcare stakeholders, and organizational factors include managing governance. There is evidence that these technical, social, and organizational factors increase medication errors (Phipps et al., 2009, p. 1).

The first theme of socio-technical factors is social factors of the pharmacy. Social factors constitute pharmacist's communication with their colleagues, other healthcare professionals, and patients (Phipps et al., 2009, p. 4). First social factor is communication of pharmacists with the colleagues. Pharmacists, and their colleagues, can have group norms to promote patient safety, but some patterns may cause harm. Some employees are part-time, some are full-time employees having different working shifts, some staff are freelance pharmacists, and sometimes the chief pharmacist is on vacation. Miscommunication during pharmacy activities can be harmful if the entities either are unaware of the incident or have only half knowledge about it. This kind of situation requires careful documentation by all stakeholders (Phipps et al., 2009, p. 3).

Second social factor is communication of pharmacists with healthcare professionals like prescribers. An issue related to this duo is that the pharmacist can dispense medicine for an incomplete or incorrect prescription, assuming that the prescriber will modify later. Pharmacists were reluctant to raise these concerns with the prescribers. They did not want to disrupt their relationships with prescribers as they had business income dependency on the prescribers. As a solution, both the pharmacist and prescriber should have "interpersonal" and "professional trust" in each other as well as stepping up mutually to take the onus of prescription errors (Phipps et al., 2009, p. 4)

Third social factor is communication of the pharmacists with the customers. Some pharmacists believe that customers should not be involved in patient safety since it will make pharmacists look like less trustworthy. Some also believed that communicating with customers increased pressure on them to deliver medicine as quickly as possible. A study

revealed the risk of dispensing errors decreased when pharmacists had enough satisfactory time to provide their services (Phipps et al., 2009, p. 5).

The second theme of socio-technical factors is technical factors of the pharmacy. This includes work demands on the pharmacists. Medication errors increase due to high workload and interruptions. Pharmacists work under either commercial or corporate pharmacies and have various business and legal constraints. To meet the financial targets, management of retail community pharmacies reduce the amount of money that they invest in staff resources. A shortage of resources is one of the causes of medication errors (Phipps et al., 2009, p. 6). On the contrary, the risk of dispensing error also increases if actual pharmacist staffing kept on growing. Hence a tradeoff between business protection and patient safety influences pharmacists (Bond & Raehl, 2001).

Corporate pharmacies may work either as independent stores or they might be integrated with superstore or general department stores thus working together as large pharmacy chains. Bigger chains of pharmacies have a centralized approach where pharmacists report errors to senior managers. Senior managers can share the error report with other pharmacies attached to the chain to prevent similar mistakes. Sharing of medication errors with other pharmacies may not be possible in independent stores. In case of independent stores, safe practice is driven by a pharmacist's motivation to avoid the risk of disciplinary action or litigation should a patient be harmed. And in such cases, sometimes, the conflict between ethical and legal onus of medication safety on the pharmacist, is a medication error source (Phipps et al., 2009, p. 6).

The third theme of socio-technical factors is the organization settings. This includes "management and governance" of pharmacies and pharmacists. Management standards involved methods like incident reporting, standardizing practice using protocols and physical configuration of workplace settings, and technological tools. All these together can influence a pharmacist working practices. Pharmacists feel that by avoiding the blame from an individual, they can develop a culture where medication errors can be openly discussed and provide an opportunity to learn from their mistakes. Reporting and learning from mistakes can be based in a formal or informal setting. For example, suppose a pharmacy store manager identifies a dispensing error. In that case, he can discuss it informally with the entities involved and resort to formal reporting if the matter in hand cannot be resolved by informal practices. Pharmacists felt that their trust in management could be influenced depending on who is managing them. Furthermore, implementing friendly training like a "social group" that supports group education as a practice known as the "pharmacist community of practice", can reduce errors due to management issues (Phipps et al., 2009, p. 7).

Official system rules that govern the healthcare professionals' practice are known as protocols. However, some participants felt that over-relying on protocols that tell them what to do could raise a conflict when it overrules the pharmacist's judgment of the right thing to do in that case. This conflict depends on the type of situation, type of protocol, and pharmacists professional experience. Deviation from standard protocols has resulted in adverse events in other healthcare zones and should be considered relevant in community pharmacies (Phipps et al., 2009, p. 8).

Configuration of workspace and technological tools available in the workspace can influence the quality of pharmacists' work. New decision-making technologies or automation can change the activities of the pharmacists' job. For example, just like a pilot during take-off or landing of a plane, "closed-loop control systems" can make the pharmacists monitor their actions rather completing the activities themselves. Orientation of workspaces can either enhance the pharmacist's activities or disrupt the pharmacist's activities. Making the workspaces too accessible to customers can also create interruptions while consulting or dispensing medications (Phipps et al., 2009, p. 8).

A solution to above is a well-designed layout that creates a sense of professionalism and can reduce medication error incidence. A survey study found similar results where the pharmacists felt that the shape and the place of the drive-through window effects the efficiency and accuracy of dispensing (Phipps et al., 2009, p. 8). The risk of dispensing errors can be reduced once the pharmacists were satisfied with the pharmacy layout (Bond & Raehl, 2001).

2.3 Impact of workload and job satisfaction on pharmacists' well-being

The workload in community pharmacies is increasing. The workload in Great Britain, England, Wales, and Scotland community pharmacies has grown with the invention of new contractual frameworks (Hassell et al., 2011, p. 562). These new contractual frameworks redesigned a pharmacist's role. Along with dispensing, pharmacists now had other duties such as to prescribe, provide emergency hormonal contraception, improve medication safety and act as consultant pharmacists like giving

advice on small illnesses and consulting on how to monitor medicine for allergic reactions. This also known as Medicine Use reviews (MURs). The MURs have increased by 589% in the period between 2005-2008. Community pharmacists spend most of their time with activities related to dispensing prescriptions and MURs. The growth of registered pharmacists by only 2% per year, shows that the supply of pharmacists is less than the demand for services provided by pharmacies (Hassell et al., 2011, p. 563).

Work pressures affect the employee's well-being. Target-driven work culture and related forces caused the pharmacists to leave the job irrespective of the pharmacist being the permanent employee or owner. A study with 30 women community pharmacists with various situations such as employees or owners revealed extensive stress, low contentment, and disappointment with work, due to high workload, high dispensing volume, longer working hours without a break, shortage of staff, and unresponsive or inexperienced management (Hassell et al., 2011, p. 571).

Another study in clinical interventions made by 14 community pharmacists revealed patient outcome due to work related stress. It showed that 37 medication errors per 10,000 items prescribed that reached patients due to workload were preventable. Work-related stress caused workers to violate safety-related procedures (Hassell et al., 2011, p. 572). Another study in community pharmacies revealed that 26 incidents were detected per 10,000 items dispensed under circumstances of busier than normal, interruptions and not having enough staff for dispensing (Hassell et al., 2011, p. 572).

2.4 Attitudes of pharmacist and GPs towards each other and it's impacts on Likelihood and barriers to medication errors reporting

In recent years, the expansion of pharmacist's role has confronted them with duties like prescribing healthcare, consulting patients, and reviewing medications. These duties require collaboration of pharmacists with general practitioners (GPs). Pharmacists can also be known as dependent prescribers or supplementary prescribers who prescribe drugs to patients after the doctor or independent prescribers' diagnosis or evaluation. To reduce medication errors, pharmacists need to access the patients' medical notes (Hughes & McCann, 2003, p. 600). In Canada, community pharmacists have access to a centralized all-province database known as PharmaNET that allows them to have access to patient information like medication and have the potential to reduce adverse drug reactions (ADRs) (Reebye et al., 1999, p. 150).

Hospital physicians are aware of the clinical pharmacist duties when pharmacists are part of wards rounds consulting and prescribing patients. But this link between community pharmacists and a GP is not much developed (Hughes & McCann, 2003, p. 600). A qualitative study tried to examine the barriers between GPs and community Pharmacists in Northern Ireland to improve inter-professional collaboration. The study revealed the shopkeeper impression of pharmacists as the central theme of the barriers. Access, hierarchy, and awareness were the smaller themes of barriers (Hughes & McCann, 2003, p. 601).

GPs thought of pharmacists as businessmen, shopkeepers, or unique retailers, and felt they did not represent the healthcare values. GPs believed that pharmacists have

commercial targets to achieve in pharmacy and, therefore, sell more medicine. If the role of prescribing is to be taken by the pharmacist, then that will be commercialized too, and pharmacists will end up prescribing more than needed (Hughes & McCann, 2003, p. 602). Therefore, GPs preferred practice pharmacists over community pharmacists for interprofessional development. Pharmacists felt such perceptions by GPs affected the development of their role as a secondary prescriber (Hughes & McCann, 2003, p. 604).

While GPs did not complain about difficulties in accessing pharmacists but felt their 9-5 job mentality as a healthcare provider would affect patients, since GPs were available 24 hours of a day. Pharmacists did have difficulties accessing GPs, and most of the times felt stuck with receptionists who put them on hold or told them to call later (Hughes & McCann, 2003, p. 603). In a study in the Netherlands and Canada, 40% pharmacists revealed difficulties communicating with older GPs. Pharmacists were dissatisfied and felt left out of communication with physicians (Reebye et al., 1999, p. 153). GPs did not have time for them and would not return their calls (Hughes & McCann, 2003, p. 603) and reject the corrections in inappropriate prescriptions (Reebye et al., 1999, p. 153). Although some pharmacists were satisfied with the communication because they had been working at the same place for 24 years and knew local physicians. They had worked hard to build a relationship for easy access to the physician (Reebye et al., 1999, p. 154).

The pharmacists felt they were more readily available to patients than doctors by eliminating patients three-week wait time for an appointment and having flexible opening hours. Pharmacists felt that they had a unique relationship with patients (Hughes & McCann, 2003, p. 603). GPs felt that giving pharmacists access to medical records for prescribing would break the patient's confidentiality. They said pharmacist's workspace

design is such that if they discuss with patients about their history, everybody in the surrounding space will hear it. Therefore, GPs were reluctant over the pharmacist roles as a secondary prescriber (Hughes & McCann, 2003, p. 603).

Pharmacists thought that GPs considered pharmacists subordinate to them in terms of hierarchy (Hughes & McCann, 2003, p. 604), and if pharmacists got the role of prescribers, GPs would feel that they were crossing their territory (Hughes & McCann, 2003, p. 603). A study with Dutch and Canadian pharmacists revealed similar thoughts (Reebye et al., 1999, p. 153).

GPs had limited awareness about the pharmacist's knowledge, training, and professional development and only knew them as working as a businessman. Such an outlook made pharmacists frustrated and undervalued (Hughes & McCann, 2003, p. 604). In a study, pharmacists from Canada and Netherlands, believed that implementing the extended roles in real life is challenging due to time constraints and other non-pharmaceutical duties (Reebye et al., 1999, p. 155). One of the pharmacists suggested that there should be joint training about the functions, specific responsibilities, and strengths of both the professions at an undergraduate and postgraduate level between GPs and pharmacists (Hughes & McCann, 2003, p. 604).

Both Canadian and Dutch pharmacists were more than willing to take up an extended role. Face to face contact, structured meetings oriented around patient care can increase satisfaction in communication (Reebye et al., 1999, p. 155). Interaction between pharmacists and physicians can be improved using the pharmacist-patient-physician triangle. The patient is at the topmost apex position, while the pharmacist and physician are

at the triangles base. Patients will directly link to pharmacists and physicians, and they can work together to enhance patient care (Reebye et al., 1999, p. 157). The collaboration between pharmacists and physicians is beneficial for successfully implementing an extended role to reduce medication error incidence (Reebye et al., 1999, p. 157).

Medication errors can also be reduced by learning from past. Countries like the US, Australia, and Denmark have developed Incident reporting schemes at national levels. The National Patient Safety Agency (NPSA) for England and Wales developed a nationwide incident reporting system known as Nation Reporting and Learning System (NRLS) in 2004. The purpose of NRLS was to improve healthcare services outcome by learning from past events and then sharing the insights nationally with other healthcare service providers (Ashcroft et al., 2006, p. 48). Features like confidentiality, non-punitiveness, feedback, and organization culture of open and fair reporting characterized previous successful implementations of reporting schemes (Ashcroft et al., 2006, p. 48). Similar high-risk industries like petrochemical and aviation reveal improved safe performance using the above-mentioned features (Barach, 2000b, p. 760).

The UK has developed voluntary reporting schemes for small community pharmacies and mandatory in-house reporting schemes for large community pharmacy chains. But such programs lack standardization in the nature and quality of data collected. NPSA expects community pharmacies to report serious as well as near-miss incidents (Ashcroft et al., 2006, p. 48).

In a study conducted by Ashcroft (2006) pharmacists and support staff said they would decide reporting based on the result of the error and the pharmacist's response towards the

error. The study revealed that harmless errors were less likely to be reported than a harmful error irrespective of pharmacists following the protocol or not. Harmful protocol compliant event is less likely to be reported than a harmful protocol non-compliant event. Overall reporting was less than the average reporting point of the research. Respondents said safe reporting and no-blame-learn-from-the-mistake culture would have a significant impact on reporting. Loyalty and sympathy towards colleagues also were a potential barrier to communicating the mistakes of the colleagues. Anonymous reporting was a vital factor in promoting reporting in community pharmacies. As a result, with low reporting of errors, there was minimal opportunity to learn from mistakes (Ashcroft, 2006, p. 50).

In another study, the staff felt that the form of reporting was complicated and challenging to understand. And some staff felt that the process of reporting itself was time-consuming and increased a lot of paperwork. Team also noted that there was no motivation from the management to report the errors. Some felt that publishing the errors would make them look incompetent and hence encouraged the anonymous reporting of medication errors. Thus, anonymous reporting might increase the reporting of medication errors and awareness about high-risk medications (Barach, 2000, p. 762).

2.5 Ethical obligations once the error occurs.

Medication errors are not always due to individual negligence and carelessness but mostly due to systemic failures. Stakeholders of healthcare organizations like a nurse, pharmacist, technician, doctor, or anyone that is aware that the medication error has just occurred, has an ethical obligation to fulfill. Sorrell in his OJIN article categorizes moral responsibility into four categories. First is "*autonomy and the right to self-determination"*,

which states that patients can decide based on their perceptions and personal views about the treatment required from the errors (Sorrell, 2017, p. 2). Second, the principle of "*beneficence and Nonmaleficence"*, where the healthcare providers should take the best possible efforts to reduce the patient harm and do what is best for the patient, which may conflict the business value of productivity on the project, causing particular damage to the patient. The third is "*disclosure and the right to knowledge"*, which is healthcare provider's ethical obligation to inform the patient about the situation where they can make an informed decision. And finally, the information provided is governed by the *principle of honesty*, which means data should be correct, unbiased, and complete to help the patient understand the situation. Providing truthful information will help to build trust with the patients (Sorrell, 2017, p. 3).

In a study, nurses said that they need continuing education on how to handle and understand the aftermath effect of the error once it occurs. This is because disclosure of errors is an interdisciplinary situation between healthcare professionals, law and ethics that prevents the medication error. This interdisciplinary domain needs more research (Sorrell, 2017, p. 3).

Students, nurses, and pharmacists who have experienced medication errors should share such events in the form of stories rather than hiding events from fear of litigation. Listening to other stories of medication errors on how they handled the event and how they wish they had dealt with the event can motivate other practice staff and help prevent such errors. Sharing such experiences as a story can help us understand medication errors. Sharing medication errors shifts the concept of detecting statistical patterns to reflective thought about the event (Sorrell, 2017, p. 4). While sharing her medication error story, one

of the nurses said she was forming a lump in her throat, realizing that the medication error had occurred and might lose her license to practice nursing. She trusted her healthcare providers and informed them and the patient of the medication error, which shows that revealing the experience as a story helps you see the values, beliefs, and the intellectual knowledge of the background. The storytelling of a medication error helps the narrator and the listener understand each other (Sorrell, 2017, p. 3).

2.6 Automation technology and medication errors

Community pharmacists play an essential role in supplying medicines. Evidence shows that the current system to dispense medication is outdated and presents an opportunity to be disrupted by technology like all industries where manual, repetitive work can be automated. In our case, the health care industry can automate error-prone activities like item selection, maintaining records, labeling, and medication packing. Automation of dispensing activities redefines the pharmacist role from just commercial suppliers of medicines to a new patient-oriented role. It helps in the acknowledgment of pharmacists for their contribution to the healthcare services profession (Spinks et al., 2017, p. 394).

A full-scale centralized model will involve a network of community pharmacies over a wide range of geographical areas with dispensing computer systems connected to an extensive centralized, automated system. The centralized system can dispense prescriptions from a central location to the customer directly or at a pickup location or to the original pharmacy. Australia, Scandinavia, the Netherlands have implemented such a centralized model for multiple dispensing of drugs in elderly patients. South Africa has also implemented this for chronic conditions like HIV and AIDS (Spinks et al., 2017, p. 395).

Such a hub and spoke model are in debate in the UK's private sector that contributes to 2/3rd of England's prescription capacity. The Central hub would receive electronic prescription from a prescriber and dispense medication to the pharmacy 'spoke' from where consumers will collect it (Spinks et al., 2017, p. 395). Only Pharmacy chains and large groups that belong to the same legal entity can undertake this presently. The national pharmacy association has proposed a different variation of the model known as the hub and satellite model to overcome the shortfalls of the original model (Spinks et al., 2017, p. 396).

Implementation of a centralized automation system will change pharmacist's interaction behavior with consumers. They would promote the quality use of medicines (QUM) by monitoring prescription and educating consumers. The pharmacist will act as the middle point for QUM services. QUM services will include the "provision of vaccinations, screening, support to manage chronic conditions, and expanded prescribing roles. QUM services will also change the form of communication between patients and pharmacists from face-to-face contact to emails and skype meetings. QUM service might also make home visits about the use and optimization of medications more common. Funding for QUM services remains an issue as to whether customers, government, or insurers will pay. Also, acceptance of payroll by the pharmacists for new QUM services become an interesting topic for debate (Spinks et al., 2017, p. 396).

Widespread implementation can cause industry-wide efficiencies like low cost of medicine to consumers, removal of the medicine warehouse of pharmacies since all the drug storage will be at a centralized location, as well as enhancement in access to drugs. The decentralized automation of community pharmacy does not provide such benefits (Spinks et al., 2017, p. 395). Changes in workforce supply and demand management, the

pharmacy curriculum as well as graduate training will be needed to support the automations successful implementation (Spinks et al., 2017, p. 396).

Positive impacts of automation like job satisfaction, low overhead cost, and an increase in pharmacist's productivity should be considered rather than negative consequences such as loss of income from the 'mechanical' supply of medicines. In a study, pharmacists claim that the automation of dispensing activities has increased their value in the healthcare profession beyond the dispenser role and has received appreciation (Spinks et al., 2017, p. 396).

2.7 Costs of medication errors

Six thousand seven hundred eighty-two adverse severe events occurred from 1995 to 2010, and 67% of them resulted in death, according to The Joint Commissioner of the US (Rattanarojsakul & Thawesaengskulthai, 2013, p. 89). Medication error was identified as one of the top 10 adverse events in the US in 2010, harming 1.5 million people annually. Additionally, each year, 5.3 million dollars was the cost of treatment of such adverse events from the use of medicines and pharmaceutical drugs. In Europe, 48-49% of adverse drug events could have prevented a loss of billions of pounds per year. Three hundred fifty million US dollars per year is the cost of adverse events in Australia, and 43% of those events due drugs were preventable. In Japan, 46.6% of the adverse events caused by medications were avoidable (Rattanarojsakul & Thawesaengskulthai, 2013, p. 89).

CHAPTER 3 METHODOLOGY

The current study attempts to explore the prevalence of medication errors within community pharmacies in the UK, using data reported to Pharmapod Inc. The identified patterns can be used in further diagnosis of the causes and can be applied to improve medication process. The study also aims to find associations within the contributory factors and error categories of the data. A data analytics approach is adopted as a research method to achieve these research objectives. This chapter consists of the following sub-sections: dataset, research design, data preparation, and data analysis. The dataset subsection explains the features and distribution of the data used in the study. The research design subsection presents the various phases of the research process. The data preparation sub-section explains the various techniques used to prepare data for data mining process. In data analysis, the statistical analyses are applied to explore the pattern in the reported medication errors. The Apriori association rule mining algorithm is adopted to identify the probability of relationships among error-factor, error-category, and event-type. Chapter 4 presents the results of the study.

3.1 Dataset

Once a medication error occurs at a community pharmacy in UK, pharmaceutical staff are required to report the event using the reporting system provided by the Pharmapod. The medication event-type is recorded in error reports to be filled and which also indicate the consequence of the events. There are two categories of event-type. Reach-patient refers to the type of event in which the errors reached patients and may have caused harm to them.

Near-miss refers to the type of event in which the error was caught before or at the point where the medication left the pharmacy (Lynskey et al., 2007, p. 111).

The Pharmapod system collected details about the events. Information that is used in the current study includes event-type, factors that are reported causing the event, etc. Appendix A presents the fields of the event data collection form.

A dataset containing two tables, Events and Factors, were extracted from a data warehouse managed by Pharmapod. The 'Events' table had 90154 records and 35 columns for UK data. The description of each column is present in Appendix B. The data were reported from 2015 to 2018 and had 72,733 medication error events reported over four years as presented in Table 1.

Year	Number of events
2015	1992
2016	13263
2017	29889
2018	27589
Grand Total	72733

Table 1: Number of events by year.

Out of 72733 medication events, 76.72% were near-miss, and 23.28% were reach-patient events. The number of near-miss and reach-patient events by each year is presented below in Table 2.

Year	Near-miss events		reach-patient events		Total events	
	Number	Percentage	Number	Percentage	Number	Percentage
2015	1304	1.79%	688	0.95%	1992	2.74%
2016	9793	13.46%	3470	4.77%	13263	18.24%
2017	23936	32.91%	5953	8.18%	29889	41.09%
2018	20770	28.56%	6819	9.38%	27589	37.93%
Grand Total	55803	76.72%	16930	23.28%	72733	100.00%

Table 2: Frequency of event-type by year..

Table 3 shows the frequency of the top five error-categories, which is further decomposed given their event-type. The most frequent error-category was *wrong drug/medicine* (18.69%). *Wrong drug/medicine* was the common error-category in reach-patient and near-miss events. A complete list of the frequency and error-categories of events is presented in Appendix C.

Error-category	Near-miss events		Reach-patient events		Total events	
	Number	Percentage	Number	Percentage	Number	Percentage
Wrong drug/medicine	10014	13.77%	3583	4.93%	13597	18.69%
Wrong quantity selected	9368	12.88%	1830	2.52%	11198	15.40%
New wrong/unclear dose strength	8133	11.18%	2254	3.10%	10387	14.28%
Wrong formulation	6984	9.60%	1186	1.63%	8170	11.23%
New wrong label	5926	8.15%	807	1.11%	6733	9.26%

Table 3: Frequency of top 5 error-category by event-type.

Frequency of top five error-factors by event-type are presented in Table 4. The most frequent error-factor overall was *interruptions* (18.83%). The most frequent error-factor of reach-patient events was *busier than normal* (4.68%). The most frequent error-factor of near-miss events was *interruptions* (15.04%) A complete list of the frequency by error-factors is presented in Appendix D.

Error-factor	Near-miss events		Reach-patient events		Total events	
	Number	Percentage	Number	Percentage	Number	Percentage
Interruptions factor	10937	15.04%	2756	3.79%	13693	18.83%
Busier than normal factor	9491	13.05%	3403	4.68%	12894	17.73%
High volume dispensing period factor	8678	11.93%	2572	3.54%	11250	15.47%
Policy/procedures not followed e.g.: double checking factor	6692	9.20%	1593	2.19%	8285	11.39%
Competence deficiency/training factor	6382	8.77%	1359	1.87%	7741	10.64%

Table 4: Frequency of top 5 error-factor by event-type.

Table 5 shows the frequency of events at each stage. Most events occurred at *dispensing/preparation* stage (81.30%).

Stage	Near-miss events		Reach-patient events		Total events	
	Number	Percentage	Number	Percentage	Number	Percentage
Dispensing/preparation stage	47527	65.34%	11714	16.11%	59241	81.45%
Product selection stage	2081	2.86%	829	1.14%	2910	4.00%
Presentation/packing stage	1586	2.18%	1168	1.61%	2754	3.79%
Computer input stage	2244	3.09%	381	0.52%	2625	3.61%
Delivery stage	446	0.61%	1003	1.38%	1449	1.99%
Supply/ordering stage	424	0.58%	756	1.04%	1180	1.62%
Prescribing stage	601	0.83%	284	0.39%	885	1.22%
Administration stage	371	0.51%	437	0.60%	808	1.11%
Storage stage	216	0.30%	124	0.17%	340	0.47%
Event advice stage	164	0.23%	171	0.24%	335	0.46%
Event monitoring stage	143	0.20%	63	0.09%	206	0.28%
Grand Total	55803	76.72%	16930	23.28%	72733	100.00%

Table 5: Frequency of events by stage.

Table 6 shows the frequency of harm level of reach-patient events. Over 85% of the errors had no harm level.

Harm-Level	Number of events	Percentage of events
None	14516	85.74%
Unknown	1245	7.35%
Low	883	5.22%
Moderate	262	1.55%
Severe	18	0.11%

Harm-Level	Number of events	Percentage of events
Death	6	0.04%
Grand Total	16930	100.00%

Table 6: Frequency of harm level of the reach-patient events.

3.2 Research design

The analyses of the data conducted in this study are exploratory. The produced results are descriptive, without an attempt to present any causal relationship. The research process adopted has three phases. The first phase consists of preparing data for statistical analysis using data preprocessing techniques. The result of this phase was a good dataset needed for exploratory data analysis. Exploratory data analysis involved summarizing the data using descriptive statistics such as frequency, mean, and mode. (Ali & Bhaskar, 2016).

The major portion of the data used in the current study consists of categorical variables like error-category, error-factor, and event-type. The second phase involved exploring the relationship between categorical variables of the data. ARM is well suited to the objective of exploring the relationships among categorical variables. To find the associations, the categorical variables were converted to binary variables using one-hot encoding. One-hot encoding is a method that converts the categorical variables into ones and zeros, a form accepted by machine learning algorithms like ARM (Vasudev, 2017). In the third phase, we filtered the original dataset into near-miss and reach-patient datasets to find the completeness of the rules. At the end, we combined association rules produced from the original dataset and missing rules produced from near-miss and reach-patient datasets to obtain a final ruleset. Interpretation and understanding of the rulesets are provided as an input to the decisive steps for community pharmacies. The diagrammatic representation of this process is shown below in Figure 2.

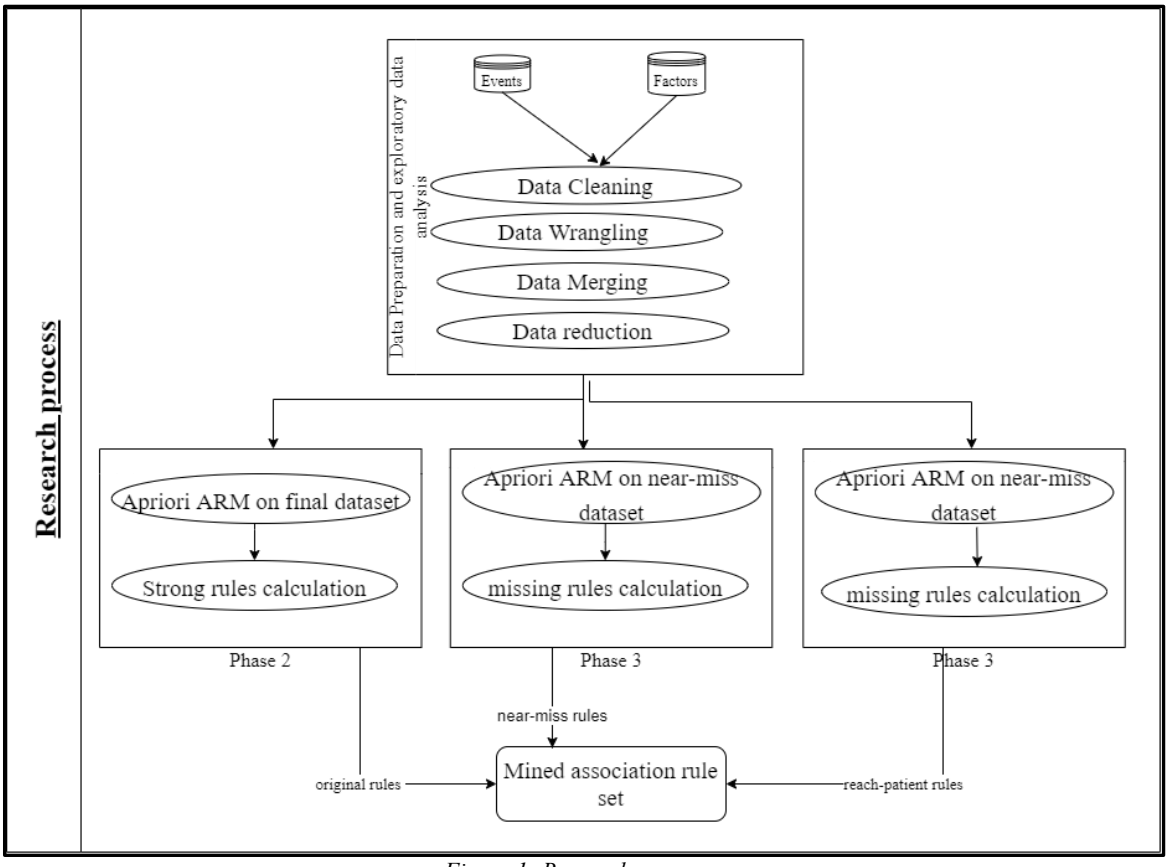

Figure 1: Research process.

Error-category and error-factor are critical in influencing medication event-type. In total there are 49 error-categories and 31 error-factors. Among them, there are 12 error-categories and 11 error-factors, each accounting for more than one percent of all the events shown in Appendix C and Appendix D. Each event can have multiple factors and categories that can influence the event-type. Their effects on event-type are explored in three parts. The exploration of these effects is illustrated in the Figure 3. First, certain error-factors can directly influence the event-type: either the reach-patient or near-miss. The Path 1 of Figure 3 implies this effect. For example, *interruptions* error-factor is associated with reach-patient medication event-type with 79% probability. Second, specific error-categories, regardless of any factors, can directly influence event-type. The Path 2 of Figure 3 implies this effect. For example, a near-miss medication event-type is associated with the error-category

wrong device/product with 80% probability. Third, a combination of error-factors and error-categories, can influence event-type. The Path 3 of Figure 3 implies this effect. For example, *busier than normal* error-factor together with *wrong drug/medicine* error-category are reported to contribute to reach-patient medication error event-type with 31% probability. The results of this test are presented in Chapter 4.

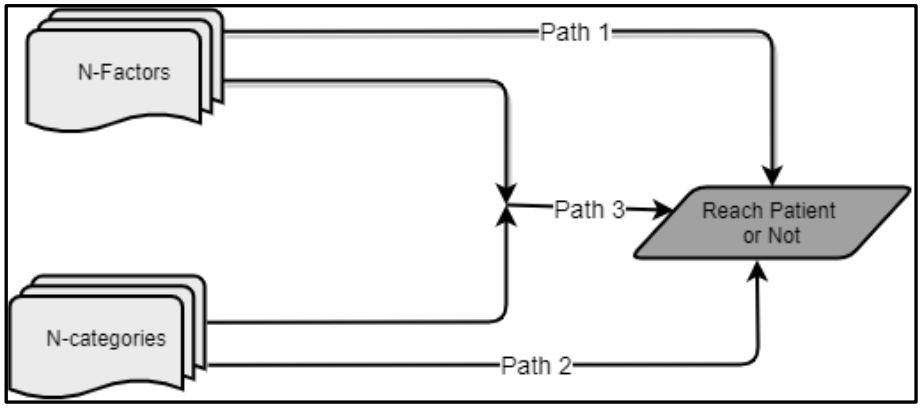

Figure 2: Influence of error-category and error-factor on event-type.

3.3 Data preparation

Bad data or rogue data is erroneous data consisting of missing values, duplicate data, defective entries like spelling mistakes, or variations in format of entered data, incorrect information, etc. (CloverDX, 2020). Such bad data degrades the performance of the data mining process (García, Luengo, & Herrera, 2014, pp. 1–3). The raw data in our case, had problems like noise, prominent sized features, inconsistent data, etc. Therefore, data preparation was needed to improve the quality of our data. Good quality data can help improve the data mining process to derive meaningful results. Data preparation involved cleaning and transforming data into efficient good quality data. (García et al., 2014, pp. 1–3).

Google Colab, a product of Google research, is used in preliminary data preprocessing and exploratory data analysis. The tool helps to write and execute the Python code through the browser. It does not need any software installation/ memory on the local computer (*Google Colab*, 2017). This software saved the local memory as it runs on Google servers. Python was chosen as a programming language as it is easy to use its libraries of statistics and machine learning frameworks. Python can help build solutions to solve complex business problems like fraud detection easily (*Python for Data Science*, 2019).

Data preprocessing involves techniques like data cleaning, data wrangling, data merging, and data reduction. Data cleaning includes operations to deal with noise and missing values in imperfect data (García, Ramírez-Gallego, Luengo, Benítez, & Herrera, 2016). This step is important because noise free data improves the performance of data mining algorithms (García et al., 2016). The missing values were filled using the string 'Missing Value'.

Categorical outliers do not exist without context, but sometimes they can be an actual rare instance and not an outlier (Ranga Suri et al., 2019). In our case, we did not consider the cluster of categories with low frequencies as outliers.

The purpose of data wrangling is to improve the quality of data to make analysis easy. One form of data wrangling is data transformation which involves modifying data that are difficult to understand (Kandel et al., 2011, p. 272). In our data, one of the columns in the events table (category_label) had values in the form of "*forms/values.event_cat_wrong_unclear_dose_or_strength*" which should be *wrong unclear dose/strength*. The extra prefix words get concatenated while exporting data from

the system. Python's replace function was used to transform such data. Similarly, all data with the prefix *"forms/values.event_cat_"* or *"forms/values.harm_levels_"* or *"forms/values.event_factors_"* were fixed using the replace function. All the strings that were converted are mentioned in Appendix E

Data extraction occurs from various sources. Data merging/ integration is required to restructure all the different datasets into one dataset containing all the necessary information for further statistical and pattern mining analysis (Malley et al., 2016, p. 118). The process of joining two datasets is based on a common attribute or column from both the datasets. The methods to merge dataset are left join, right join, inner join, and outer join. We combined the events tables and factor tables using left join (Lee, 2019). Left join on dw_event_id column that was common in both the tables merged the events table, and factor table. After the dataset cleaning, transformation, and merging, we obtained a final dataset.

3.4 Data analysis

Python's Panda library and Excel were used in exploring patterns within the data. Pandas is a software library available in the Python programming language used for data manipulation and exploratory analysis. Data mining algorithms are used to mine patterns of the consumers from huge user-generated data. ARM is one of the data mining algorithms that helps discover interesting patterns, associations, and relationships within the grouped items in a large transaction database (Jibril et al., 2019, p. 674-675). Apriori ARM algorithm was used to identify association between categorical data of the study. Apriori ARM algorithm was applied using the mlxtend library available for Python.

ARM consists of two steps: step 1 is to extract all the frequent itemset; Step 2 is to generate strong association rules from the frequent itemset such that support and confidence of the rules are greater than or equal to minimum support and minimum confidence, respectively. To calculate association rules,

Let $I = \{i_1, i_2, i_3 \ldots\ldots i_n\}$ be the set of n binary items.

Let $D = \{t_1, t_2, t_3 \ldots t_n\}$ be the set of all the transactions known as a database D.

Each transaction in D has a unique identifier known as TID. In an association rule $X \Rightarrow Y$, where X and $Y \subseteq I$, X is antecedent, and Y is consequent.

Apriori ARM algorithm is a frequently used ARM algorithm (Yoosofan et al., 2015). Apriori ARM has been used in the medical field to identify frequent diseases and their associative characteristics (Ilayaraja & Meyyappan, 2013, p. 1), and to identify associations between heart disease and its characteristics like age, gender, blood sugar, etc. (Akbas et al., 2019, p. 1). Apriori ARM can be used on multi-dimensional data and can handle data with more than two categories, which has been useful in our research as most of the data is categorical (Wikipedia contributors, 2020a).

Various measures decide the selection of interesting rules. The two most used criteria are minimum thresholds of support and confidence. For rule $X \Rightarrow Y$ support of rule $X \Rightarrow Y$ is the ratio of transactions that contain both X and Y to the total number of transactions in set D (Wikipedia contributors, 2020a).

$$SUPP(X \Rightarrow Y) = \frac{|Tx \cap Ty|}{|D|}$$

Equation 1: Support of rule X and Y.

The confidence of association rule is the degree to which antecedent X and consequent Y in the itemset are correlated (Wikipedia contributors, 2020a). Confidence of rule X ⇒ Y is

$$C(X \Rightarrow Y) = \frac{SUPP(X \Rightarrow Y)}{SUPP(X)} = \frac{|Tx \cap Ty|}{|Tx|}$$

Equation 2: Confidence of rule X and Y.

In general, a rule X ⇒ Y is frequent if SUPP (X ⇒ Y) $\geqslant$ *minsupp* and C (X ⇒ Y) $\geqslant$ *minconf*.

There are various ways to select minimum support and minimum confidence. In our study, the value of thresholds of support and confidence was tested until it returned association rules (Manimaran & Velmurugan, 2015, p. 6). Selecting the minimum threshold value for support and confidence may affect the pattern analysis and decision-making process. Therefore, interestingness measures (IM) together with support and confidence are used as a solution. There are various interesting measures used to identify strong rules. In our research, we utilize the Lift and Certainty Factor (CF) to identify the strong rules.

CF is a measure of the variation of the probability of Y existing in a transaction when we think of the transaction where the only X is. A positive CF means a reduction in the probability that the Y is not in the transactions where X is (Berzal et al., 2002, p. 225). Calculation of Certainty factor is

$$CF(X \Rightarrow Y) = \frac{C(X \Rightarrow Y) - SUPP(Y)}{1 - SUPP(Y)} \quad \text{if } C(X \Rightarrow Y) > SUPP(Y) \text{ and}$$

$$CF(X \Rightarrow Y) = \frac{C(X \Rightarrow Y) - SUPP(Y)}{SUPP(Y)} \quad \text{if } C(X \Rightarrow Y) < SUPP(Y), \text{ and } 0.$$

Equation 3: Certainty factor of rule X and Y.

CF value of rules approaching 100 have high accuracy and are strong rules (Akbas et al., 2019, p. 2).

The lift of an association rule signifies the ratio of the observed frequency of the rule to that of the expected frequency if X and Y were independent. Lift of 1 implies X and Y are independent of each other and cannot be used for association analysis. A lift value greater than 1 states X and Y are dependent on each other and can be used for predicting the consequent in the future data sets. Lift less than 1 implies that the X and Y are substitutes of each other and have a negative effect on each others presence (Wikipedia contributors, 2020a). The value of lift is given as

$$lift(X \Rightarrow Y) = \frac{supp(X \Rightarrow Y)}{supp(X) * supp(Y)} \quad \text{(Manimaran and Velmurugan,2015, p. 4).}$$

Equation 4: Lift of rule X and Y.

In the current study, the value of lift greater than 1 has been considered to generate the strong rules.

Reliable rules based on objective and quantitative judgement are rare. In this study we adopt the concept of reliable association rules based on accuracy and completeness.

Accurate association rules have been found using CF and lift. Consistency of the rules in multiple datasets of the same domain is known as integrity of the rules. We find the integrity of the rules to uncover correlations within the data using the concept of completeness (Chen et al., 2016, p. 54).

Completeness measures the degree of integrity of rules in a research dataset. The underlying fundamental is to determine whether there are any rules missing in the association ruleset of the research data (Chen et al., 2016, p. 54). Missing rules can be identified by comparing the ruleset of the research data with the ruleset of a different dataset of the same domain. To achieve a different dataset, first we filtered the dataset containing only the near-miss events known as near-miss dataset. Then we generated a ruleset for the near-miss dataset. Missing rules were identified after comparing this original ruleset with the ruleset of near-miss dataset. Similarly, the original dataset is filtered to have only reach-patient events which becomes the reach-patient dataset. Missing rules of the reach-patient dataset were identified as well. The completeness of the association rules is the ratio of number of rules in the original ruleset to the sum of number of rules in the original ruleset and the missing ruleset (Chen et al., 2016, p. 54).

$$\text{Completeness} = \frac{|K|}{|K|+|M|}$$

Equation 5: Completeness of ruleset.

The number of rules missing is denoted by M. The number of rules in the original ruleset of the research data are denoted by K (Chen et al., 2016, p. 54). Missing rules will be combined with original rules to form the final ruleset. The next section contains the results.

CHAPTER 4 RESULTS

This chapter presents the results of strong association rules that can influence event-type. We identified three relationships as discussed below.

4.1 Associations between error-factor and event-type: path one

Associations between the error-factor and event-type were illustrated using path 1 in Figure 3. The minimum support and confidence of 1% together with value of lift greater than 1, generated 18 asymmetric rules. If antecedents and consequents are interchanged and the resulting support and confidence changes, then such rules are called asymmetric rules. Six strong rules were identified with CF greater than 10%. The top five rules are shown in Table 7. All the rules of Path 1 are present in Appendix F.

Rule	Antecedents	Consequent	Support	Confidence	Lift	CF
1	not concentrating	near-miss	0.015	0.957	1.253	81.968
2	quieter than normal factor	near-miss	0.014	0.893	1.168	54.506
3	competence deficiency/training factor	near-miss	0.088	0.823	1.078	25.224
4	staff resource issue	reach-patient	0.019	0.384	1.626	19.346
5	policy/procedures not followed e.g.: double checking factor	near-miss	0.091	0.806	1.055	17.858

Table 7: Path 1 top 5 associations between error-factor and event-type .

We found six strong rules originally in the first run of the ARM. The near-miss dataset and reach-patient dataset generated rules with lift equal to 1. Rules with lift equal to 1 are independent and cannot be used for association analysis. This means missing rules were zero. After comparing the missing rules of the near-miss dataset with the original rules, we found completeness of the rules. The completeness of the original rules for near-miss events

was (6/ (6+0) = 100%. The completeness of the original rules for reach-patient events was (6/ (6+0)) = 100%. The ruleset of path 1 of the 'near-miss dataset' and 'reach-patient dataset' is mentioned in Appendix F.

4.2 Associations between error-category and event-type: path two

Associations between error-category and event-type were identified in path 2 of Figure 3. A minimum support value of 5%, minimum confidence value of 1%, and lift value greater than 1, generated 26 asymmetric rules. The group of asymmetric rules is presented as forward and backward CF and confidence. The rule that has high CF in the group will be selected. CF value greater than 10% gave nine strong rules. The top 5 rules are shown in the table below 10. All the rules generated for Path 2 are present in Appendix G.

Rule	Antecedent	Consequent	Support	Confidence	Lift	CF
1	medical device/bag given/delivered to the wrong person	reach-patient	0.009	0.840	3.558	79.049
2	wrong dosage time	near-miss	0.018	0.918	1.202	65.478
3	wrong label	near-miss	0.081	0.881	1.153	49.538
4	wrong frequency	near-miss	0.011	0.854	1.118	38.203
5	wrong formulation	near-miss	0.096	0.854	1.117	37.957

Table 8: Path 2 top 5 associations between error-category and event-type.

We found nine strong rules originally in the first run of the ARM. The near-miss dataset and reach-patient dataset generated rules with lift equal to 1. Rules with lift equal to 1 are independent and cannot be used for association analysis. This means missing rules were zero. After comparing the missing rules of the near-miss dataset with the original rules, we found completeness of the rules. The completeness of the original rules for near-miss events was (9/ (9+0) = 100%. The completeness of the original rules for reach-patient

events was (9/ (9+0)) = 100%. The ruleset of path 2 of the 'near-miss dataset' and 'reach-patient dataset' is mentioned in Appendix G.

4.3 Associations between error-category, error-factor, and event-type: path three

Associations between error-category, error-factor, and event-type were identified in Path 3 of Figure 3. Support 1 percent, 10 percent confidence and lift value greater than 1 resulted in 73 asymmetric rules. The rules that have higher certainty factor in the group of asymmetric rules is selected as the strong rule. The top five rules with CF greater than 10% are shown below in table 9. All the rules generated for Path 3 are present in Appendix H.

Rule	Antecedents	Consequents	Support	Confidence	Lift	CF
1	wrong formulation, policy/procedures not followed e.g.: doublechecking factor	near-miss	0.012	0.908	1.189	61.003
2	wrong formulation, competence deficiency/training factor	near-miss	0.013	0.907	1.188	60.699
3	interruptions factor, wrong label	near-miss	0.021	0.899	1.177	57.212
4	competence deficiency/training factor, wrong quantity selected	near-miss	0.015	0.894	1.171	55.298
5	high volume dispensing period factor, wrong label	near-miss	0.014	0.890	1.165	53.233

Table 9: Path 3 top 5 associations between error-category, error-factor, and event-type.

We found 16 strong rules originally in the first run of the ARM. The near-miss dataset generated two rules with lift greater than 1 and CF greater than 10%. The reach-patient dataset generated four rules with lift greater than 1 and CF greater than 10%. After

comparing the missing rules of the near-miss dataset with the original rules, we found completeness of the rules. We found two missing rules for the near-miss dataset and four missing rules for the reach-patient dataset. The completeness of the original rules for near-miss events was (16/ (16+2) = 88.89%. The completeness of the original rules for reach-patient events was (16/ (16+4)) = 80%. The ruleset of Path 3 of the 'near-miss dataset' and 'reach-patient dataset' is mentioned in Appendix H.

4.4 Combined Ruleset

Combining all the results from Path 1, Path 2 and Path 3 of the research process gives a final ruleset that can be used by community pharmacies to take next steps to reduce medication error incidents. The combined ruleset is as follows in Figure 5,6 and 7.

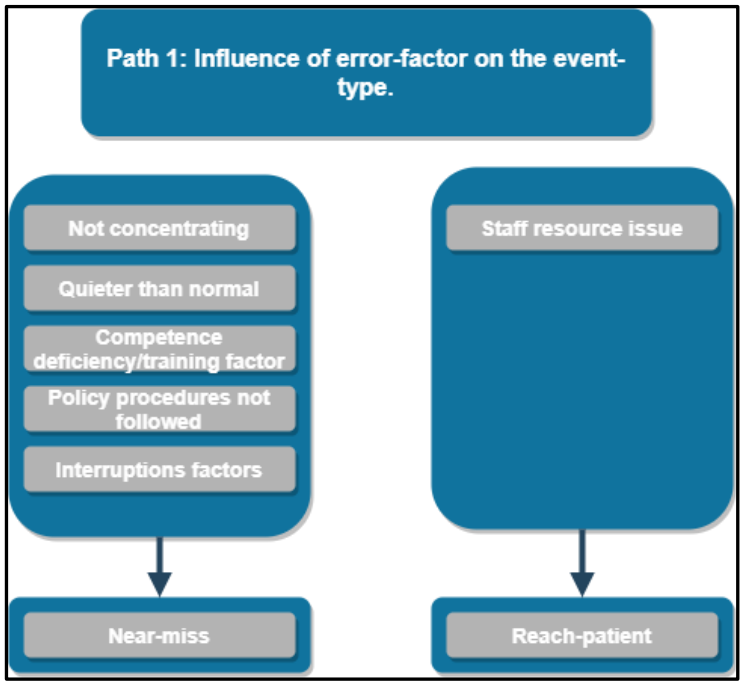

Figure 3: Path 1 error-factors that influence event-type.

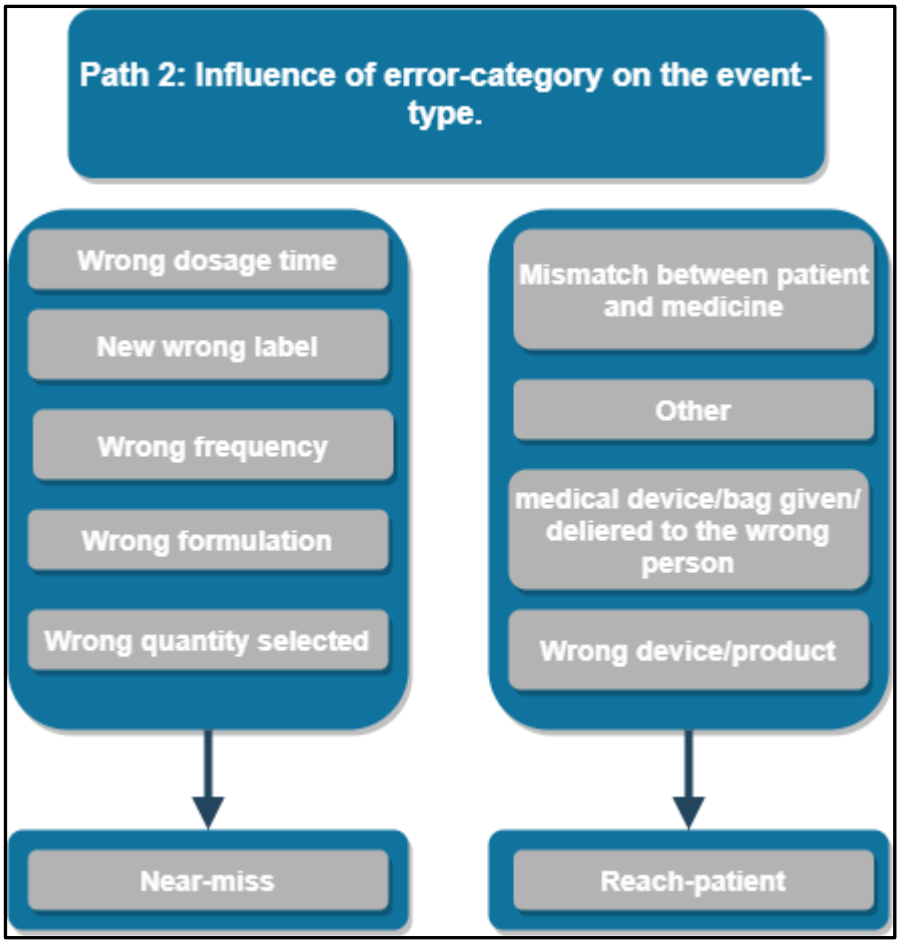

Figure 4: Path 2 error-categories that influence event-type.

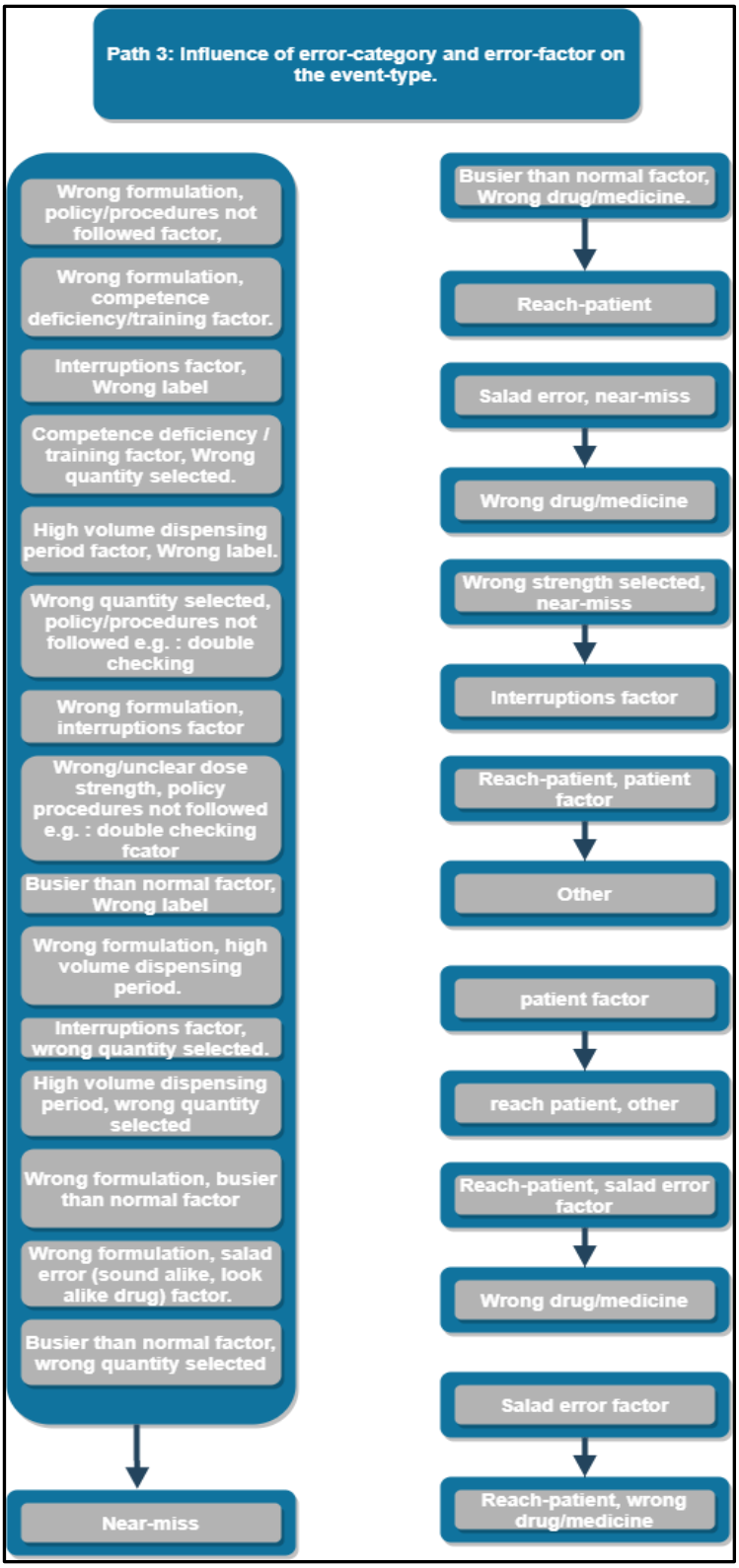

Figure 5: Path 3 error-factor and error-category that influence event-type.

CHAPTER 5 DISCUSSIONS, LIMITATIONS, AND IMPLICATIONS

This is an in-depth study of medication errors in community pharmacies in the UK. Some findings and methods of this study can be of interest to international pharmacies since pharmacists in other countries such as the US and elsewhere are experiencing the same concerns with regard to medication error. Countries like Canada and, Ireland that also use the Pharmapod incident management system (Pharmapod Ltd, 2020), can use our research method for investigation. Collaborative studies from different countries can help the development of policies and schemes' in various practical settings.

In our study, first, we analyzed 72,733 instances of medication events to explore the prevalence of medication errors in community pharmacies in the UK. Near-miss events were reported with more frequency than the reach-patient events. A study by Chua et al. (2003) of four community pharmacies in the UK found similar results with six times more near-miss than dispensing. Quality assurance practices of community pharmacies such as independent double-checking, are essential in reducing errors that reach-patients.

The largest error-category of our study was the *wrong drug/medicine*, followed by the *wrong quantity selected*. In a study carried out at the Cardiovascular ward of Duke University hospital, the most common error category was found to be the *wrong drug*, followed by the *wrong dose*. The findings from this study aligned with those of the current study, despite of the difference in the second-highest category, which can be due to the

different methods of error categorization and the differences in work environment (LaPointe & Jollis, 2003, p. 1461).

In our study, *wrong drug/medicine* errors were due to *salad* error-factor and *interruptions*. In a 2005 study of UK community pharmacies, the wrong drug selection, or incorrect quantity selection, were caused by similar packaging (7.6%) or similar drug name (16.8%) (Ashcroft et al., 2005). The study found that emerging technologies like barcoding of drugs or computerized system selection of drugs that show alerts can be used to reduce medication error incidents (Ashcroft et al., 2005).

In our study, most of the incidents happened at the dispensing/preparation stage (81.30%). This dispensing error rate is much higher than the error rate of the previous studies in community pharmacies where the error rate was found to be 3% over a period of seven months (Franklin & O'Grady, 2007, p. 275). Community pharmacies dispense more medicines than they prescribe. Hence there is more opportunity for error at the dispensing stage than at the prescribing stage.

Organizational factors like *interruptions* factor (18.81%), *busier than normal* factor (17.50%), and *high-volume dispensing period* factor (15.54%) are taking account of a large proportion of the total medication events in our study. Ashcroft's study also found organizational factors involved in medication errors in community pharmacies such as poor relationships with supervisors, dissatisfaction with the job, no breaks, long working hours, inadequate lighting and equipment, location of the drive-through window, and work setting (Ashcroft et al., 2005). Studying organizational factors can have important implications for developing risk mitigation strategies in community pharmacies.

In our study only 0.17% out of 16930 reach-patients were reported as harmful events that caused severe injury and fatal. Rest 99.83% reach-patient events were reported as either no harm or moderate harm events. In our study 81% of 72733 events were reported at dispensing stage. The rest 19% of events were distributed among 10 error-stages of the events. The difference in the number of harmful and harmless events; and the difference in the number of dispensing stage events and events at rest of the 10 stages, is very high This signifies minimal reporting of harmful events and events at stages other than dispensing stage. As the study involves self-reporting as part of the routine, there may be a prevalence of under-reporting of medication events in community pharmacies. Underreporting can be due to an individual's fear of the disciplinary actions. For this reason, it is crucial to make error non-punishable (de las Mercedes Martínez Sánchez, 2012). This obstacle can also hinder the concept of acceptance of medication errors to increase patient safety. It will slow the organizations' ability to learn from the quantification of medication errors and result in a lost opportunity to change.

In our study, secondly, we identified likely associations between reported error-factors, error-categories, and event-types. ARM generated 37 strong rules belonging to the original dataset, near-miss dataset, and reach-patient dataset that influence medication event-type. Of these 37 rules, six rules belonged to path 1, nine rules belonged to path 2 and twenty-two rules belonged to path 3. Path 3 had 16 original strong rules, two near-miss dataset missing rules and four reach-patient dataset missing rules.

One of the original strong rules of path 1 (Quieter than normal factor ⇒ near-miss) was that if it was too quiet than normal sound while working, then this factor would contribute to a near-miss medication event-type with an 89% probability.

One of the original strong rules of path 2 (medical device/bag given/delivered to the wrong person ⇒ Reach-patient) was that if the error-category is *medical device/bag given/delivered to the wrong person* then a reach-patient medication event-type could occur with a probability of 84%.

One of the original rules of path 3 (policy/procedures not followed e.g.: double checking factor, wrong formulation ⇒ Near-miss) was that if the participants created *wrong formula* by not following the pharmacy's procedures and policies (such as double checking), then such a practice would result in a near-miss medication event-type with 90% probability. One of the near-miss dataset missing rules was that if a participant selects the *wrong drug or medicine* because of confusion between two look-alike or sound-alike drugs (known as salad error), then such a situation will result in near-miss medication event-type with 34% probability. One of the reach-patient dataset missing rules was that if a reach-patient event-type has error-factor category as *patient factor*, then a such an incident can have the error-category of *other* with 44% probability.

Lift is a symmetric measure while confidence and CF are asymmetric measures to find strong rules. Symmetric and asymmetric measures behave differently. Fjällström's study (2016) lost information while standardizing measures, so, our way of applying properties of the measures as they behave on the rules was carried to prevent the loss of information, and to generate complete rules. Completeness of the Path 1 and 2 for the near-miss and reach-patient dataset was 100%. Completeness of path 3 for the near-miss dataset was 88.89% and for the reach-patient dataset was 80%. Selecting different ARM techniques and measures may or may not generate different rules than ours. A testing of rules with different ARM algorithms and measures could be conducted as part of future research.

Most errors are spread throughout the institutions and happen as a result of institutional failures. We should not simply attribute the events to staff's carelessness. This is also evident from our study results where only 0.03% of events were caused to carelessness. Therefore, we should examine the functions within the community pharmacy system that fail and improve these functions to reduce their contribution to medication error events. This is known as a system-based approach to reduce medication error incidence. The system-based process helps in focusing on why the error occurred and will provide opportunities for improvement that will reduce incident medication errors (Ross, 2000, p. 495). Some studies attempted to understand why medication events occur and tries to improve the system to reduce medication error (Ross, 2000, p. 495).

Initiatives have been called to set a foundation to promote safe medication practices like forming a medication safety group which can meet monthly to discuss various topics (Cousins et al., 2012, p. 603). The topics of discussion could include error-prone medicines, medication error reports, and agreeing on new actions required to reduce incident medication errors. The meeting could also include not only the staff but also a local physician, be oriented around patient safety and thereby find solutions for reducing prescription errors. Furthermore, healthcare institutions could also publish an annual medication report for other healthcare organizations and stakeholders to provide transparency in managing medication errors (Cousins et al., 2012, p. 603).

An NHS hospital organization in England mentions that community pharmacies can appoint a medication safety officer dedicated explicitly to managing patient safety incidents in the organization (Cousins et al., 2012, p. 603). The benefits of medication safety officers not only include reducing medication errors but also enhancing the community

pharmacist's role in the healthcare system. The role of the medicine safety manager can be directed to the investigation of medication errors and report them to a higher authority in terms of actions needed. They can facilitate the education and training of the staff about patient safety initiatives and error reporting. (Kowiatek et al., 2004, p. 61)

UK ICU unit staff suggests including information about medication errors as a part of an introductory package of training for new staff. The package would include previous lessons learned from analysis of medication errors, and a copy of a medication error reporting form (Sanghera et al., 2007, p. 55). Other suggestions for material to include in the package are information about the most common and uncommon high-risk medications accessible by the team, images of the products, paper display about high-risk medications at the dispensing stage. The pharmacy's employee website could also display the data (Knudsen et al., 2007, p. 287)

One study carried out at a hospital in the US observed a reduction in dispensing errors from 0.19% to 0.07% by using a bar-code system. But the profit from using this system was observed in the first quarter of the fourth year of use of the system (Cheung et al., 2009, p. 677). Another study involved implementing a computerized drug-drug interaction alerting system in community pharmacies and the physician's office. Once the automated system went online in 95% of the pharmacies and 90% of the physicians' offices under study, the dispensing error was reduced by 68% (Cheung et al., 2009, p. 679).

To solve the error-factor of *interruptions*, cultural changes like a written interruptions policy could reduce incident medication errors at pharmacies. If there are fewer interruptions, then the pharmacists can focus better and reduce salad errors (Knudsen et al.,

2007, p. 288). Reducing distractions can also increase employee engagement with patients to keep them safe. Team expansion, and location of the telephone away from frontline workers can also reduce distractions. Centralizing refilling requests to a center can streamline the work, free up space in the cramped workplace, and reduces distractions. These changes reduce repetitive activities. Collecting data about the potential of such new interventions should be considered to avoid negative change in the culture of safety (Hagen et al., 2019).

A proper dispensing workflow where the dispensing of medicines can be improved by packaging and labelling distinct medicine names. Tracible procedures to check the dispensing medication can not only reduce incident medication errors, but also reduce pharmacists' workload. Training junior professionals about excellent and safe prescribing, confidentially, and counseling patients at the time of giving medications can also reduce error incidence (Peterson et al., 1999, p. 58).

Incident medication errors can also be reduced by double-checking all error-prone medicines. If staff are unsure about the medicine, they should talk to a pharmacist or seek support. They should not dispense illegibly written or incomplete prescriptions. They should also recheck the calculations to make sure the patient is getting the correct medicine and dose. They can also get the calculation recalculated by another clinician (Tariq et al., 2020).

Higher engagement of the patient in the medical decision-making process is a low-cost method of improving patient safety. Patients should be provided with information on possible medication errors and treatments, and on how to protect themselves from mistakes.

For vulnerable patients and children, this information should be provided to family members (Ferner, 2012).

Once we know what changes are needed to reduce errors within an organization, implementing the changes should be done in the best way possible (Ferner, 2012). It is understood that the interventions mentioned above have worked for hospitals and pharmacies but there are numerous pharmacy distribution systems, and each pharmacy has its own method of dispensing medicines (Ferner, 2012). Successful implementation of new models can use a combination of qualitative and quantitative analysis. The secondary data from interviews with participants like pharmacy staff, technicians, owners, or managers can identify challenges and barriers to medication safety within the community pharmacy. Improper implementation can cause negative changes in the system of an organization. A small reduction of errors in one system area may increase mistakes in other areas of the system. Therefore, it is essential to understand the socio-technical factors around implementing changes to reduce harm (Ferner, 2012). System implementation requires more research on gathering and testing in a controlled setting before and after study within the organization (Ferner, 2012,). Development of additional knowledge about the causes and solutions of medication errors, more in-depth data collection and analysis, as well as policies for community pharmacies, will help in forming future incident reporting schemes (Phipps et al., 2017, p. 12)

The first limitation of this study was that there was no indicator in the data to know whether the patients were informed of the medication event or not. The column 'identified_by' had null values thereby omitting an essential piece of evidence that could have helped explain the pattern in the occurrence of errors. This does not mean that we

must report the name of the person involved in medication error, but rather that it would be possible to collect information about the role of the participant and to know for example, whether they are a pharmacy technician, intern, freelance pharmacist, support staff, pharmacy manager, counter assistants, dispensers, and preregistration pharmacist. Etc. These categories could be added to the error identification column. A study in Sanaa, Yemen, revealed that pharmacy technicians were fewer in number, but dispensed most in the pharmacy (Al-Worafi et al., 2018, p. 2). Information like this in our research would have helped us understand the characteristics of 81% of the dispensing stage errors.

The second limitation of this study is that, approximately 72000 observations were reported over four years by 859 pharmacies, but this number of observations are still not enough. Collecting more data from each pharmacy may reveal various error rates. Analysis of the data revealed only operational failures that led to medication errors. The investigation did not reveal latent failures such as decisions about staffing resources or skill mixing issues, since they were not captured by reporting systems, even though they could be a cause of medication events.

Another limitation of the study was that the data analyzed was from structured columns such as category, type of events, etc., but the form also collects unstructured information, like comments, that was unavailable for analysis. Textual information from fields like comments would be generally helpful for sentiment analysis.

CHAPTER 6 CONCLUSION

According to British Medical Journal (BMJ) (2020), More than 237 million medication events occur in the National Health Service in England every year, and about one quarter of the events are preventable. Preventing 1 out of 4 events would save a cost of £98 million and more than 1700 lives each year. The WHO recognizes medication error events as a global issue, but not much information is available about medication events in community pharmacies in UK. Therefore, it is important to investigate the prevalence and association of factors and error categories in medication events.

This study adopted a descriptive data analytical approach to identify frequency, factors, error categories, and harm of medication errors in community pharmacies in the UK over a four-year period. The study revealed that 76.72% of the medication errors were near-miss events. The most prevalent error-category of medication events was *wrong drug/medicine* and most of the medication events occurred at the *dispensing/preparation stage*. Over 85% of the medication events had no harm level. Association analysis revealed some high probable connections between error-category and error-factor can contribute to medication error events. ARM analysis results identified six error-factors associated with near-miss medication event-type with high probability. For example, the factor of *not concentrating* while working can contribute to a near-miss medication event-type. Nine categories are highly associated with near-miss or reach-patient medication event-type. For example, *wrong dosage time* error-category has a likelihood to result in a near-miss medication event-type. Twenty-two Combinations of error-factors and error-categories can

be likely associated with near-miss and reach-patient medication events. For example, *policy or procedures not followed* and *wrong formulation* error-category are highly associated with near-miss medication event-type. *Patient factor* and reach-patient event-type are highly associated with *other* error-category.

The analysis from this research will help community pharmacies to bring data driven changes and implement new policies in community pharmacies that reduce incident medication events and improve patient safety. Along with these new changes, practices like overall training and education of current staff, collaboration between pharmacists and physicians, and automating barcode systems can be adopted by community pharmacies to reduce medication error events. Medication errors and adverse medical incidents are identified openly in the UK medical profession, but it is only by comprehending the causes and then making changes in the system that we can reduce their incidence. The results derived from analysis of the data can help lay a foundation for future projects aiming to reduce incident medication errors and increase patient safety. Implications of projects should also be considered before implementing them to avoid negative impacts. There are abundant opportunities for promising changes in community pharmacies.

Despite the interesting findings produced from the current study, the interpretation of the results needs to be examined by the professionals serving in community pharmacies. Future research can be helpful if the results of the study are communicated with the relevant stakeholders, who could then conduct qualitative research by sharing the results to verify and diagnose the underlying causes. These results of the study can be used to educate staff about the existing pattern of medication events even before the causes can be identified. It is helpful to improve the awareness of the prevalence of medication errors in community

pharmacies even prior to new policies are implemented, to reduce incident medication errors. They can develop a training package of medication errors for the new team and a refresher training package for the existing staff that makes them aware of the possibility of medication errors and prevent errors before any new reporting systems or policies are implemented.

Limitations of the research also provide an opportunity for future work. This could include improvement in the data collection form to include pharmacy staff roles and thereby identify which level of staff detected the medication error. Collaborating pharmacists' perception with physicians, patients, and business stakeholders in medication errors could also improve and add valuable information to the literature body.

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APPENDICES

Appendix A: The form used for error report.

The form was divided into sections for the UK for incident form:

1. Patient details
2. Incident details
3. Prescriber details
4. Details of medication/devices involved
5. Details of staff involved
6. Patients follow up

Fields of each section are as follows (marked in asterisks are compulsory)

1. Patient details
    a. Full name
    b. Event stage
    c. Insurance NO.
    d. Address
    e. Gender
    f. Ethnicity
    g. Date of birth
2. Incident details
    a. Location of incident
    b. Type of the incident
    c. Tell us what happened text field
    d. Contributory factors dropdown
    e. Initial action taken
    f. Date initial step was taken
    g. Has the GP been informed?
    h. Has the NHS been informed?
    i. Have you contacted your insurance?
    j. If yes, what advice have they given?
    k. Patient harm caused
    l. If harm occurred, describe the injury
    m. Add incident date (by default today)
3. Prescriber details
    a. Prescriber full name
    b. Phone
    c. Address
4. Details of medication/ devices involved
    a. At what stage of the medication process did the incident occur?
    b. Device Name
    c. Products Prescribed
    d. Products Dispensed
    e. Has the copy of the prescription (front and back) been retained?
    f. Dispensing label/ original container retained
5. Details of the staff involved
    a. Full name
    b. Directly dispensing
    c. Informed of incident
    d. Assisting/checker
    e. Overall responsibility
    f. Witness to the incident
    g. Engaged in the lead up to the incident
    h. Other
    i. Delete

6. Patient Follow Up:
    a. Has the feedback about the incident and investigation been provided to the patient?
    b. Does the patient want to pursue the matter further?
    c. What outcome does the patient want?
7. Once save is clicked, the portal navigates to the event summary page that has details of the event that were filled earlier on the left and CQI (a continuous quality improvement on the right-hand side). CQI includes root cause Analysis, Learning Points, Actions, Documents, Recent activities, Risk Matrix, Comments, etc.
8. The portal is also capable of audit trail, meaning it can keep versions of the form and track changes between the versions

9. The event summary page also provides options like print PDF, Export, edit the event, etc. options at the top and bottom of the page.

Appendix B: Columns in the dataset and their description.

Column name	Description
ID	Unique identifier for the instances and the primary key for the event table column
Type	Unique identifiers for type label column categories
Type_label	Type of event-Near-miss or Reach-patient
Country_id	Unique identifier for the values of country name column
Country_name	Included country name of the instances, e.g., UK
Organisation_id	Organization number to which the instances belonged
Membership_groups_id	Memberships id of the groups to which pharmacies belonged
Pharmacy_id	Pharmacy number of the instances
Administrative_bodies_id	Administrative Id's of the bodies that govern pharmacies
Pharmacy_active	If pharmacy was active-all, the instances had a value one.
Average_prescriptions	Average prescriptions -null column
Average_prescriptions_invers e	Null column
Region_code	Null column
Sub_region_code	Null column
Post_code	Postal code of the region where the pharmacy was present
Category_id	Unique identifier for the categories of the category label column
Category_label	Error category column
Sub_category_id	Null column
Sub_category_label	Null column
Stage_id	Unique identifier for the stage label column values
Stage_label	The stage at which the error occurred
Harm_level_id	Unique identifier for the harm level column values
Harm_level_label	Harm level of the events
Event_date	The date at which the event occurred.
Indication	Null column
Identified_by	Null column
Identified_by_value	Null column
Staff_involved	Null column
Staff_involved_inverse	Null column
Patient_gender	Null column
Patient_dob	Null column
Patient_age	Null column
Event_misfiled_types_id	Null column
Id	Unique Identifier for the table
Dw_event_id	Secondary key to the event_id column of the event table
Label	Factor categories

Appendix C: Frequency of error-category by event-type.

Error category	Near-miss events		Reach-patient events		Total errors	
	Number	Percentage	Number	Percentage	Number	Percentage
Wrong drug/medicine	10014	13.77%	3583	4.93%	13597	18.69%
Wrong quantity selected	9368	12.88%	1830	2.52%	11198	15.40%
New wrong/unclear dose strength	8133	11.18%	2254	3.10%	10387	14.28%
Wrong formulation	6984	9.60%	1186	1.63%	8170	11.23%
New wrong label	5926	8.15%	807	1.11%	6733	9.26%
Other	3106	4.27%	2009	2.76%	5115	7.03%
Wrong strength selected	2670	3.67%	1004	1.38%	3674	5.05%
Wrong device/product	2617	3.60%	628	0.86%	3245	4.46%
Mismatch between patient and medicine	1044	1.44%	881	1.21%	1925	2.65%
Wrong dosage time	1328	1.83%	116	0.16%	1444	1.99%
Wrong frequency	846	1.16%	135	0.19%	981	1.35%
Medical device/bag given/delivered to the wrong person	113	0.16%	639	0.88%	752	1.03%
Wrong method of preparation/supply	474	0.65%	139	0.19%	613	0.84%
Omitted medicine/ingredient	433	0.60%	169	0.23%	602	0.83%
Prescribing error	395	0.54%	123	0.17%	518	0.71%
Breach of confidentiality	114	0.16%	315	0.43%	429	0.59%
Expired item	235	0.32%	162	0.22%	397	0.55%
Device/product failure	232	0.32%	99	0.14%	331	0.46%
Item omitted from bag	155	0.21%	164	0.23%	319	0.44%
Wrong name on bag	166	0.23%	57	0.08%	223	0.31%
Device/product user error	180	0.25%	20	0.03%	200	0.27%
Wrong address on bag	174	0.24%	24	0.03%	198	0.27%
Lack of device/product	148	0.20%	42	0.06%	190	0.26%
Extra item in bag	55	0.08%	130	0.18%	185	0.25%
Wrong duration of treatment	144	0.20%	29	0.04%	173	0.24%
Inappropriate/incorrect monitored	127	0.17%	30	0.04%	157	0.22%
Duplication of drug (e.g.-brand overlap)	91	0.13%	41	0.06%	132	0.18%
New wrong storage	75	0.10%	31	0.04%	106	0.15%
Delay in obtaining item	30	0.04%	75	0.10%	105	0.14%
New wrong rate	87	0.12%	16	0.02%	103	0.14%
Wrong/omitted verbal patient directions/instructions	63	0.09%	12	0.02%	75	0.10%
Wrong route	58	0.08%	17	0.02%	75	0.10%
Wrong patient information leaflet	70	0.10%	2	0.00%	72	0.10%
Administered incorrectly	21	0.03%	42	0.06%	63	0.09%

Error category	Near-miss events		Reach-patient events		Total errors	
	Number	Percentage	Number	Percentage	Number	Percentage
Contra-indication to the use of medicine in relation to drugs or conditions	30	0.04%	22	0.03%	52	0.07%
Adverse drug reaction	21	0.03%	29	0.04%	50	0.07%
Drug-drug interaction	28	0.04%	10	0.01%	38	0.05%
Patient allergic to treatment	17	0.02%	18	0.02%	35	0.05%
Professional services incident e.g.: vaccination service	3	0.00%	30	0.04%	33	0.05%
Drug-food interaction	8	0.01%	2	0.00%	10	0.01%
Wrong dosage	9	0.01%		0.00%	9	0.01%
Medication incident	2	0.00%	5	0.01%	7	0.01%
Omission	4	0.01%	1	0.00%	5	0.01%
Wrong backing sheet	2	0.00%		0.00%	2	0.00%
Inappropriate patient handling / positioning	0	0.00%	1	0.00%	1	0.00%
Patient crossover	1	0.00%	0	0.00%	1	0.00%
Wrong brand	1	0.00%	0	0.00%	1	0.00%
Wrong pack size	1	0.00%	0	0.00%	1	0.00%
Absconder / missing patient	0	0.00%	1	0.00%	1	0.00%
Grand Total	55803	76.72%	16930	23.28%	72733	100.00%

Appendix D: Frequency of error-factor by event-type.

	Near-miss events		Reach-patient events		Total errors	
Factors	**Number**	**Percentage**	**Number**	**Percentage**	**Number**	**Percentage**
Interruptions factor	10937	15.04%	2756	3.79%	13693	18.83%
Busier than normal factor	9491	13.05%	3403	4.68%	12894	17.73%
High volume dispensing period factor	8678	11.93%	2572	3.54%	11250	15.47%
Policy/procedures not followed e.g.: double checking factor	6692	9.20%	1593	2.19%	8285	11.39%
Competence deficiency/training factor	6382	8.77%	1359	1.87%	7741	10.64%
Salad error (sound alike, look alike drug) factor	5236	7.20%	1558	2.14%	6794	9.34%
Staff resource issue	2218	3.05%	1352	1.86%	3570	4.91%
Medicine/product related issue factor	1604	2.21%	643	0.88%	2247	3.09%
Quieter than normal factor	1043	1.43%	125	0.17%	1168	1.61%
Not concentrating	1090	1.50%	43	0.06%	1133	1.56%
Patient factor	358	0.49%	464	0.64%	822	1.13%
Unknown	568	0.78%	59	0.08%	627	0.86%
Prescription clarity e.g. unclear instruction/handwriting factor	411	0.57%	192	0.26%	603	0.83%
Prescribing error factor	411	0.57%	189	0.26%	600	0.82%
Medical equipment (e.g. clear machine displays, poor working order, size, placement, ease of use) factor	328	0.45%	119	0.16%	447	0.61%
Supervision deficiency factor	178	0.24%	233	0.32%	411	0.57%
Pharmacist patient communicating factor	80	0.11%	228	0.31%	308	0.42%
Lack of attention/tiredness	35	0.05%	5	0.01%	40	0.05%
Nonspecific factors - human error	16	0.02%	12	0.02%	28	0.04%
Multi-tasking	19	0.03%	6	0.01%	25	0.03%
Carelessness	20	0.03%	4	0.01%	24	0.03%
Robot loading error	4	0.01%	7	0.01%	11	0.02%
Medication factors (where one or more drugs directly contributed to the incident)	1	0.00%	1	0.00%	2	0.00%
Still learning computer system	2	0.00%		0.00%	2	0.00%
Communication factors (includes verbal, written and non-verbal between individuals, teams, and/or organizations)	0	0.00%	2	0.00%	2	0.00%

Factors	Near-miss events		Reach-patient events		Total errors	
	Number	Percentage	Number	Percentage	Number	Percentage
Task factors (includes work guidelines / procedures / policies, availability of decision-making aids)	1	0.00%	0	0.00%	1	0.00%
Education and training factors (e.g. availability of training)	0	0.00%	1	0.00%	1	0.00%
other	0	0.00%	1	0.00%	1	0.00%
work and environment factors (e.g. poor/excess administration, physical environment, workload and hours of work, time pressures)	0	0.00%	1	0.00%	1	0.00%
Eps	0	0.00%	1	0.00%	1	0.00%
Organization and strategic factors (e.g. organizational structure, contractor / agency use, culture)	0	0.00%	1	0.00%	1	0.00%
Grand Total	55803	76.72%	16930	23.28%	72733	100.00%

Appendix E: Event table-category label column

Old string	Count	New string	Count
Wrong directions on the label	3045	Wrong label	7759
Forms/values.event_cat_wrong_transposed_omitted_medicine_label	3002		
Wrong quantity on the label	1163		
Wrong patient name on the label	951		
Wrong drug strength on the label	766		
Wrong drug form on the label	503		
Wrong drug name on the label	475		
A wrong label on the container	422		
No label on the medication	117		
Wrong/transposed/omitted medicine label	23		
Labeling - Wrong quantity	14		
Labeling - Wrong drug/form on the label	4		
Labeling - Wrong patient's name	4		
Labeling - Wrong strength on the label	4		
Labeling - Wrong directions on the label	3		
Wrong bag label	2		
Wrong dose on label or backing sheet	1		
Wrong label	1		
Forms/values.event_cat_wrong_unclear_dose_or_strength	20765	Wrong/unclear dose stre ngth	21199
Wrong/unclear dose or strength	162		
Selection - Wrong strength (name of drug/brand)	120		
Wrong strength	96		
Pearns: Picking error - strength	56		
Forms/values.event_cat_wrong_storage	234	Wrong storage	235
Wrong storage	1		
Forms/values.event_cat_wrong_rate	192	Wrong rate	193
Wrong rate	1		
Forms/values.event_cat_wrong_quantity	15103	Wrong quantity selected	19439
Wrong quantity selected	4159		
Wrong quantity	154		
Selection - Wrong quantity	23		
Forms/values.event_cat_adverse_drug_reaction_when_used_as_inten ded	126 34	Adverse drug reaction	160
Adverse Drug reaction			
Forms/values.event_cat_breach_of_confidentiality	862	Breach of confidentialit y	894
Breach of confidentiality	32		
Forms/values.event_cat_contra_indication_to_the_use_of_the_medic ine	102 25	Contra- indication to the use of medicine in relation to d rugs or conditions	127
Contra-indication to the use of medicine in relation to drugs or conditions			
Forms/values.event_cat_device_product_failure	492	Device/product failure	494
Device/product failure	2		
Forms/values.event_cat_device_product_user_error	338	Device/product user error	342
Device/product user error	4		
Forms/values.event_cat_lack_of_device_product	368	Lack of device/product	372
Lack of device/product	4		
Bag given to the wrong person	796	Medical device/bag giv en/delivered to the wron g person	1040
Delivered to the Wrong Person	214		
Medical device - bag given to the wrong person	24		
Medical device - delivered to the Wrong Person	6		
Forms/values.event_cat_wrong_device_product	6166	Wrong device/product	6200
Wrong device/product	34		
Forms/values.event_cat_duplication_of_drug_e_g_brand_overlap_	363	Duplication of drug (e.g -brand overlap)'	364
Duplication of drug (e.g.: brand overlap)	1		

Old string	Count	New string	Count
Forms/values.event_cat_wrong_duration_of_treatment Wrong duration of treatment	421 2	Wrong duration of treat ment	423
Forms/values.event_cat_inappropriate_incorrect_monitoring Forms/values.event_cat_test_results_incorrectly_recorded Inappropriate / incorrect monitoring	321 6 1	Inappropriate/incorrect monitored	328
Administered incorrectly	109		109
Forms/values.event_cat_drug_food_interaction	25	Drug-food interaction	25
Forms/values.event_cat_drug_drug_interaction Drug - drug interaction	94 25 1	Drug-drug interaction	120
Forms/values.event_cat_wrong_route	138	Wrong route	138
Forms/values.event_cat_professional_services_incident Professional services incident (e.g. vaccination service)	70 2	Professional services in cident e.g.: vaccination service	72
Forms/values.event_cat_mismatching_between_patient_and_medicin e Mismatching between patient and medicine	3747 35	Mismatch between patie nt and medicine'	3782
Forms/values.event_cat_other Other	9989 40	Other	10020
Forms/values.event_cat_patient_allergic_to_treatment Patient allergic to treatment	89 3	Patient allergic to treat ment	92
Forms/values.event_cat_prescribing_error Forms/values.event_cat_treatment_prescription_inappropriate Prescribing error Treatment/prescription inappropriate	893 4 1 1	Prescribing error	899
Forms/values.event_cat_wrong_dosage_time Wrong dosage time	2698 19	Wrong dosage time	2867
Forms/values.event_cat_wrong_drug_medicine Wrong drug/medicine	18590 166	Wrong drug/medicine	18756
Wrong drug selected Selection - Wrong strength (name of drug/brand) Selection - Wrong drug/form (name of drug/brand)	4713 120 102	Wrong drug/strength selected	4935
Forms/values.event_cat_wrong_frequency Wrong frequency	2026 16	Wrong frequency	2042
Forms/values.event_cat_wrong_formulation Wrong formulation selected Wrong formulation	12017 1646 104	Wrong formulation	13767
Wrong method of preparation Forms/values.event_cat_wrong_method_of_preparation_supply Wrong method of preparation/supply	587 388 5	Wrong method of prepa ration/supply	980
Forms/values.event_cat_wrong_omitted_patient_information_leaflet Wrong/omitted patient information leaflet	142 1	Wrong patient informati on leaflet	143
Forms/values.event_cat_omitted_medicine_ingredient Omitted medicine/ingredient	1613 11	Omitted medicine/ingre dient	1624
Forms/values.event_cat_wrong_omitted_verbal_patient_instructions Wrong/omitted verbal patientdirections	237 11	Wrong/omitted verbal p atient directions/instruct ions	248

Event Table-Type Label Column

Old string	Count	New string	Count
Near-miss Near-miss (PLS) NEAR MISS (BRANCH TO RECORD AS 'CLOSED' EVENT ALWA Near-miss (MDS) Near-miss	86801 4414 4379 471 310	Near-miss	96375

Old string	Count	New string	Count
Abuse Incident 156 Abuse	156 75	Abuse	231
Incident Dispensing incident Incident/error report Incident Abuse incident PATIENT SAFETY INCIDENT FORM risk_incident Incident2	30449 1317 351 316 156 46 16 1	Reach-patient	32496
IPU NMS Pilot	393	IPU NMS pilot	393
Misuse	172	Misuse	172
Flu vaccination	2	Flu vaccination	2
Decision to make or refuse a sale	1	Decision to make or refuse a sale	1
Hazard	14	Hazard	14

Event Table-Stage Label Column

Old string	Count	New string	Count
Forms/values.event_points_prescribing Prescribing	1911 5	Prescribing stage	1916
Forms/values.event_points_dispensing_preparation Dispensing / preparation	103228 280	Dispensing/preparation Stage	1340
Forms/values.event_points_presentation_packaging Presentation / packaging	5592 2	Presentation/packing stage	5594
Forms/values.event_points_supply_ordering Supply / ordering	2099 4	Supply/ordering stage	2103
Forms/values.event_points_storage	651	Storage stage	651
Forms/values.event_points_delivery Delivery	2373 5	Delivery stage	2378
Forms/values.event_points_administration	1524	Administration stage	1524
Forms/values.event_points_during_computer_input During computer input	5125 65	Computer input stage	5180
Forms/values.event_points_product_selection Product selection	5573 9	Product selection stage	5582
Forms/values.event_points_advice	836	Event advice stage	836
Forms/values.event_points_monitoring	417	Event monitoring stage	417

Event table-harm label column

Old string	Count	New string	Count
Forms/values.harm_levels_none	110174	None	110174
Forms/values.harm_levels_unknown	11491	Unknown	11491
Forms/values.harm_levels_low	5954	Low	5954
Forms/values.harm_levels_moderate	1654	Moderate	1654
Forms/values.harm_levels_severe	338	338	338
Forms/values.harm_levels_death	88	88	88

Factor table-label column

Old string	Count	New string	Count
Forms/values.event_factors_interruptions Interruptions	201244	Interruptions factor	20128
Forms/values.event_factors_busier_than_normal Busier than normal	1986215	Busier than normal factor	19877
Forms/values.event_factors_high_volume_dispensing_period High volume dispensing period	161347	High volume dispensing period factor	16141
Forms/values.event_factors_competence_deficiency_training_factor Competence deficiency / training factor	1191210	Competence deficiency/training factor	11922
Forms/values.event_factors_policy_procedures_not_followed Policy / procedures not followed e.g. double checking	116418	Policy/procedures not followed e.g. double-checking factor	11649
Forms/values.event_factors_salad_error_sound_alike_look_alike_drug SALAD error (Sound-Alike, Look-Alike Drug).	999811	Salad error (sound-alike, look-alike drug) factor	10009
Forms/values.event_factors_staff_resource_issue Staff resource issue	50704	Staff resource Issue	5074
Forms/values.event_factors_quieter_than_normal Quieter than normal	17472	Quieter than Normal factor	1749
Forms/values.event_factors_prescription_clarity Prescription clarity eg. unclear instruction / handwriting	16101	Prescription clarity e.g. unclear instruction/handwriting factor	1611
Not concentrating	1412	Not concentrating	1412
Forms/values.event_factors_prescribing_error	1130	Prescribing error factor	1130
Forms/values.event_factors_supervision_deficiency	786	Supervision deficiency factor	786
Forms/values.event_factors_pharmacist_patient_communication_factor	756	Pharmacist patient communicating factor	756
Unknown	720		720
Forms/values.event_factors_equipment_factor Medical equipment factor Equipment factor Equipment and resources factors (e.g., clear machine displays, poor Working order, size, placement, ease of use)	666 120 1 1	Medical equipment (e.g., clear machine displays, poor working order, size, placement, eas e of use) factor	788
Nonspecific factors - Human error	40	Nonspecific factors - Human error	40
Lack of attention/tiredness	40	Lack of attention/tiredness	40
Forms/values.event_factors_medicine_product_related_issue Medicine / product related issue	367301	Medicine/product related issue factor	3674
Forms/values.event_factors_patient_factor Patient factor	12891	Patient factor	1290

Old string	Count	New string	Count
Multi-tasking	25	Multi-tasking	25
Carelessness	24	Carelessness	24
Robot loading error		Robot loading error	13
Communication factors (includes verbal, written, and non-verbal between individuals, teams, and/or organizations).	2	Communication factors (includes verbal, written, and non-verbal between individuals, teams, and/or organizations).	2
Still learning computer system	2	Still learning computer system	2
Medication factors (where one or more drugs directly contributed to the incident).	2	Medication factors (where one or more drugs directly contributed to the incident).	2
Acute walk-in prescription	2	Acute walk-in prescription	2
Similar Packaging	2	Similar Packaging	2
Other	1	Other	
Education and training factors (e.g., availability of training).	1	Education and training factors (e.g., availability of training).	1
Non-EPS prescription	1	Non-EPS prescription	1
EPS	1	EPS	1
Task factors (includes work guidelines/procedures/policies, availability of decision-making aids).	1	Task factors (includes work guidelines/procedures/policies, availability of decision-making aids).	1
Work and environment factors (e.g., poor/excess administration, physical environment, workload and hours of work, time pressures).	1	Work and environment factors (e.g., poor/excess administration, physical environment, workload and hours of work, time pressures).	1
Organization and strategic factors (e.g., organizational structure, contractor/agency use, culture).	1	Organization and strategic factors (e.g., organizational structure, contractor/agency use, culture).	1

Appendix F: Influence of error-factor on event-type.

Original association rules between error-factor and event-type are as follows:

Rule	Antecedents	Consequents	Support	Lift	Confidence		CF	
					For ward	Back ward	For ward	Back ward
1	Not concentrating	near-miss	0.015	1.253	**0.957**	0.02	**81.968**	0.476
2	Quieter than normal factor	near-miss	0.014	1.168	**0.893**	0.018	**54.506**	0.268
3	Competence deficiency/training factor	near-miss	0.088	1.078	**0.823**	0.115	**25.224**	0.934
4	Staff resource issue	reach-patient	0.019	1.626	**0.384**	0.079	**19.346**	3.196
5	Policy/procedures not followed e.g.: double checking factor	near-miss	0.091	1.055	**0.806**	0.12	**17.858**	0.706
6	Interruptions factor	near-miss	0.15	1.043	**0.797**	0.196	**13.932**	0.997
7	Busier than normal factor	reach-patient	0.048	1.133	0.268	0.205	4.116	2.934
8	High volume dispensing period factor	near-miss	0.118	1.003	0.766	0.155	1.032	0.058
9	Salad error (sound alike, look alike drug) factor	near-miss	0.07	1.002	0.765	0.092	0.59	0.018

Missing association rules between error-factor and event-type for near-miss dataset are as follows:

Rule	Antecedents	Consequents	Support	Confidence	Lift
1	Busier than normal factor	Near-miss	0.173	1	1
2	Competence deficiency/training factor	Near-miss	0.115	1	1
3	Near-miss	High volume dispensing period factor	0.154	0.154	1
4	Near-miss	Interruptions factor	0.196	0.196	1
5	Near-miss	Medicine/product related issue factor	0.028	0.028	1
6	Near-miss	Not concentrating	0.019	0.019	1
7	Near-miss	Policy/procedures not followed e.g.: double checking factor	0.119	0.119	1
8	Quieter than normal factor	Near-miss	0.018	1	1

Rule	Antecedents	Consequents	Support	Confidence	Lift
9	Salad error (sound alike, look alike drug) factor	Near-miss	0.091	1	1
10	Near-miss	Staff resource issue	0.039	0.039	1

Missing rules between error-factor and event-type in reach-patient dataset are as follows:

Rule	Antecedents	Consequents	Support	Confidence	Lift
1	Reach-patient	Busier than normal factor	0.204	0.204	1
2	Reach-patient	Competence deficiency/training factor	0.080	0.080	1
3	Reach-patient	High volume dispensing period factor	0.152	0.152	1
4	Reach-patient	Interruptions factor	0.161	0.161	1
5	Reach-patient	medicine/product related Issue factor	0.038	0.038	1
6	Reach-patient	Patient factor	0.028	0.028	1
7	Reach-patient	Pharmacist patient communicating factor	0.013	0.013	1
8	Reach-patient	Policy/procedures not followed e.g.: double checking factor	0.093	0.093	1
9	Reach-patient	Prescribing error factor	0.010	0.010	1
10	Reach-patient	Prescription clarity e.g. unclear instruction/handwriting factor	0.011	0.011	1
11	Reach-patient	Salad error (sound alike, look alike drug) factor	0.091	0.091	1
12	Reach-patient	Staff resource issue	0.078	0.078	1

Appendix G: Influence of error-category on event-type.

Original association rules between error-category and event-type are as follows:

Rule	Antecedents	Consequents	Support	Lift	Confidence		CF	
					For ward	Back ward	For ward	Back ward
1	Reach-patient	Medical device/bag given/delivered to the wrong person	0.009	3.558	0.036	**0.84**	2.65	**79.049**
2	Wrong dosage time	Near-miss	0.018	1.202	**0.918**	0.024	**65.478**	0.406
3	Near-miss	New wrong label	0.081	1.153	0.106	**0.881**	1.554	**49.538**
4	Near-miss	Wrong frequency	0.011	1.118	0.015	**0.854**	0.158	**38.203**
5	Wrong formulation	Near-miss	0.096	1.117	**0.854**	0.125	**37.957**	1.48
6	Wrong quantity selected	Near-miss	0.128	1.094	**0.836**	0.168	**30.328**	1.699
7	Reach-patient	Mismatch between patient and medicine	0.012	1.926	0.051	**0.455**	2.542	**28.626**
8	Other	Reach-patient	0.028	1.669	**0.394**	0.118	**20.674**	5.112
9	Near-miss	Wrong device/product	0.036	1.055	0.047	**0.806**	0.255	**17.786**
10	Wrong method of preparation/supply	Near-miss	0.007	1.017	0.777	NA	5.588	NA
11	New wrong/unclear dose strength	Near-miss	0.112	1.017	0.777	0.147	5.429	0.284
12	Wrong strength selected	Reach-patient	0.013	1.156	0.273	0.056	4.831	0.793
13	Reach-patient	Wrong drug/medicine	0.051	1.142	0.215	0.27	3.295	4.4

Missing association rules between error-category and event-type for near-miss dataset are as follows:

Rule	Antecedents	Consequents	Support	Confidence	Lift
1	Mismatch between patient and medicine	Near-miss	0.019	1	1
2	New wrong label	Near-miss	0.106	1	1
3	New wrong/unclear dose strength	Near-miss	0.147	1	1
4	Omitted medicine/ingredient	Near-miss	0.007	1	1
5	Near-miss	Other	0.056	0.056	1
6	Prescribing error	Near-miss	0.007	1	1
7	Wrong device/product	Near-miss	0.046	1	1
8	Near-miss	Wrong dosage time	0.023	0.023	1
9	Near-miss	Wrong drug/medicine	0.179	0.179	1
10	Wrong formulation	Near-miss	0.125	1	1
11	Wrong frequency	Near-miss	0.014	1	1

Rule	Antecedents	Consequents	Support	Confidence	Lift
12	Wrong method of preparation/supply	Near-miss	0.008592	1	1
13	Wrong quantity selected	Near-miss	0.167818	1	1
14	Near-miss	Wrong strength selected	0.045943	0.045943	1

Missing association rules between error-category and event-type for reach-patient dataset are as follows:

Rule	Antecedents	Consequents	Support	Confidence	Lift
1	Reach-patient	Breach of confidentiality	0.021	0.021	1
2	Device/product failure	Reach-patient	0.005	1	1
3	Expired item	Reach-patient	0.009	1	1
4	Extra item in bag	Reach-patient	0.008	1	1
5	Item omitted from bag	Reach-patient	0.009	1	1
6	Reach-patient	Medical device/bag given/delivered to the wrong person	0.036	0.036	1
7	Reach-patient	Mismatch between patient and medicine	0.051	0.051	1
8	Reach-patient	New wrong label	0.046	0.046	1
9	Reach-patient	New wrong/unclear dose strength	0.136	0.136	1
10	Reach-patient	Omitted medicine/ingredient	0.010	0.010	1
11	Reach-patient	Other	0.118	0.118	1
12	Prescribing error	Reach-patient	0.007	1	1
13	Reach-patient	Wrong device/product	0.0364	0.036	1
14	Wrong dosage time	Reach-patient	0.006	1	1
15	Reach-patient	Wrong drug/medicine	0.214	0.214	1
16	Wrong formulation	Reach-patient	0.069	1	1
17	Wrong frequency	Reach-patient	0.008	1	1
18	Wrong method of preparation/supply	Reach-patient	0.007	1	1
19	Reach-patient	Wrong quantity selected	0.106	0.106	1
20	Reach-patient	Wrong strength selected	0.055	0.055	1

Appendix H: Influence of error-category and error-factor on event-type.

Original association rules between error-factor, error-category and event-type are as follows:

Rule	Antecedents	Consequents	Support	Confidence	Lift	CF
1	Near-miss, policy/procedures not followed e.g.: double checking factor	Wrong formulation	0.012	0.129	1.151	1.901
2	Policy/procedures not followed e.g.: doublechecking factor	Wrong formulation, near-miss	0.012	0.104	1.087	0.917
3	Wrong formulation, near-miss	Policy/procedures not followed e.g.: doublechecking factor	0.012	0.123	1.087	1.110
4	Wrong formulation	Near-miss, policy/procedures not followed e.g.: doublechecking factor	0.012	0.105	1.151	1.517
5	**Wrong formulation, policy/procedures not followed e.g.: doublechecking factor**	**near-miss**	**0.012**	**0.908**	**1.189**	**61.003**
6	Wrong formulation	Competence deficiency/training factor, near-miss	0.013	0.120	1.361	3.486
7	Competence deficiency/training factor	Wrong formulation, near-miss	0.013	0.126	1.313	3.308
8	**Wrong formulation, competence deficiency/training factor**	**near-miss**	**0.013**	**0.907**	**1.188**	**60.699**
9	Competence deficiency/training factor, near-miss	Wrong formulation	0.013	0.152	1.361	4.551
10	Wrong formulation, near-miss	Competence deficiency/training factor	0.013	0.140	1.313	3.749
11	**Interruptions factor, wrong label**	**Near-miss**	**0.021**	**0.899**	**1.177**	**57.212**
12	Wrong label	Interruptions factor, near-miss	0.021	0.232	1.549	9.686
13	Interruptions factor	Near-miss, wrong label	0.021	0.114	1.402	3.548
14	Near-miss, wrong label	Interruptions factor	0.021	0.264	1.402	9.303
15	Interruptions factor, near-miss	Wrong label	0.021	0.143	1.549	5.578
16	**Competence deficiency/training factor, wrong quantity selected**	**Near-miss**	**0.015**	**0.894**	**1.171**	**55.298**
17	Wrong quantity selected, near-miss	Competence deficiency/training factor	0.015	0.120	1.124	1.484
18	Competence deficiency/training factor, near-miss	Wrong quantity selected	0.015	0.175	1.140	2.543

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
19	Wrong quantity selected	Competence deficiency/training factor, near-miss	0.015	0.100	1.140	1.356
20	Competence deficiency/training factor	Wrong quantity selected, near-miss	0.015	0.144	1.124	1.822
21	High volume dispensing period factor, near-miss	Wrong label	0.014	0.121	1.316	3.207
22	Near-miss, wrong label	High volume dispensing period factor	0.014	0.177	1.145	2.646
23	**High volume dispensing period factor, wrong label**	**Near-miss**	**0.014**	**0.890**	**1.165**	**53.233**
24	Wrong label	High volume dispensing period factor, near-miss	0.014	0.156	1.316	4.240
25	Near-miss, policy/procedures not followed e.g.: doublechecking factor	Wrong quantity selected	0.021	0.228	1.483	8.749
26	Wrong quantity selected	Near-miss, policy/procedures not followed e.g.: doublechecking factor	0.021	0.136	1.483	4.860
27	Policy/procedures not followed e.g.: doublechecking factor	Wrong quantity selected, near-miss	0.021	0.183	1.430	6.330
28	Wrong quantity selected, near-miss	Policy/procedures not followed e.g.: doublechecking factor	0.021	0.162	1.430	5.511
29	**Wrong quantity selected; policy/procedures not followed e.g.: doublechecking factor**	**Near-miss**	**0.021**	**0.880**	**1.151**	**48.988**
30	**Wrong formulation, interruptions factor**	**Near-miss**	**0.015**	**0.873**	**1.143**	**46.285**
31	Policy/procedures not followed e.g.: doublechecking factor, wrong drug/medicine	Near-miss	0.013	0.803	1.052	16.701
32	**Wrong/unclear dose strength, policy/procedures not followed e.g.: doublechecking factor**	**Near-miss**	**0.016**	**0.871**	**1.140**	**45.270**
33	Near-miss, policy/procedures not followed e.g.: doublechecking factor	Wrong/unclear dose strength	0.016	0.176	1.218	3.687
34	Wrong/unclear dose strength	Near-miss, policy/procedures not followed e.g.: doublechecking factor	0.016	0.111	1.218	2.195
35	Policy/procedures not followed e.g.: doublechecking factor	Wrong/unclear dose strength, near-miss	0.016	0.142	1.264	3.342
36	Wrong/unclear dose strength, near-miss	Policy/procedures not followed e.g.: doublechecking factor	0.016	0.143	1.264	3.379
37	Wrong label	Busier than normal factor, near-miss	0.016	0.174	1.315	4.805
38	**Busier than normal factor, wrong label**	**Near-miss**	**0.016**	**0.854**	**1.118**	**38.258**
39	Near-miss, wrong label	Busier than normal factor	0.016	0.197	1.094	2.064

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
40	Wrong formulation	High volume dispensing period factor, near-miss	0.015	0.129	1.094	1.261
41	High volume dispensing period factor, near-miss	Wrong formulation	0.015	0.123	1.094	1.185
42	**Wrong formulation, high volume dispensing period factor**	**Near-miss**	**0.015**	**0.849**	**1.111**	**35.974**
43	Wrong quantity selected	Interruptions factor, near-miss	0.027	0.179	1.193	3.399
44	Wrong quantity selected, near-miss	Interruptions factor	0.027	0.214	1.138	3.186
45	Interruptions factor, near-miss	Wrong quantity selected	0.027	0.183	1.193	3.495
46	**Interruptions factor, wrong quantity selected**	**Near-miss**	**0.027**	**0.848**	**1.111**	**35.821**
47	Interruptions factor	Wrong quantity selected, near-miss	0.027	0.146	1.138	2.023
48	Wrong quantity selected, near-miss	High volume dispensing period factor	0.022	0.168	1.091	1.654
49	High volume dispensing period factor, near-miss	Wrong quantity selected	0.022	0.182	1.189	3.425
50	**High volume dispensing period factor, wrong quantity selected**	**Near-miss**	**0.022**	**0.833**	**1.091**	**29.473**
51	High volume dispensing period factor	Wrong quantity selected, near-miss	0.022	0.140	1.091	1.332
52	Wrong quantity selected	High volume dispensing period factor, near-miss	0.022	0.141	1.189	2.536
53	**Wrong formulation, busier than normal factor**	**Near-miss**	**0.015**	**0.828**	**1.084**	**27.193**
54	Wrong formulation	Busier than normal factor, near-miss	0.015	0.135	1.022	0.331
55	Busier than normal factor, near-miss	Wrong formulation	0.015	0.114	1.022	0.274
56	Wrong formulation, near-miss	Salad error (sound alike, look alike drug) factor	0.013	0.136	1.484	4.883
57	Near-miss, salad error (sound alike, look alike drug) factor	Wrong formulation	0.013	0.185	1.655	8.268
58	Salad error (sound alike, look alike drug) factor	Wrong formulation, near-miss	0.013	0.142	1.484	5.120
59	**Wrong formulation, salad error (sound alike, look alike drug) factor**	**Near-miss**	**0.013**	**0.819**	**1.072**	**23.294**
60	Wrong formulation	Near-miss, salad error (sound alike, look alike drug) factor	0.013	0.116	1.655	4.940
61	Wrong quantity selected	Busier than normal factor, near-miss	0.023	0.147	1.112	1.709
62	**Busier than normal factor, wrong quantity selected**	**Near-miss**	**0.023**	**0.797**	**1.043**	**13.839**
63	Busier than normal factor, near-miss	Wrong quantity selected	0.023	0.171	1.112	2.032
64	**Busier than normal factor, wrong drug/medicine**	**Reach-patient**	**0.011**	**0.319**	**1.352**	**10.884**
65	Busier than normal factor, reach-patient	Wrong drug/medicine	0.011	0.219	1.163	3.778

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
66	Reach-patient, wrong drug/medicine	Busier than normal factor	0.011	0.208	1.154	3.391
67	Interruptions factor, wrong/unclear dose strength	Near-miss	0.017	0.783	1.026	8.257
68	High volume dispensing period factor	Wrong/unclear dose strength, near-miss	0.021	0.133	1.182	2.303
69	High volume dispensing period factor, wrong/unclear dose strength	Near-miss	0.021	0.779	1.020	6.600
70	Wrong/unclear dose strength, near-miss	High volume dispensing period factor	0.021	0.182	1.182	3.322
71	High volume dispensing period factor, near-miss	Wrong/unclear dose strength	0.021	0.173	1.198	3.348
72	Wrong/unclear dose strength	High volume dispensing period factor, near-miss	0.021	0.142	1.198	2.657
73	Interruptions factor, wrong drug/medicine	Near-miss	0.025	0.771	1.009	2.899

Missing association rules between error-factor, error-category and event-type for near-miss dataset are as follows:

Rule	Antecedent	Consequent	Support	Confidence	Lift	CF
1	**Salad error (sound alike, look alike drug) factor, near-miss**	**Wrong drug/medicine**	**0.032**	**0.348**	**1.939**	**20.571**
2	Salad error (sound alike, look alike drug) factor	Wrong drug/medicine, near-miss	0.032	0.348	1.939	20.571
3	Wrong drug/medicine	Salad error (sound alike, look alike drug) factor, near-miss	0.032	0.178	1.939	9.492
4	Wrong drug/medicine, near-miss	Salad error (sound alike, look alike drug) factor	0.032	0.178	1.939	9.492
5	**Wrong strength selected, near-miss**	**Interruptions factor**	**0.013**	**0.279**	**1.421**	**10.271**
6	Wrong strength selected	Interruptions factor, near-miss	0.013	0.279	1.421	10.271
7	New wrong label, near-miss	Interruptions factor	0.028	0.264	1.344	8.389
8	Interruptions factor, near-miss	New wrong label	0.028	0.143	1.344	4.087
9	Interruptions factor	New wrong label, near-miss	0.028	0.143	1.344	4.087
10	New wrong label	Interruptions factor, near-miss	0.028	0.264	1.344	8.389
11	Policy/procedures not followed e.g.: double checking factor, near-miss	Wrong quantity selected	0.027	0.228	1.356	7.172

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
12	Policy/procedures not followed e.g.: double checking factor	Wrong quantity selected, near-miss	0.027	0.228	1.356	7.172
13	Wrong quantity selected, near-miss	Policy/procedures not followed e.g.: double checking factor	0.027	0.162	1.356	4.838
14	Wrong quantity selected	Policy/procedures not followed e.g.: double checking factor, near-miss	0.027	0.162	1.356	4.838
15	Salad error (sound alike, look alike drug) factor, near-miss	Wrong formulation	0.017	0.185	1.482	6.890
16	Salad error (sound alike, look alike drug) factor	Wrong formulation, near-miss	0.017	0.185	1.482	6.890
17	Wrong formulation, near-miss	Salad error (sound alike, look alike drug) factor	0.017	0.136	1.482	4.865
18	Wrong formulation	Salad error (sound alike, look alike drug) factor, near-miss	0.017	0.136	1.482	4.865
19	Other, near-miss	Busier than normal factor	0.012	0.206	1.189	3.952
20	Other	Busier than normal factor, near-miss	0.012	0.206	1.189	3.952
21	Policy/procedures not followed e.g.: double checking factor, near-miss	New wrong/unclear dose strength	0.021	0.176	1.198	3.413
22	New wrong/unclear dose strength, near-miss	Policy/procedures not followed e.g.: double checking factor	0.021	0.143	1.198	2.692
23	New wrong/unclear dose strength	Policy/procedures not followed e.g.: double checking factor, near-miss	0.021	0.143	1.198	2.692
24	Policy/procedures not followed e.g.: double checking factor	New wrong/unclear dose strength, near-miss	0.021	0.176	1.198	3.413
25	New wrong/unclear dose strength, near-miss	High volume dispensing period factor	0.027	0.182	1.178	3.266
26	High volume dispensing period factor, near-miss	New wrong/unclear dose strength	0.027	0.173	1.178	3.073
27	High volume dispensing period factor	New wrong/unclear dose strength, near-miss	0.027	0.173	1.178	3.073

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
28	New wrong/unclear dose strength	High volume dispensing period factor, near-miss	0.027	0.182	1.178	3.266
29	Competence deficiency/training factor, near-miss	Wrong formulation	0.018	0.152	1.218	3.118
30	Wrong formulation, near-miss	Competence deficiency/training factor	0.018	0.140	1.218	2.841
31	Wrong formulation	Competence deficiency/training factor, near-miss	0.018	0.140	1.218	2.841
32	Competence deficiency/training factor	Wrong formulation, near-miss	0.018	0.152	1.218	3.118
33	New wrong label, near-miss	Busier than normal factor	0.021	0.197	1.141	2.944
34	New wrong label	Busier than normal factor, near-miss	0.021	0.197	1.141	2.944
35	Busier than normal factor, near-miss	New wrong label	0.021	0.121	1.141	1.672
36	Busier than normal factor	New wrong label, near-miss	0.021	0.121	1.141	1.672
37	New wrong label, near-miss	High volume dispensing period factor	0.019	0.177	1.141	2.589
38	High volume dispensing period factor, near-miss	New wrong label	0.019	0.121	1.141	1.679
39	High volume dispensing period factor	New wrong label, near-miss	0.019	0.121	1.141	1.679
40	New wrong label	High volume dispensing period factor, near-miss	0.019	0.177	1.141	2.589
41	Wrong quantity selected, near-miss	Interruptions factor	0.036	0.214	1.091	2.211
42	Wrong quantity selected	Interruptions factor, near-miss	0.036	0.214	1.091	2.211
43	Interruptions factor, near-miss	Wrong quantity selected	0.036	0.183	1.091	1.827
44	Interruptions factor	Wrong quantity selected, near-miss	0.036	0.183	1.091	1.827
45	High volume dispensing period factor, near-miss	Wrong quantity selected	0.028	0.182	1.087	1.756
46	Wrong quantity selected, near-miss	High volume dispensing period factor	0.028	0.168	1.087	1.596
47	Wrong quantity selected	High volume dispensing period factor, near-miss	0.028	0.168	1.087	1.596
48	High volume dispensing period factor	Wrong quantity selected, near-miss	0.028	0.182	1.087	1.756

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
49	Competence deficiency/training factor, near-miss	Wrong quantity selected	0.020	0.175	1.043	0.859
50	Competence deficiency/training factor	Wrong quantity selected, near-miss	0.020	0.175	1.043	0.859
51	Wrong quantity selected, near-miss	Competence deficiency/training factor	0.020	0.120	1.043	0.555
52	Wrong quantity selected	Competence deficiency/training factor, near-miss	0.020	0.120	1.043	0.555
53	Salad error (sound alike, look alike drug) factor, near-miss	New wrong/unclear dose strength	0.014	0.151	1.026	0.455
54	Salad error (sound alike, look alike drug) factor	New wrong/unclear dose strength, near-miss	0.014	0.151	1.026	0.455
55	Policy/procedures not followed e.g.: double checking factor, near-miss	Wrong formulation	0.015	0.129	1.030	0.427
56	Policy/procedures not followed e.g.: double checking factor	Wrong formulation, near-miss	0.015	0.129	1.030	0.427
57	Wrong formulation, near-miss	Policy/procedures not followed e.g.: double checking factor	0.015	0.123	1.030	0.406
58	Wrong formulation	Policy/procedures not followed e.g.: double checking factor, near-miss	0.015	0.123	1.030	0.406
59	Wrong quantity selected, near-miss	Busier than normal factor	0.030	0.176	1.017	0.352
60	Wrong quantity selected	Busier than normal factor, near-miss	0.030	0.176	1.017	0.352
61	Busier than normal factor, near-miss	Wrong quantity selected	0.030	0.171	1.017	0.339
62	Busier than normal factor	Wrong quantity selected, near-miss	0.030	0.171	1.017	0.339
63	Competence deficiency/training factor, near-miss	New wrong/unclear dose strength	0.017	0.148	1.005	0.087
64	Competence deficiency/training factor	New wrong/unclear dose strength, near-miss	0.017	0.148	1.005	0.087
65	New wrong/unclear dose strength, near-miss	Competence deficiency/training factor	0.017	0.116	1.005	0.066

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
66	New wrong/unclear dose strength	Competence deficiency/training factor, near-miss	0.017	0.116	1.005	0.066

Missing association rules between *error-factor*, error-category and event-type for Reach-patient dataset are as follows:

Rule	Antecedents	Consequents	Support	Confidence	Lift	CF
1	**Reach-patient, patient factor**	**Other**	**0.012**	**0.440**	**3.717**	**36.516**
2	**Patient factor**	**Reach-patient, other**	**0.012**	**0.440**	**3.717**	**36.516**
3	Reach-patient, other	Patient factor	0.012	0.104	3.717	7.831
4	Other	Reach-patient, patient factor	0.012	0.104	3.717	7.831
5	**Reach-patient, salad error (sound alike, look alike drug) factor**	**Wrong drug/medicine**	**0.040**	**0.443**	**2.065**	**29.100**
6	**Salad error (sound alike, look alike drug) factor**	**Reach-patient, wrong drug/medicine**	**0.040**	**0.443**	**2.065**	**29.100**
7	Reach-patient, wrong drug/medicine	Salad error (sound alike, look alike drug) factor	0.040	0.188	2.065	10.665
8	Wrong drug/medicine	Reach-patient, salad error (sound alike, look alike drug) factor	0.040	0.188	2.065	10.665
9	Reach-patient, wrong formulation	Salad error (sound alike, look alike drug) factor	0.012	0.175	1.924	9.256
10	Wrong formulation	Reach-patient, salad error (sound alike, look alike drug) factor	0.012	0.175	1.924	9.256
11	Reach-patient, salad error (sound alike, look alike drug) factor	Wrong formulation	0.012	0.134	1.924	6.902
12	Salad error (sound alike, look alike drug) factor	Reach-patient, wrong formulation	0.012	0.134	1.924	6.902
13	Reach-patient, wrong strength selected	Interruptions factor	0.013	0.225	1.389	7.522
14	Wrong strength selected	Reach-patient, interruptions factor	0.013	0.225	1.389	7.522
15	Reach-patient, salad error (sound alike, look alike drug) factor	New wrong/unclear dose strength	0.018	0.197	1.440	6.978
16	Salad error (sound alike, look alike drug) factor	Reach-patient, new wrong/unclear dose strength	0.018	0.197	1.440	6.978

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
17	Reach-patient, competence deficiency/training factor	Other	0.013	0.166	1.404	5.427
18	Competence deficiency/training factor	Reach-patient, other	0.013	0.166	1.404	5.427
19	Reach-patient, new wrong label	Interruptions factor	0.010	0.219	1.353	6.818
20	New wrong label	Reach-patient, interruptions factor	0.010	0.219	1.353	6.818
21	Reach-patient, new wrong label	Busier than normal factor	0.012	0.249	1.218	5.600
22	New wrong label	Reach-patient, busier than normal factor	0.012	0.249	1.218	5.600
23	Reach-patient, new wrong/unclear dose strength	Salad error (sound alike, look alike drug) factor	0.018	0.131	1.440	4.411
24	New wrong/unclear dose strength	Reach-patient, salad error (sound alike, look alike drug) factor	0.018	0.131	1.440	4.411
25	Reach-patient, wrong quantity selected	Interruptions factor	0.021	0.194	1.199	3.841
26	Wrong quantity selected	Reach-patient, interruptions factor	0.021	0.194	1.199	3.841
27	Reach-patient, interruptions factor	Wrong quantity selected	0.021	0.128	1.199	2.380
28	Interruptions factor	Reach-patient, wrong quantity selected	0.021	0.128	1.199	2.380
29	Reach-patient, other	Competence deficiency/training factor	0.013	0.112	1.404	3.512
30	Other	Reach-patient, competence deficiency/training factor	0.013	0.112	1.404	3.512
31	Reach-patient, new wrong/unclear dose strength	High volume dispensing period factor	0.025	0.180	1.175	3.162
32	New wrong/unclear dose strength	Reach-patient, high volume dispensing period factor	0.025	0.180	1.175	3.162
33	Reach-patient, high volume dispensing period factor	New wrong/unclear dose strength	0.025	0.161	1.175	2.778
34	High volume dispensing period factor	Reach-patient, new wrong/unclear dose strength	0.025	0.161	1.175	2.778
35	Reach-patient, wrong strength selected	High volume dispensing period factor	0.010	0.180	1.175	3.155

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
36	Wrong strength selected	Reach-patient, high volume dispensing period factor	0.010	0.180	1.175	3.155
37	Reach-patient, wrong quantity selected	Busier than normal factor	0.024	0.228	1.116	2.984
38	Wrong quantity selected	Reach-patient, busier than normal factor	0.024	0.228	1.116	2.984
39	Reach-patient, busier than normal factor	Wrong quantity selected	0.024	0.119	1.116	1.389
40	Busier than normal factor	Reach-patient, wrong quantity selected	0.024	0.119	1.116	1.389
41	Reach-patient, high volume dispensing period factor	Wrong drug/medicine	0.036	0.234	1.089	2.434
42	High volume dispensing period factor	Reach-patient, wrong drug/medicine	0.036	0.234	1.089	2.434
43	Reach-patient, wrong drug/medicine	High volume dispensing period factor	0.036	0.166	1.089	1.606
44	Wrong drug/medicine	Reach-patient, high volume dispensing period factor	0.036	0.166	1.089	1.606
45	Reach-patient, wrong quantity selected	Policy/procedures not followed e.g.: double checking factor	0.012	0.113	1.211	2.171
46	Reach-patient, policy/procedures not followed e.g.: double checking factor	Wrong quantity selected	0.012	0.129	1.211	2.528
47	Policy/procedures not followed e.g.: double checking factor	Reach-patient, wrong quantity selected	0.012	0.129	1.211	2.528
48	Wrong quantity selected	Reach-patient, policy/procedures not followed e.g.: double checking factor	0.012	0.113	1.211	2.171
49	Reach-patient, wrong quantity selected	High volume dispensing period factor	0.018	0.171	1.118	2.131
50	Wrong quantity selected	Reach-patient, high volume dispensing period factor	0.018	0.171	1.118	2.131
51	Reach-patient, high volume dispensing period factor	Wrong quantity selected	0.018	0.120	1.118	1.414

Rule	Antecedents	Consequents	Support	Confidence	Lift	Rule
52	High volume dispensing period factor	Reach-patient, wrong quantity selected	0.018	0.120	1.118	1.414
53	Reach-patient, new wrong/unclear dose strength	Busier than normal factor	0.030	0.220	1.076	1.958
54	New wrong/unclear dose strength	Reach-patient, busier than normal factor	0.030	0.220	1.076	1.958
55	Reach-patient, busier than normal factor	New wrong/unclear dose strength	0.030	0.147	1.076	1.207
56	Busier than normal factor	Reach-patient, new wrong/unclear dose strength	0.030	0.147	1.076	1.207
57	Reach-patient, staff resource issue	Other	0.011	0.135	1.140	1.880
58	Staff resource issue	Reach-patient, other	0.011	0.135	1.140	1.880
59	Reach-patient, wrong strength selected	Busier than normal factor	0.012	0.213	1.043	1.098
60	Wrong strength selected	Reach-patient, busier than normal factor	0.012	0.213	1.043	1.098
61	Reach-patient, policy/procedures not followed e.g.: double checking factor	Other	0.012	0.126	1.064	0.854
62	Policy/procedures not followed e.g.: double checking factor	Reach-patient, other	0.012	0.126	1.064	0.854
63	Reach-patient, wrong formulation	High volume dispensing period factor	0.011	0.157	1.030	0.538
64	Wrong formulation	Reach-patient, high volume dispensing period factor	0.011	0.157	1.030	0.538
65	Reach-patient, busier than normal factor	Wrong drug/medicine	0.045	0.219	1.018	0.500
66	Busier than normal factor	Reach-patient, wrong drug/medicine	0.045	0.219	1.018	0.500
67	Reach-patient, wrong drug/medicine	Busier than normal factor	0.045	0.208	1.018	0.471
68	Wrong drug/medicine	Reach-patient, busier than normal factor	0.045	0.208	1.018	0.471