Adoption of Bayesian Network Model to Investigate Organizational Factors Influencing Incident Reporting Practice

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by

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Abstract

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There is an increasing realization that patient safety has a significant influence on quality improvement in healthcare organizations. Patient lives can be put at high risk due to medical errors. Many organizational factors can affect the incident reporting practices in hospitals. As a multidimensional concept, patient safety is mainly measured through surveys in healthcare settings One of the most common and largest workforce surveys in the world is the United Kingdom *National Health Service (NHS) Staff Survey*, which is owned by NHS England and NHS Improvement and carried out every year to improve staff experiences across the NHS. However, there has been limited research regarding the relationships and interdependencies between the organizational factors and the incident reporting practice. To shed light on this, the author of this study collected data from the *NHS Staff Survey* from different hospitals over multiple years to assess the effects of several organizational factors on incident reporting practice using a data-driven Bayesian belief network (BBN) model. Multiple algorithms were tested to develop the BBN model, and the results explored the relationships between nine organizational factors and incident reporting practices. The model reveals that morale and staff engagement are the primary factors that influence the reporting of incidents in organizations. This study contributes the general understanding of the function of organizational factors and their importance in assisting decision-makers and improving safety.

Indexing Terms: patient safety, incident reporting, Bayesian network, data analytics, healthcare operations

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Salma Albreiki

Declaration and Copyright

Declaration

I declare that the work in this thesis was carried out in accordance with the regulations of Khalifa University of Science and Technology. The work is entirely my own except where indicated by special reference in the text. Any views expressed in the thesis are those of the author and in no way represent those of Khalifa University of Science and Technology. No part of the thesis has been presented to any other university for any degree.

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Chapter 1. Introduction

1.1 Chapter Introduction

This chapter provides a general outline of this research, starting with the research motivation and proceeding to the problem statement, objectives, and aim of the research, and finally, the overall thesis structure.

1.2 Background

Medical errors are the third leading cause of mortality in the United States (Makary and Daniel, 2016). According to an Institute of Medicine (IOM) research, every year, medical errors cause 44,000 to 98,000 deaths in hospitals that could have been prevented (Kohn et al., 2000). Medical errors arise as a result of a variety of organizational factors in today's dynamic and complicated healthcare delivery systems (Simsekler et al., 2019). Furthermore, previous research has shown that the limited application of statistical methods may have resulted in the failure to discover the complex links between organizational factors and patient safety (Reis et al., 2018). As a result of these concerns, we constructed a data-driven BBN model to study organizational factors that may affect incident reporting practice and reduce medical error rates. The BBN model identifies statistical dependencies or causal probabilistic interactions among interrelated variables. Furthermore, by utilizing BBN characteristics, the researcher reached beyond simple data analysis to show deep insights, probabilistic results, and useful conclusions.

1.3 Research Motivation

The main motivation for this study is the need to improve healthcare and patient safety. Incident reporting is affected by a range of organizational factors, but the interdependencies between and among these factors are unknown. Thus, to improve understanding, we utilized a BBN to identify what drives incident reporting practices. We also need to identify whether there are any relationships or interdependencies between the organizational factors. A BBN is a probabilistic graphical model that presents a set of variables and their probabilistic relationships (Salini and Kenett, 2009).

1.4 Problem Statement

There are many organizational factors that may affect the patient safety culture in hospitals, and as previously mentioned, incident reporting practice is one of the important factors that might have a great impact on patient safety. We should determine whether different organizational factors cause or impact incident reporting and what leading factors drive incident reporting practice.

Different methods have been applied to help identify the factors that affect incident reporting. There is a need to determine the best methods and tools for assessing the incident reporting in a healthcare organization with the involvement of safety and measurement experts whenever possible. The current tools used to measure incident reporting and patient safety are surveys and questionnaires, where the analysis of the results is confined to simple statistical models. This simple analysis may not identify the complex relationships between multiple organizational factors and incident reporting practice, leading to fewer results and outcomes for decision-making in the area of healthcare management. We present a data-driven BBN model that can be used to predict the incident reporting attribute and the factors that can influence it in response to these concerns. BBN analysis goes beyond simple data analysis to show deep insights, probabilistic results, and meaningful conclusions.

1.5 Research Aims and Objectives

The aim of this research is to explore organizational factors that influence incident reporting practices in healthcare organizations by adopting a BBN model. The objectives of this research are as follows:

- Analyze the different organizational factors that impact incident reporting
- Identify the relationships between these organizational factors and incident reporting
- Apply the BBN model to show the probabilistic dependencies between the organizational factors and incident reporting practices
- Visualize these relationships to show the dependencies among interconnected variables

1.6 Thesis Structure

This section outlines the structure of the thesis. The aim of each chapter is explained in the following list.

Chapter 1. Introduction: This chapter covers the general aspects of this research, including the research background, motivation, problem statement, aims and objectives, and finally, an outline of the thesis structure.

Chapter 2. Literature review: This chapter reviews background information on the general concepts of incident reporting. The organizational factors affecting near miss and incident reporting found in the literature are reviewed and factors facilitating the reporting of near misses and incidents. The NHS organizational factors were also introduced. Finally, the main research question is then formulated and introduced at the end of the chapter.

Chapter 3. Research methodology: In this chapter, the research approach used in this study is discussed. The selected research method is the design research methodology (DRM). In addition, ethical constraints and research issues linked with healthcare research are discussed.

Chapter 4. Dataset analysis: The data source and analysis process are presented in this chapter.

Chapter 5. Results: This chapter presents the results obtained after applying the analysis.

Chapter 6. Discussion: This chapter discusses the implications of the study.

Chapter 7. Conclusion: A review of the major findings along with the study's contributions and limitations and suggestions for potential future work is provided in this chapter.

Chapter 2. Literature Review

2.1 Chapter Introduction

This section begins with the definition of incident reporting in healthcare, followed by a discussion of several organizational factors that affect near-miss and incident reporting practice in healthcare settings. Next, it contains a review of the factors that facilitate reporting culture. The UK NHS organizational factors are also introduced. Finally, the research question is presented.

2.2 Incident Reporting

Patient safety has become a growing concern around the world in recent decades, and healthcare organizations have been progressively implementing policies and changes to enhance it. According to Naome et al. (2020), patient safety is about preventing incidents that can unintentionally harm patients. Incident reporting refers to a voluntary patient safety initiative whereby stakeholders in a patient care process, especially nurses and physicians, provide comprehensive and in-depth information concerning medical mistakes, including near misses and unsafe conditions (Pham et al., 2013). For an incident reporting system to be effective, healthcare organizations must establish a supportive environment, ensure the privacy of those who report events, summarize reported incidents, disseminate analyses on time, and develop action plans. Thus, incident reporting involves tracking, tracing, and reporting adverse events, such as medication errors, that can harm patients or lead to devastating outcomes.

Incident reporting is widely accepted as an effective approach to enhancing patient safety. In particular, incident reporting enables medical professionals to identify the nature and frequency of adverse occurrences in healthcare, facilitating the implementation of corrective measures, such as the institution of policies to preclude recurrence (Al-zain and Althumairi, 2021; Rafter et al., 2015). Moreover, Stavropoulou et al. (2015) claimed that incident reporting can lead to the introduction of staff training to raise people's awareness of risk and create a culture of safety. According to these authors, training also improves healthcare providers' competencies, such as enhancing nurses' drug administration skills, leading to improved patient safety (Stavropoulou et al., 2015). However, despite these benefits, Mjadu and Jarvis (2018) argued that adverse events are highly underreported or not reported at all. According to the authors, these outcomes are associated with staff attitudes, confidentiality concerns, and failure to give feedback after reporting (Mjadu and Jarvis, 2018). Hence, the benefits of incident reporting are not fully realized due to significant barriers that discourage reporting.

Near-miss events are incidents that are addressed before causing harm to a patient but had the potential to do so (Crane et al., 2015). The main concern surrounding near-miss incidents lies in their potential to cause patient injuries, economic losses, and other devastating outcomes when actual accidents occur due to neglecting the significance of near misses. According to Patterson and Pace (2016) and Van Spall et al. (2015), these events are 3–300 times more frequent than adverse incidents causing harm. Given this frequency and significance, increasing attention to near-miss events is necessary to develop effective approaches to enhancing overall patient safety. For example, ElKhider and Savage (2019) identified and assessed incidents that could have become disastrous if not addressed in time, providing healthcare decision-makers with the opportunity to examine root causes and develop solutions, thereby improving patient safety. Thus, health organizations should consider near misses as opportunities for instituting a culture of safety, which is instrumental in ensuring high-quality and safe patient care.

2.3 Organizational Factors Affecting Incident Reporting

Researchers, scholars, and other relevant stakeholders have investigated near-miss incidents and reported on the various factors that discourage nurses and other staff from reporting such occurrences. These factors can be grouped into various categories, such as work environment conditions, which encompass the workload burden on the caregivers, especially increased responsibilities due to the use of a reporting system. Another category is organizational management and managerial behaviours, in which barriers, such as reduced confidence on whether positive change shall be attained after reporting and employees' concerns over punitive actions following incident reporting, feature. Another category is organizational culture, which includes barriers, such as staff perceptions toward error reporting and patient safety.

2.3.1 Work Environment Conditions

Workplace conditions play a significant role in influencing a healthcare provider's willingness to report near misses and incidents. Rajah et al. (2019) identified several work-related factors, including workload and workplace stressors, that contribute to the failure to report near-miss incidents. For example, a working environment that made employees susceptible to distractions and interruptions or one characterized by increased workload was found to be associated with a high number of near misses that were not reported (Rajah et al., 2019). Furthermore, Haw et al. (2014) reported that overwhelmed nurses lacked adequate time to record each incident and often thought that reporting events was not useful. Similarly, Almutary and Lewis (2012), Hartnell et al. (2012), and Sharac et al. (2010) noted that busy and unpredictable working environments were associated with poor incident reporting because nurses were occupied with clinical demands that consumed most of their nursing time. Another work-related factor that influences reporting practice is staffing levels (Shanty, 2011; Vrbnjak et al., 2016). For instance, according to Aveyard (2012), adequately staffed healthcare organizations with nurses attending to between one and five patients had higher rates than understaffed medical institutions regarding incident reporting. In addition, nurses were found to be most likely to report near-miss events when they worked in an environment characterized by healthy relationships among them, patients, and management. Therefore, the conditions in a healthcare organization's working environment play a major role in influencing incident reporting.

2.3.2 Organizational Culture

Organizational culture is an integral component influencing the implementation of high-quality and safe patient care. Mrayyan and Al-Atiyyat (2011) and Shanty (2011) found that healthcare institutions with an organizational culture of continuous quality improvement had staff who were more willing to report incidents than their counterparts in facilities without a well-defined quality improvement culture. In addition, Vrbnjak et al. (2016) concluded that some significant elements of organizational culture, such as power hierarchy, impacted reporting culture. For example, according to Hartnell et al. (2012), staff in organizations that lacked a culture of trust were less likely than others to report medical errors, including near misses. Furthermore, while investigating the impact of patient safety culture on the willingness of staff to report incidents, Armstrong (2021) found that organizations with a culture of patient safety encouraged nurses to report and use incidents as learning opportunities. et al. (2019) echoed this finding, arguing that a culture of patient safety combined with a learning culture promoted error reporting and ensured that staff members were attentive and willing to report events. Thus, organizational culture is a significant contributor or barrier to effective incident reporting.

2.3.3 Management

Fear of Consequences of Reporting

Although incident reporting is critical to improving patient safety, poor managerial behaviors discourage it, leading to adverse outcomes. Near-miss incidents across healthcare institutions are significantly underreported due to various barriers present at the organizational level. One of the reasons for the lack of reporting is ineffective management leading to fear and associated consequences among staff. For example, ElKhider and Savage (2019) and Castel et al. (2015) found that nurses were afraid of reporting near-miss incidents because they felt that doing so would damage their reputation and lead to departmental consequences. In addition, ElKhider and Savage (2019) argued that witnesses of near-miss incidents were less likely to report such events than the people involved because they did not want to get their colleagues in trouble. Similarly, Hashemi et al. (2012) concluded that fear was a major barrier to incident reporting, arguing that practitioners were afraid of being perceived as incompetent. Correspondingly, Vrbnjak et al. (2016) indicated that healthcare providers were less likely to report than others due to the fear of being blamed, facing reprimands, losing their license, and having patients develop negative attitudes toward them. In addition, Hartnell et al. (2012) and Hashemi et al. (2012) argued that physicians, nurses, and other healthcare providers feared that they might get exposed to malpractice suits that could lead to legal actions, job threats, and economic losses after reporting near misses or incidents. Moreover, Haw et al. (2014) concluded that nurses feared that reporting incidents could cause conflicts with colleagues and teams, which could adversely impact the healthcare they provide. As a result, fear of negative outcomes is a significant obstacle to reporting near-miss incidents.

Reporting System

Effective management is needed to promote the attainment of healthcare goals, including patient safety and the provision of a high quality of care. Medical institutions that recognize the significance of near-miss and incident reporting in enhancing the quality and safety of patient care create systems, policies, processes, and standards for reporting. For instance, Vrbnjak et al. (2016), Oshikoya et al. (2013), and Mostafaei et al. (2014) reported that policies and well-defined processes were significant determinants of effective reporting practice. According to Vrbnjak et al. (2016), the lack of effective reporting and recording systems increased the likelihood that near-miss errors or incidents would go unreported.

Furthermore, Bahadori et al., (2013) and Mostafaei et al., (2014) concluded that the absence of reporting standards, especially guidelines regarding what defines a medical error and a near-miss incident, discourages reporting. Moreover, ineffective management fails to encourage nurses and other staff to use reporting systems. For instance, Hartnell et al. (2012) and Hashemi et al. (2012) argued that clinicians had a negative perception of reporting systems because they perceived them as a burden, especially due to the associated paperwork and cumbersome forms. As a result, nurses were unlikely to report because they felt that they had insufficient time or that reporting increased their workload (Hartnell et al., 2012; Hashemi et al., 2012). In such a situation, it can be concluded that the management has failed to establish policies and standards that require or encourage nurses to recognize and report medical errors and near misses as they occur.

Managerial Behavior

The behavior of management toward medical errors and near-miss incidents is another significant determiner of staff reporting intentions. According to Mohammad et al. (2016) and Almutary and Lewis (2012), managers who treat medical errors individually instead of assessing them from a system's point of view discourage reporting. For example, inappropriate managerial behaviors, such as focusing on finding culprits and blaming nurses for medical errors and near-miss incidents, discourage reporting. Furthermore, how healthcare leaders react to medical errors and near-miss incidents is a significant determinant of nurse willingness to report such events. For example, managers who overreact may instill fear and cause deterrence toward reporting (Almutary and Lewis, 2012). Management's failure to provide feedback after near misses or incident reporting or use data related to reporting to institute positive change discourages reporting. For instance, according to Vrbnjak et al. (2016), this behavior causes nurses and other staff to develop the perception that no action was taken after they reported medical errors and near-miss incidents. Regarding feedback, Vrbnjak et al. (2016) noted that managers who provided positive feedback, such as corrective measures that should be taken to avoid incidents, to all staff without focusing solely on the adverse outcomes encouraged reporting. Hence, managerial behavior when dealing with reported medical errors and near-miss events, such as providing meaningful feedback and focusing on the whole system instead of individuals, influences nurses' perceptions of and intentions to report such events.

2.4 Factors Facilitating the Reporting of Near-Miss Errors

Reporting near-miss and incident events is critical to improving patient safety and mitigating recurrences. According to Crane et al. (2015), near-miss incidents provide opportunities for healthcare providers to recognize and rectify mistakes that endanger patient safety. However, although errors in the healthcare delivery system are unavoidable, and providers, including nurses, have an obligation to disclose errors, including near misses, these incidents are largely underreported in many medical institutions. This outcome makes health organizations miss out on opportunities to enhance patient care. For example, according to Armstrong (2021), although near-miss incidents have the potential to cause patient harm, reporting them may be a significant resource for developing and improving safety. Thus, healthcare organizations can implement various methods, such as establishing a functional reporting system and addressing workplace conditions that discourage reporting, to encourage staff to report incident events.

2.4.1 Anonymous Near-Miss Reporting Systems

Management is critical in motivating employees to report incidents. A significant barrier to near-miss and incident reporting is the absence of reporting guidelines and standards (Mostafaei et al., 2014; Bahadori et al., 2013). In addition, the fear of facing negative repercussions after reporting incidents, such as damaging one's reputation, taking the blame, getting exposed to malpractice suits and legal actions, and being perceived as incompetent, discouraged reporting culture (Hashemi et al., 2012; ElKhider and Savage, 2019; Castel et al., 2015; Vrbnjak et al., 2016; Hartnell et al., 2012). To address these barriers, Crane et al. (2015) argued that implementing an anonymous reporting system encourages reporting because it reduces people's concerns about possible punitive actions. Similarly, in a study on the barriers to medical error reporting, AAnal and Seren (2016) concluded that anonymous reporting systems created a fear-free workplace atmosphere that encouraged error reporting. In implementing the strategy, Vrbnjak et al. (2016) and Hartnell et al. (2012) claimed that the anonymous reporting system must have well-defined policies, processes, standards, and definitions to ensure staff members understand what constitutes medication errors and the significance and procedure of incident reporting. In addition, the reporting system is designed such that it does not increase physician and nurse workloads. This requirement ensures that nurses and other providers perceive it positively and are motivated to use it to report errors, including near-miss events (Vrbnjak et al., 2016; Hartnell et al., 2012). Thus, an anonymous reporting system eliminates the fear associated with reporting and improves the general understanding of reporting significance and processes, encouraging near-miss and incident reporting.

2.4.2 Organizational Culture of Learning

Managerial behaviour toward the reporting culture can lead to deterrence. For instance, according to Almutary and Lewis (2012) and Vrbnjak et al. (2016), some managers respond to near-miss and incident events in ways that can instil fear and discourage reporting. In addition, Vrbnjak et al. (2016) noted that some organizations do not provide feedback regarding incident reports, giving physicians and nurses the impression that nothing would be done even if they reported the incidents. According to Haw et al. (2014), healthcare organizations address these barriers by replacing the blame culture, which focuses on finding culprits and blaming nurses, with an organizational culture of learning. This strategy entails educating practitioners about medical errors, including near-miss incidents, and the significance of learning from them (Haw et al., 2014). Lee (2021) supported this claim by arguing that incident events should be perceived as cases that can improve nursing practice or important issues that should be shared and learned. Similarly, Uribe et al. (2002) echoed these findings, arguing that establishing an organizational culture of learning helps staff realize how error reporting contributes to patient care quality and safety improvement. In addition, according to Armstrong (2021), this initiative is essential and worthy of consideration because it makes nurses consciously and willingly report near-miss events, ensuring that all near misses, including events with the potential to cause more severe harm than perceived by providers, are reported. Furthermore, Armstrong (2021) supported the creation of a learning and supportive workplace environment, arguing that it can reduce organizations' reliance on traditional punitive responses to medical errors. Therefore, concrete and practical efforts that create an organizational culture in which near-miss incidents are perceived as learning opportunities are essential to promoting reporting.

2.4.3 Improved Workplace Conditions That Include Practices in the Workplace that Facilitate the Reporting culture

Workplace conditions significantly influence physician and nurse willingness and capacity to report near misses and incident events. For example, Rajah et al. (2019) and Haw et al. (2014) identified a negative relationship between increased nurse workload and reporting culture. In particular, increased workload made nurses occupied with clinical demands around the clock, meaning that they lacked time to focus on reporting events. Furthermore, Rajah et al. (2019) noted that some work settings made employees susceptible to distractions and interruptions, reducing the possibility that they would report near-miss and incident events. In addressing workplace-related issues, especially high workloads, healthcare organizations focus on improving staffing levels. For example, in a study on the causes, reporting, and prevention of medication errors, Aveyard (2012) found that adequately-staffed medical institutions had higher rates of near-miss reporting than understaffed healthcare facilities. To improve staffing levels, health organizations can hire staff or encourage the retiring workforce to continue to work. In addressing workplace distractions and interruptions that adversely impact reporting events, health organizations can collaborate with the relevant stakeholders to create reporting forms that can be filled within two minutes to save time. Furthermore, management can advise nurses to set reminders to stimulate events or integrate reporting into quality improvement efforts. Therefore, improving staffing levels to reduce nurse workloads and encouraging nurses to report events by creating fast-to-fill reporting forms and setting reminders can improve near-miss and incident reporting.

2.5 NHS Organizational Factors

This study will mainly focus on the UK *NHS Staff Survey* data. The NHS data summarizes 10 different organizational indicators to provide an overview of staff experience.

- **Equality, Diversity, and Inclusion**

Equality, diversity, and inclusion (EDI) involve fair treatment and equal opportunities for all people, regardless of personal characteristics, such as religion, gender, ethnic background, age, sexual orientation, and disability (Nair and Vohra, 2015). EDI's primary goal is to eliminate prejudice and discrimination, including bullying, harassment, and victimization, based on people's protected traits.

- **Health and Wellbeing**

Health and wellbeing involve the link between work, an employee's health status, and the role of organizational stakeholders, including management, in adopting organization-wide strategies that enhance staff health and wellbeing (Hafner et al., 2015). This factor involves creating an environment that continuously facilitates a state of satisfaction, benefiting both employees and employers.

- **Morale**

Morale refers to practitioners' attitude, contentment, and overall outlook during their tenure with an organization. The term reflects how healthy a health organization's workers are satisfied, motivated, engaged, respected, recognized, and supported at the workplace. In addition, morale assesses how happy employees are to the extent of contributing willingly towards the attainment of organizational objectives (Sania et al., 2015).

- **Immediate Managers**

The immediate manager refers to the individual from whom a medical expert receives instructions, assignments, and work-related projects. This person is often a departmental manager or a staff supervisor and is responsible for employees' day-to-day operations, including supervision and the provision of work-related feedback. One's immediate manager is the closest member of an organization's management and takes an interest in worker health, opinions, and concerns related to their work (Paillé et al., 2019).

- **Quality of Care**

Quality of care refers to the extent to which provided health services increase the likelihood of achieving targeted health outcomes. Care perceived as high-quality is effective, safe, person-centered, timely, equitable, integrated, and efficient (World Health Organization, 2020). Quality care also includes the application of modern medical technology and should be non-discriminatory.

- **Safe Environment-Bullying**

Bullying in the workplace refers to inappropriate behaviors or actions that psychologically, mentally, or physically harm medical employees. Bullying can occur in various forms, including excessive supervision from immediate managers, overly harsh or unjust criticism from supervisors, continued denials of requests, threats, verbal abuse, and physical assault (Canadian Center for Occupational Health and Safety, 2022). Bullying may be perpetrated by managers, colleagues, patients, and their families.

- **Safe Environment-Violence**

Violence refers to actions of physical assault, including harassment and intimidation, directed toward medical professionals in the workplace. The most common types of violence perpetrated against health workers, such as nurses, include physical aggression, verbal abuse, and mobbing from patients and their families, and sexual harassment, discrimination, and intimidation from managers and colleagues (Mento et al., 2020; Phillips, 2016; Zhang et al., 2017).

- **Safety Culture**

Safety culture refers to healthcare professionals' shared beliefs, perceptions, and values surrounding health and safety management. Safety culture in medical institutions is characterized by elements such as collaboration, organizational learning, effective communication, shared cultural perception, and the provision of constructive and non-punitive feedback and responses to medical errors. Safety culture guides health experts' discretionary behaviors toward attaining high-quality and safe patient care, such as reporting errors, near misses, and incidents (Khoshakhlagh et al., 2019).

- **Staff Engagement**

Staff engagement in healthcare refers to the involvement of medical professionals in vital organizational activities, including decision-making and problem-solving, to the extent that they show enthusiasm and dedication toward contributing to the attainment of organizational goals. Engaged staff members are happy and motivated, and perceive their organizations positively (Shantz et al., 2016).

- **Team Working**

Team working means working in a group to achieve shared objectives (Casimiro et al., 2015). Successful teamwork requires leadership, effective communication, training, well-defined team rules, and a clarified purpose.

2.6 Research Question

As stated in the first chapter, the thesis objective is to investigate organizational factors that influence near misses and incidents reporting practice in healthcare organizations by adopting BBN models. The literature review on incident reporting revealed that there has been little research dedicated to identifying the determinants that influence the reporting culture in hospitals. As a result, the research question is the following:

RQ: What is the organizational factor that most influences incidents reporting practices in healthcare?

2.7 Chapter Summary

This chapter presented the concept of near-miss and incident reporting along with their definitions. A variety of factors that influence reporting culture have been researched and recorded in the related literature. In addition, some factors that facilitate the reporting of events were explored in this section. The last part of this chapter covers the study question, which was developed based on the gaps that exist in the literature on the reporting culture in healthcare. The applied research methodology will be provided in the next chapter to address the research question in a symmetrical way.

Chapter 3. Research Approach

3.1 Chapter Introduction

The purpose of this study is to provide a comprehensive framework for understanding and mapping the causes of incident reporting by identifying the main independent variables that impact reporting practice. This will enable healthcare organizations to gather the knowledge they need to develop and improve their systems. The research methodology is outlined in this chapter, along with a practical research approach for systematically developing this knowledge. The DRM framework will be utilized as a supporting framework and guide in this study. Its phases and research design considerations are investigated later in this chapter.

3.2 Design Research Methodologies

The purpose of design research is to developed techniques, approaches, suggestions, and tools to help overcome challenges in the healthcare industry (Gericke and Blessing, 2011). To gain deep scientific knowledge through research, a methodology must be used, and this knowledge must be well-defined, produced, and systematically validated (Simsekler et al., 2018). It is essential to understand what sort of research methodology to utilize in any research paper because it improves the efficiency of scientific research in achieving research goals and objectives (Blessing and Chakrabarti, 2009). A variety of approaches are available to assist researchers in selecting the most appropriate method and approach.

The current study may be classified as design research because the goal is to discover the key factors of incident reporting practice to develop improved healthcare environments for patients. In general, there are a variety of methodologies used in design research. However, the DRM chosen in this research was proposed by Blessing and Chakrabarti (2009). This was due to its widespread application and success in the field of healthcare design. Hinrichs and John, (2009) and Simsekler et al. (2018) demonstrated the DRM framework's efficiency and effectiveness.

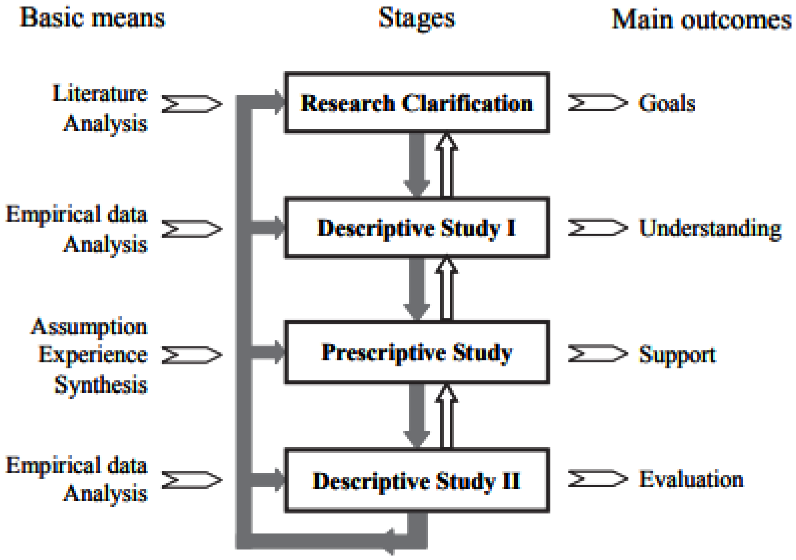

Figure 1: The DRM Framework by (Blessing and Chakrabarti, 2009)

Blessing and Chakrabarti (2009) defined and explained the DRM framework, which was utilized as a supporting framework and guide in this study. The framework includes four main stages: research clarification (RC), descriptive study I (DS-I), prescriptive study (PS), and descriptive study (DS-II). As shown in Table 4, there are seven different types of design research projects; Type 2 was chosen for this study. The main focus and expected outcomes of each stage are shown in Figure 1.

In general, the DRM framework, including all seven types and stages, may be implemented in parallel and iteratively. As a result, the phases do not have to be completed in order. Furthermore, the researcher might focus on a few stages or start at any of the previously-listed stages. The seven different types of DRM frameworks are shown in Table 1. Within the DRM framework, Blessing and Chakrabarti (2009) propose many forms of design research, which are based on needs such as being a comprehensive and review-based study.

Table 1: Design Research Project Types (Blessing and Chakrabarti, 2009)

Research Clarification	Descriptive Study I	Prescriptive Study	Descriptive Study II
1. Review-based	Comprehensive		
2. Review-based	Comprehensive	Initial	
3. Review-based	Review-based	Comprehensive	Initial
4. Review-based	Review-based	Review-based Initial/ Comprehensive	Comprehensive
5. Review-based	Comprehensive	Comprehensive	Initial
6. Review-based	Review-based	Comprehensive	Comprehensive
7. Review-based	Comprehensive	Comprehensive	Comprehensive

As shown in the table above, Type 2 was a suitable research design for the current study. It begins with the RC stage, followed by the comprehensive stage (i.e., DS-I), and finally, the PS, which can then suggest how the outcomes should improve the final design. The results of each phase, as well as the expected outcomes, are discussed in detail below.

3.2.1 Research Clarification

The main goal at this stage is to clarify the scope and focus of the study by conducting a literature review and identifying the main outcomes and research goal. The aim of the literature review was to gain deep insight into the topic. The success criterion was defined as the determination of the relationship between different organizational factors and the main drivers that influence incident reporting.

3.2.2 Descriptive Study I

After identifying the main goal and gaining sufficient insight, this stage provides an in-depth understanding of the defined goal. To clearly understand the current situation, it is essential to obtain an understanding of the factors that influence the success criteria (Blessing and Chakrabarti, 2009). A variety of related empirical studies were studied to emphasize the importance of the current situation and get additional knowledge about the primary description.

3.2.3 Prescriptive Study

During the PS stage, researchers worked on establishing the design support tool to improve the quality of problem definition using the insights gained. Identifying the most effective tool is an important aspect of resolving the success criterion to identify the major drivers of incident reporting. The Python programming language and GeNIe modeler were the tools chosen for this research. The discretization of the data was conducted in the Python programming language while the BBN model was developed in Genie. These tools are briefly explained below in the next subsections.

Bayesian Belief Networks

A Bayesian Belief Network (BBN) is a probabilistic graphical model that presents a number of variables and their probabilistic relationships (Salini and Kenett, 2009). BBNs are represented as directed acyclic graphs (DAGs), which are widely used in the fields of statistics, machine learning, and artificial intelligence. A DAG is made up of a set of variables (nodes) and the relationships between them (arcs) (Bhushan et al., 2018). Probability distributions capture the intensity of the relationships among interconnected variables. Any variable node's probability distribution is determined only by its parents. As a result, the probability distribution in a Bayesian network (BN) with n nodes (X1, …, Xn) may be expressed as follows:

$$P(X_1, \dots, X_n) = \prod_{i=1}^{n} P(X_i | P_a(X_i)) \qquad \text{Eq. 1}$$

Where Pa(Xi) is the set of probability distributions corresponding to node Xi's parents. BBNs are now recognized as an effective tool for risk analysis and decision support in real-world problems. Despite the fact that BBNs have been successfully investigated in a wide range of applications, they still do not have much impact in the patient safety context, especially incident reporting practice. Therefore, it is aimed to study the application of BBNs in finding the cause of incident reporting using a survey dataset.

Applications of BBN

BBNs have been successfully used in different fields, such as healthcare and education. Some of the applications of the use of BBN are discussed in this section. BBNs provide the best method of showcasing interactions between data points. They account for noise in stochastic events, ensuring that only strong interactions are highlighted across the data. They can also be used to identify causation, which makes them particularly useful in understanding gene interactions (Isci et al., 2012). Isci utilized the experimental data available on KEGG, BioGrid, Reactome, and NPI databases to create naive BNs (Isci et al., 2012). This data was then used to identify 25 independent variables that could affect gene interactions. Of the total available data, 80% was used to train the model while the remaining 20% was used to test it (Isci et al., 2012). The resulting model, consisting of learned parameters of interaction, was then used with external knowledge to assess its efficiency at predicting gene interactions. The authors found that it was able to predict such interactions at a 90% efficiency rate (Isci et al., 2012). Given the high levels of biological data being generated continuously, the model can be used in the future to immediately identify pathways and interactions between genes, helping to make sense of the data.

Large datasets also exist within clinical practices, and BNs can aid in understanding this data. For instance, the availability of large volumes of electronic patient records can enable people to increase the accuracy of their risk assessments. Historically, however, clinical analyses have involves the use of regression-based models. In contrast, in a review, Arora et al. (2019) highlighted the advantages of BNs over regression-based models. As stated by the authors, BNs are able to visually represent causal relationships between variables (Arora et al., 2019). They can also be used to generate "what if" scenarios and aid in precision medicine by providing individual risk assessments. Arora et al. (2019) used a BN to illustrate their point, presenting a patient with no prior information other than an x-ray result who had a 6% chance of having either cancer or tuberculosis. When additional symptoms, like being a smoker or having dyspnea were added, the probability increased to 21%. Unlike regression-based models, BNs can be constantly updated as new information comes in (Arora et al., 2019). This feature makes BNs a better choice than regression-based models for individual risk assessment and enabling decision-making under conditions of uncertainty. Consequently, in the future, BNs will provide the required flexibility to include advancements in interventions and knowledge, ensuring the use of relevant and up-to-date clinical practices.

In contrast, other studies have found both BNs and regression models to be equally effective. Twardy et al. (2006) compared networks with existing predictive models in the field to test their efficacy in predicting coronary heart disease. They used the data from two previous studies to create BNs. These models were then compared to each other, to the regression model and "points-based" model originally used in other studies, and the goodness of fit of the engineered BN models (Twardy et al., 2006). The authors found that the BNs and logistic regression models performed similarly well. However, the most advantageous features were found to be their easy-to-use user interface and intuitiveness, which enable clinicians to use them without any background technical knowledge (Twardy et al., 2006). These models can be further expanded to include decision-making and costing, enabling practitioners to evaluate potential interventions concerning their efficacy and healthcare cost.

The efficacy of healthcare management also extends to the effective use of limited resources. Aktas et al. (2007) used a BN to create a decision support system (DSS) that could help healthcare managers improve the efficiency of the existing decision support systems. The authors first identified the key variables that were influencing efficiency and created a BN to understand their conditional dependency and uncertainty and highlight which of the variables was the most critical in this regard (Aktas et al., 2007). The model was then applied to a private hospital in Turkey. Aktas found that "time spent on scrutiny" was the biggest problem faced by healthcare managers. According to their BN, this variable is most affected by the variable called type of scrutiny. Thus, managers could reduce the time spent on scrutiny by offering different services on different days (Aktas et al., 2007). In essence, the BN provided an easily visualized means of understanding where primary resources should be allocated and could be used by any healthcare manager without a technical background (Aktas et al., 2007). This model can also be used by policymakers to improve the efficiency of healthcare systems and provide high-quality healthcare on a limited budget.

Patient management also includes the reduction of medical errors, which can occur within a healthcare system due to a variety of organizational factors. Previous statistical approaches have not been successfully used to identify the relationship between such factors and patient safety. To rectify this, Simsekler and Qazi (2020) used a data-driven BN model to not only identify which factors affect medical error but also their relative importance. The authors utilized British *NHS Staff Survey* data to pinpoint eight factors that could impact patient safety, which were then fed into a BN model to understand their interconnectedness (Simsekler and Qazi, 2020). The model revealed that health and wellbeing and bullying and harassment in the work environment were the primary causes of medical errors (Simsekler and Qazi, 2020).

These two factors were identified as unique factors that healthcare managers might employ to improve healthcare quality. The use of a data-driven BN to affect evidence-based practice could also encourage practitioners to collect new data that could be updated in the model to provide deeper insights into the underlying conditions that affect patient care.

Few researchers have used BNs to address the complex relationship between factors contributing to natural disaster risk management. Qazi and Simsekler (2021) assessed the risk exposure of 191 countries using an INFORM dataset that contained 21 continuous variables. On the basis of their negative performance, they were categorized into three distinct groups: low, medium, and high. The grouped data was then used to create a BN model that could visually represent the complex interdependencies among the factors (Qazi and Simsekler, 2021). This is particularly significant for disaster risk assessment because ignoring the interconnectedness of different factors could lead to subpar strategizing and poor resource allocation (Qazi and Simsekler, 2021). The BN model could also be used in countries with varying levels of risk to prioritize their resources (Qazi and Simsekler, 2021). Policymakers will be better able to appreciate the complex networks between the factors, enabling them to design holistic strategies with which to manage natural disasters.

Finally, BNs have proven to be effective in analyzing the reasons for student attrition from higher education institutions. In a study conducted by Delen et al. (2020), a large dataset on freshman students was obtained from a number of sources within the university. After processing, this data was discretized and used to create a naive BN (Delen et al., 2020). Delen et al. (2020) found that the BN model they created was able to predict student attrition at an efficiency rate of 83%. Importantly, the model highlights the need to include knowledge from domain experts, such as administrators, when studying attrition (Delen et al., 2020). The ability of BNs to be updated with incoming information enables researchers to create highly sensitive predictive models that can be used by education administrators to improve student retention at their institutions.

BBN Algorithms

Many different algorithms may be used to learn the structure of a Bayesian network. These algorithms are classified as constraint-based or score-based. The constraint-based approach involves constructing a network utilizing data by using conditional independence statements (Kelangath et al., 2012). The score-based approach, on the contrary, involves the use of a scoring function to assess the quality of Bayesian network models and choose the one with the highest score (Behjati and Beigy, 2018). In this study, we investigated the models of the tree augmented naive Bayes (TAN) algorithm, and it to two other algorithms: Peter and Clark (PC) and greedy thick thinning (GTT). All models found were compared according to their prediction accuracy.

- **TAN:**

The TAN algorithm is a semi-naive structure learning algorithm that is based on the Bayesian search method (Friedman et al., 1997). It is a tree-like expanded Naive Bayes algorithm in which the only parent of all variables in the network is the class variable.

The TAN model only allows for one level of interaction between random variables. The class node has a direct edge with all the feature variables. As a result, while computing the P(C|A1, A2… AN), it will take all the variables into account. Furthermore, each variable is connected to another variable by a direct edge, except for the specialized property known as the root. Because the interaction between the variables is limited to one, the computational complexity of this model is reduced. “Thus, TAN maintains the robustness and computational complexity of the Naive Bayes model while improving accuracy” (Friedman et al., 1997).

- **PC:**

The Peter and Clark (PC) algorithm is one of the oldest constraint-based algorithms that was used in this study. It starts with an undirected graph that is fully linked (Spirtes and Glymour, 1991). The PC algorithm begins by determining whether each pair of variables is independent of one another. If they are independent, then the approach eliminates the edge between them because such an edge would indicate dependency. Then the algorithm uses conditioning sets of increasing size to look for conditional independencies between each pair of variables. If a conditional independency is identified, then edges between them are removed. The outcome is a network of undirected edges, including all the right edges, but none are oriented (Spirtes and Glymour, 1991).

- **GTT:**

The GTT algorithm, which is based on Bayesian search, was published in the work of Cheng et al. (1998). It begins with an empty graph at a certain location in the structure space then continues to add surrounding arcs until no further arc enhances the Bayesian score, to maximize the Bayesian score (i.e., the thickening phase). Next, it begins to reduce arcs until it reaches a local optimum (i.e., the thinning phase). The end outcome is the model that best matches the provided data (Calle-Alonso et al., 2019).

Python Programming Language

The Python language was used as a tool to categorize the continuous variables before performing the BBN, because most BBN algorithms only function with categorized data, and the K-means clustering method was used to discretize the data. Python is a scripting language that is high-level, interpreted, interactive, and object-oriented. It has significantly been used in industrial applications and academic research since the early 2000s. Python is being compared to a variety of other computer languages for data analysis, interactive, exploratory computing, and data visualization, including R, MATLAB, SAS, and Stata (McKinney, 2013).

GeNIe modeler

The GeNIe modeler was used in this study to create the Bayesian network structure. It is a graphical user interface (GUI) for BayesFusion (2020) Structural Modeling, Inference, and Learning Engine (SMILE). GeNIe enables users to build models of unlimited size and complexity, with the only constraint being the operational memory of the computer you are using. SMILE is an interactive model building and learning engine for graphical models, such as Bayesian networks, influence diagrams, and structural equation models (BayesFusion, 2020).

3.2.4 Descriptive Study II

The research design Type 2 was chosen for this study. As a result, the DS-II will not be implemented. Therefore, there will be no assessment or evaluation of the support tools produced during the PS stage of this study.

3.3 Procedure

The proposed process for exploring the relationships between the different organizational factors and reporting culture is presented in Figure 2. First, the organizational factors that can influence incident reporting culture were identified from the NHS survey data. The data were checked for missing values then discretized into states using the k-means clustering method in Python. Next, BBN models were created using various algorithms using different discretization schemes. The best BBN model was chosen based on the prediction accuracy found in GeNIe. Next, different tools in GeNIe, such as diagnostic analysis and scenario analysis, were implemented to identify the main organizational factors that influence reporting practice. These approaches assist decision-makers in ranking significant risk drivers and enable them to assess the relative importance of factors in successful resource allocation.

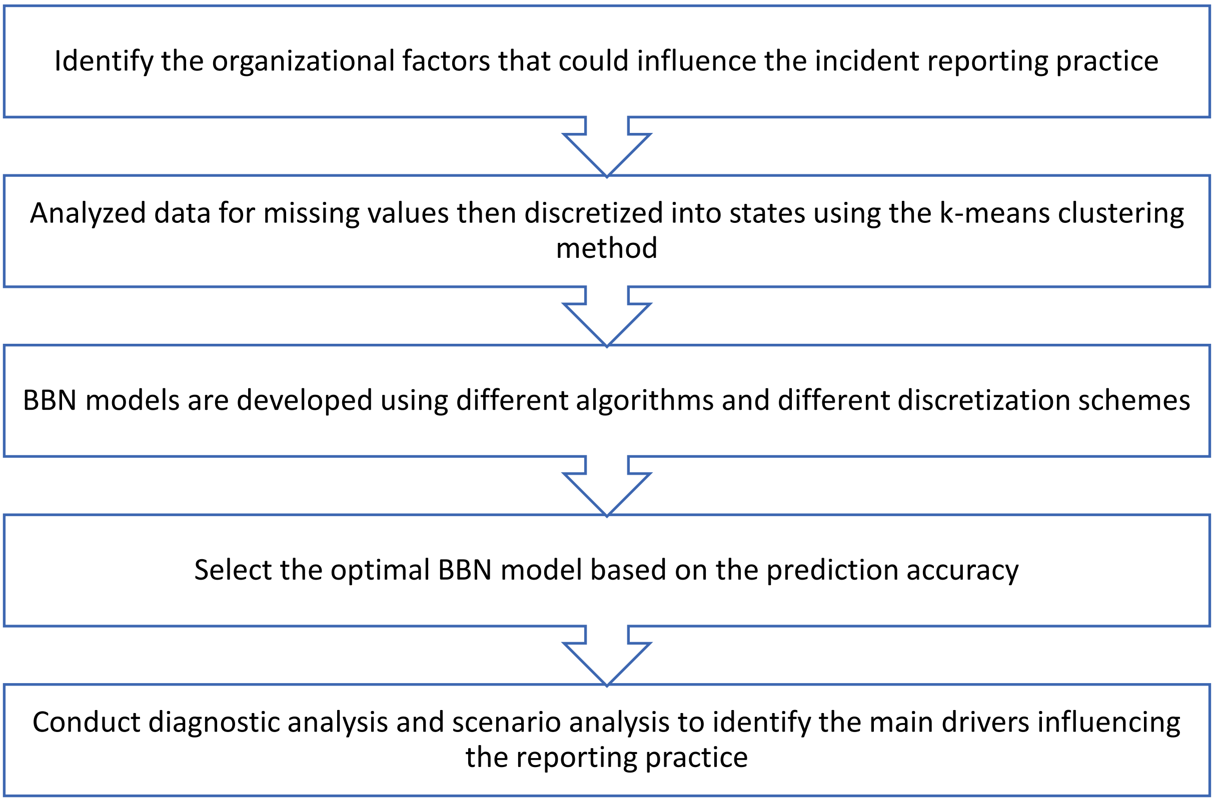

Figure 2: Process for identifying the main drivers influencing the reporting practice

3.4 Chapter Summary

This chapter contained an introduction to the research methodology used in the research. The selected methodology, DRM, has been effectively used in design-related healthcare studies and has proven validity. Furthermore, the stages of such a procedure were well outlined. Finally, this chapter contained a discussion of study issues, as well as the method and standards for ethical approval.

Chapter 4. Dataset

4.1 Chapter Introduction

This chapter contains a discussion of the dataset utilized in this study. The procedure followed to analyse the dataset is then explained in detail.

4.2 Descriptive Statistics

The National Health Service (NHS) Staff Survey has been performed yearly since 2003, and is one of the most comprehensive workforce surveys in the world (Newton, 2021). Over a million NHS staff have been encouraged to join and share their perspectives on their experiences working for their respective NHS organizations. The Staff Survey questions have been created to ensure a complete understanding of working experience across the NHS in England by distributing strong and validated questions and indexes to employers and national stakeholders concerning staff experience. To guarantee good data quality, NHS England performs high-level validations on the data given by NHS trusts (NHS SSCC, 2020). Allowing all employees to participate in the survey ensures that the results are representative of the workforce and therefore reliable.

The dataset used in this research is from the UK NHS Staff Survey between 2018 and 2020, which enables organizations to survey their employees in a regular and systematic manner. There are nine reporting themes in the data that might be relevant to patient safety: (X1) Equality, diversity & inclusion; (X2) Health & wellbeing; (X3) Immediate managers; (X4) Morale; (X5) Quality of care; (X6) Safe environment – Bullying & harassment; (X7) Safe environment – Violence; (X8) Staff engagement; (X9) Team working. The "Safety culture" theme was not considered because our outcome measure was one of the questions under the safety culture theme (NHS SSCC, 2020).

All themes are assessed on a 0-10 point scale and the mean scores are presented. A higher theme score always suggests a better outcome. Each theme addresses two to nine questions. Our outcome measure is one of the questions from the survey data, "when errors, near misses or incidents are reported, the organization takes action to ensure that they do not happen again" (X10, item q16c).

We utilized descriptive analysis to detect missing data and potential distributional outliers for the whole dataset prior to analysis. The analysis was performed in Python using the Pandas library. First, the *NHS Staff Surveys* across hospitals for the years between 2018 and 2020 were merged and had a total of 384 observations. Some survey items were missing from the data. As a result, they were eliminated, leaving 371 observations for the final analysis. The goal of the descriptive analysis summarized in Table 2 was to understand the behavior of the data.

Table 2: Descriptive Analysis of Data

Variable	Count	Mean	Median	SD	Min	Max	Range
Diversity	371	9.03	9.10	0.29	8.06	9.63	1.57
Health & wellbeing	371	5.95	5.95	0.28	5.19	6.87	1.69
Immediate managers	371	6.81	6.81	0.21	6.20	7.49	1.29
Quality of care	371	7.47	7.47	0.20	6.96	8.13	1.17
Morale	371	6.16	6.17	0.25	5.42	6.90	1.47
Staff engagement	371	7.03	7.03	0.23	6.39	7.65	1.26
SE – Bullying & harassment	371	7.98	8.01	0.28	7.11	8.69	1.58
SE – Violence	371	9.45	9.45	0.10	9.08	9.76	0.68
Team working	371	6.56	6.55	0.22	5.91	7.31	1.40
Incident Reporting	371	0.71	0.71	0.05	0.56	0.84	0.28

4.3 Data Discretization

Most BBN algorithms work with discrete data. Therefore, the simplest method is to discretize the continuous variables such that the algorithms discussed in Chapter 3 may be used (Scanagatta et al., 2019). Moreover, Beretta et al. (2018) found that the results achieved for the BBN of discrete variables are better than those obtained for continuous variables concerning accuracy. The K-means clustering method was used to discretize the data before modeling it in this study. This method was conducted in Python using the Scikit-learn library (Scikit-Learn User Guide, 2017).

K-means clustering is one of the most widely used discretizing methods. It is useful for discretizing continuous variables because it computes a continuous distance-based similarity measure to cluster data points (Palaniappan and Hong, 2008). It originates from signal processing aimed at partitioning and observing k clusters in which each observation is the cluster that has the nearest mean, which serves as the cluster's prototype (Pandey and Singh, 2016). The discretization strategy for input data occurs via the use of the maximum and minimum dataset values, computed cluster centers, and the midpoints between every two clusters. The elbow method and the silhouette method are both used to calculate the value of K.

4.3.1 Elbow Method

The elbow method entails plotting the various cost values with changing K values (Umargono et al., 2020). It performs k-means clustering on the dataset for a range of K values (e.g., 1 to 10), and then computes an average score for all clusters for each k value. The score of distortion is computed by default, and the total of the square distances from each point is allocated to its center. After plotting the overall metrics for each model, it is possible to visually find the best value for K (Umargono et al., 2020).

As the value of K increases, increasingly few elements remain in the cluster, resulting in decreased average distortion. The lower the number of elements presented, the closer they get to the centroid. The point at which the distortion declines is mostly called the elbow point. At such a point, the arm can be facing either up or down with a strong inflection point, which is an indication that the underlying model suits best at such a point (Umargono et al., 2020).

4.3.2 Silhouette Method

Silhouette analysis is used to determine the similarity of a point to its own cluster (cohesion) when compared to other clusters (separation). The silhouette value varies from +1 to -1 (Lengyel and Botta-Dukát, 2019). A high value is desirable and is an indication that the point has been placed in the correct cluster. When the majority of the objects have a high value, it indicates that the clustering setup is appropriate (Lengyel and Botta-Dukát, 2019). To identify the value of k using the silhouette method, a range of potential K values is picked (i.e., a number of clusters), then k-means clustering is trained for each K value (Lengyel and Botta-Dukát, 2019).

After the graph analysis of both methods was completed, there was difficulty determining the value of K using the elbow method because it is difficult to decide where the bend of the elbow was. The silhouette graph automatically gives the output of the K value with the highest silhouette coefficient and might be considered a better way to find the K value compared to the elbow method (Saputra et al., 2020).

The Python library Scikit-learn was used to find the K values for each variable in the dataset by following the silhouette method. The results of the silhouette method are shown in Table 3.

Table 3: K Values of the Organizational Factors

Variable	K value
Diversity	2
Health & wellbeing	2
Immediate managers	3
Quality of care	2
Morale	2
Staff engagement	3
SE – Bullying & harassment	2
SE – Violence	3
Team working	3
Incident Reporting	3

As seen in the table above, some of the variables resulted in two clusters while the others had three. Therefore, in this study, we worked with three various discretization schemes to change the continuous variables to categorical variables before modeling in GeNIe.

Chapter 5. Results and Analysis

5.1 Chapter Introduction

This chapter contains the results of the use of different algorithms in GeNIe to identify the most influential variables on incident reporting. Diagnostic and scenario analysis are also conducted for further analysis.

5.2 Models prediction accuracy

We used GeNIe to create our models and adopted the discretization scheme described in the previous section. Three different algorithms (i.e., PC, GTT, and TAN) were tested using three different discretization schemes. The BBN models were verified using a k-fold cross-validation approach (Marcot and Hanea, 2021) implemented in GeNIe (BayesFusion, 2020), which consists of dividing a dataset into k equal-sized parts, training the network on k-1 parts, and testing it on the final kth part. The procedure is then repeated k times, with each testing iteration using a new part of the data (Qazi et al., 2020). There are differing views on the best value of k; a value that is too low might lead to biased findings while a value that is too high can lead to excessive computing times. A value of $k = 10$ is generally seen as reasonable (Kuhn and Johnson, 2013). The validation result demonstrates the class node accuracy in testing the algorithm's efficacy for various discretization schemes. Equation 2 can be used to calculate the prediction accuracy of such data-driven models.

$$Accuracy = \frac{number\ of\ correct\ predictions}{total\ number\ of\ records} \qquad \text{Eq. 2}$$

The prediction accuracies for various discretization schemes and algorithms are shown in Table 4.

Table 4: Prediction Accuracy of Models with Different Discretization Schemes and Algorithms

Discretization Scheme (Number of States)	Algorithms	Prediction Accuracy (In Percentage)
Two states	PC	74.6
	GTT	77.89
	TAN	**78.7**
Three states	PC	71.4
	GTT	71.15
	TAN	70.0
Mix states	PC	64.9
	GTT	71.1

TAN	69.0

As shown in Table 4, TAN surpasses the PC and GTT algorithms with a prediction accuracy of 78.7%. As a result, the remaining procedure was implemented in a two-state discretization scheme using the TAN algorithm. Figure 3 shows the network structure of the TAN algorithm.

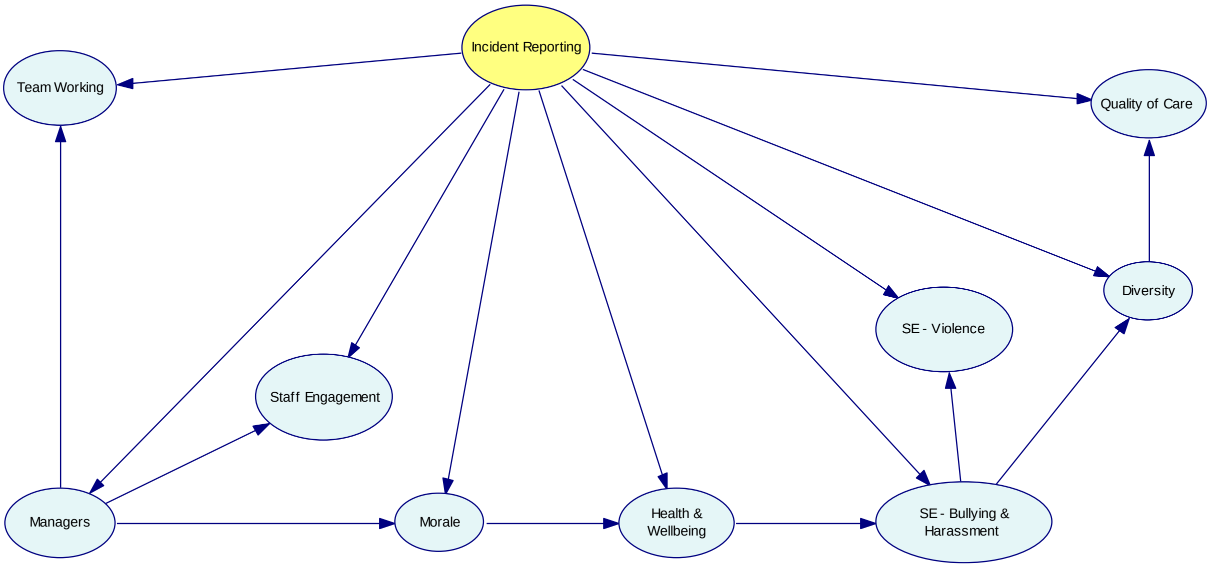

Figure 3: Network structure developed using the TAN algorithm

The model found in Figure 3 using the TAN algorithm shows the arcs between the 10 variables. It does not take into consideration the interdependence of the factors. This model, on the contrary, illustrates statistical interdependence among variables regarding the dataset used for this research. All variables are dependent variables and each one has a direct relationship between the class node and one extra variable, except for *managers*. Managers is the only independent variable that only depends on incident reporting practice. This node is called the "root" (i.e., a node without any parent).

Table 5: TAN Confusion Matrix with two states

		Predicted	
		State 0	State 1
Actual	State 0	**136**	32
	State 1	47	**156**

The confusion matrix in Table 5 illustrates the relationship between the TAN algorithm's actual and predicted states. The bold numbers represent the numbers of accurately detected predictions for the class node. In the validation stage, out of 371 records tested, 292 were correctly identified with an accuracy of 78.7%.

5.3 Tree Augmented Naïve Bayes Model

The probability distribution of the organizational factors associated with the incident reporting practice is displayed as a bar chart in Figure 4. According to this model, 55% of the cases were related to State 1 (high state) of incident reporting practice, while 45% of the cases were related to State 0 (low state). Diversity had the highest probability of State 1 (80%) among all the factors considered in the model.

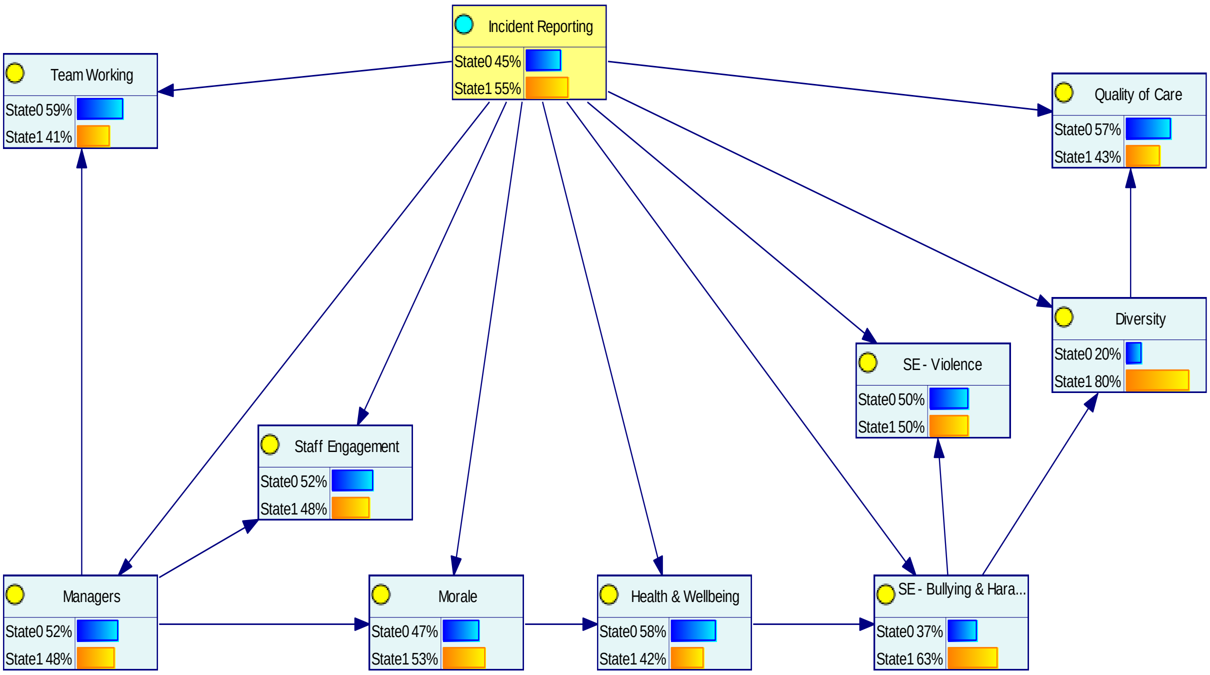

Figure 4: Probability distribution of factors associated with incident reporting

The model in Figure 4 was then examined for the low state (Figure 5) and high state (Figure 6) of the incident reporting to evaluate the change across variables in the network.

In Figure 5, it can be seen that almost all the variables, except *safe environment - bullying & harassment* and *safe environment - violence* and *diversity*) had an impact on their State 0 which had increased to above 75% when the class node was at a low state (State 0). In Figure 6, team working, quality of care, health and wellbeing, and safe environment–violence were the variables that did not face a great impact when the class node had a high state (State 1). The other variables faced increases in their high state in parallel to the class node.

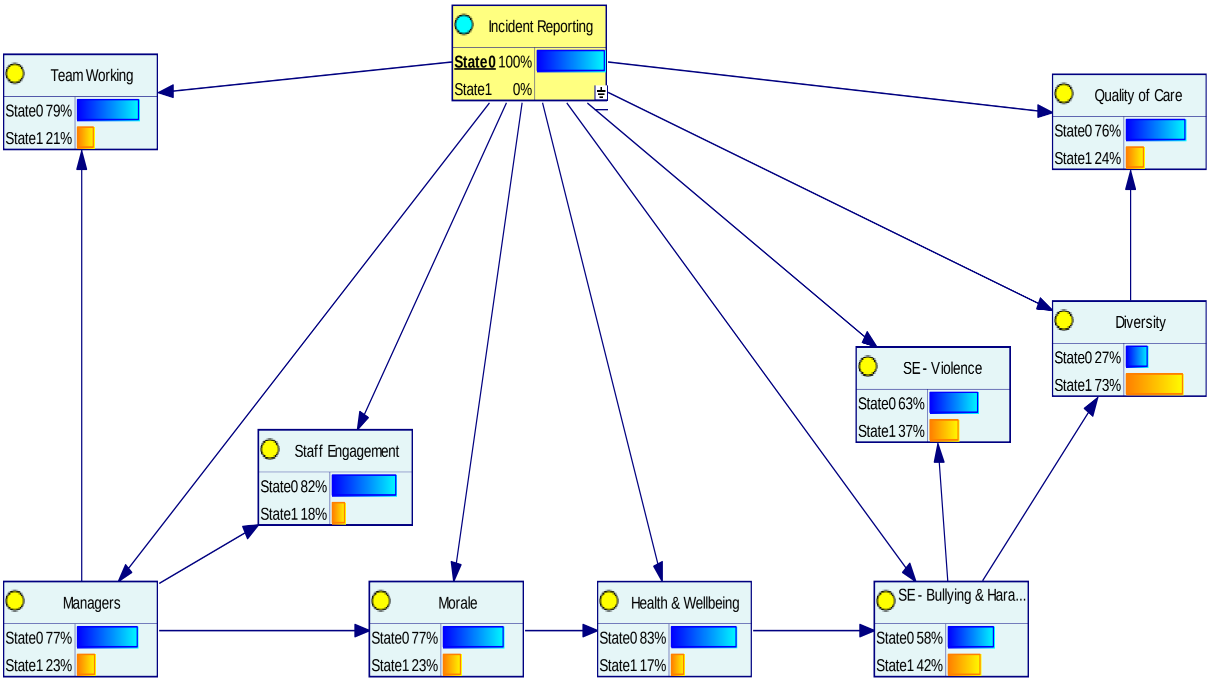

Figure 5: Backward propagation of variable once the low state incident reporting is established

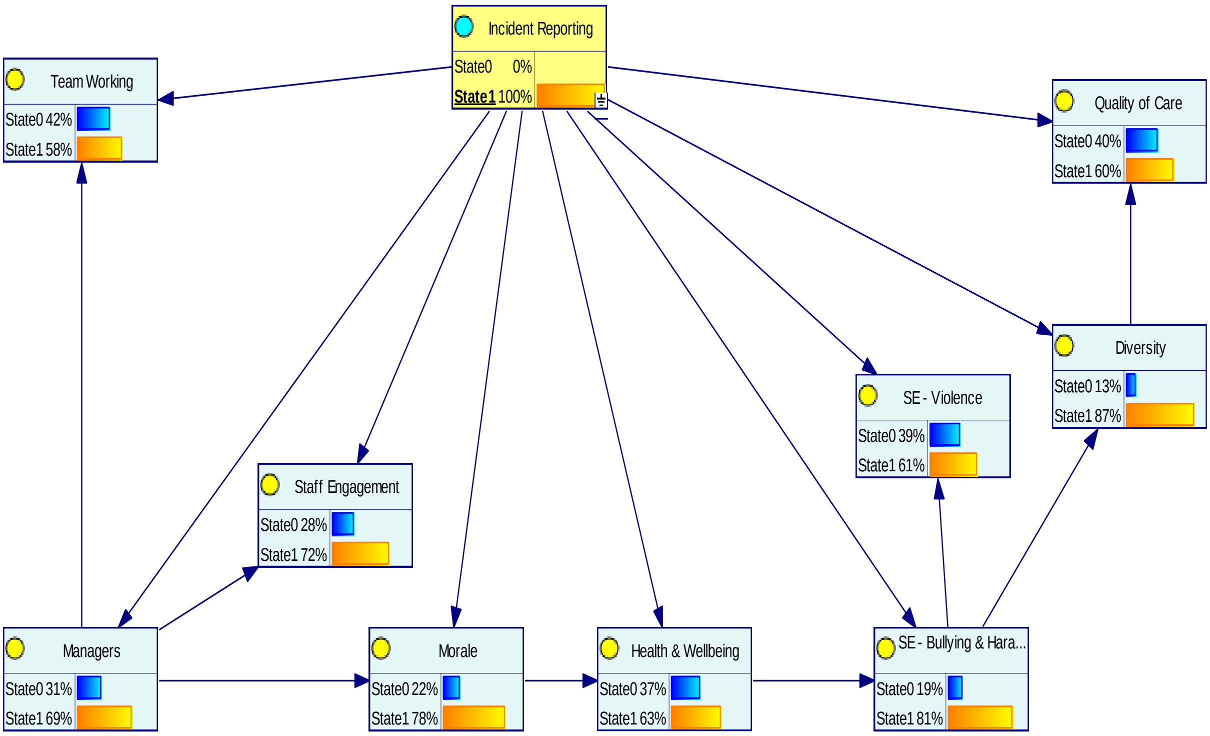

Figure 6: Backward propagation of variable once the high state incident reporting is established

The impact assessment of the organizational factors given the high state of incident reporting is summarized in Figure 7. The figure shows the increase in the probability of State

1 (as a percentage) for each variable. This assessment is done to identify how much improvement is required across different variables to be able to optimize the target variable. Overall, the results showed that morale and staff engagement are the two leading factors in the backpropagation assessment given a high state of incident reporting.

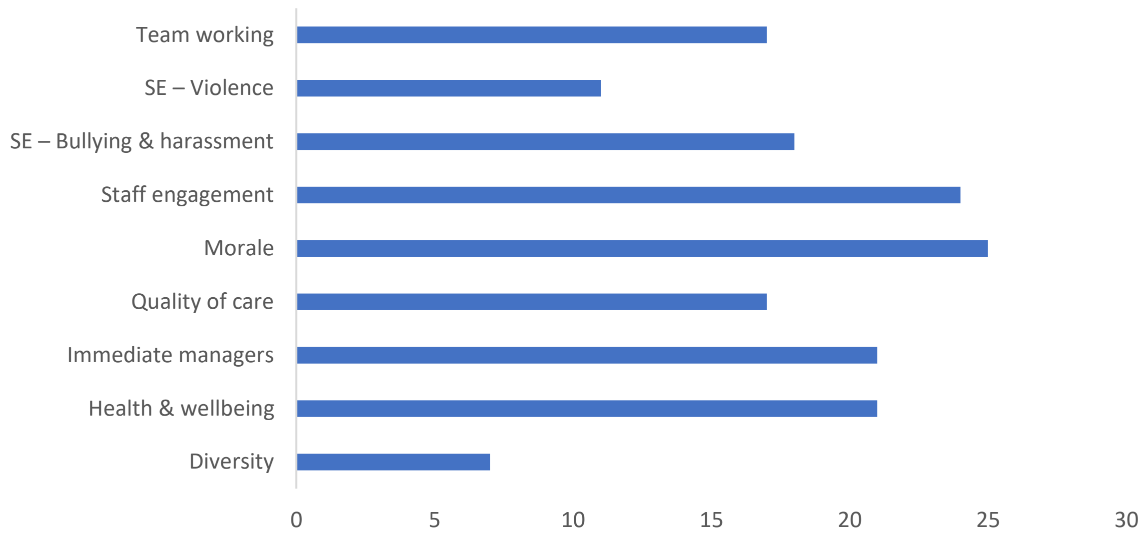

Figure 7: Back propagation impact assessment given the incident reporting in the high state

5.3.1 Diagnostic Analysis

Diagnostic analysis is a feature users can gain an understanding of the variables that can influence incident reporting practice. Therefore, this method is about looking into the association between individual variables and the target variable. The objective of diagnostic analysis is to determine the causes of a problem so classification-based decisions can be made. The ranking is based on cross-entropy, an information-theoretic measure that reflects the predicted reduction in entropy of the probability distribution across the target variable after viewing each domain separately. Cross-entropy is a utility-free measure of information value that provides an accurate evaluation of the value of the data in diagnosing the disorder in question (BayesFusion, 2020). Figure 8 shows the observations ranked from the most to the least informative. Morale was identified as the most influential domain because it yielded the highest diagnostic value (0.232), and staff engagement was identified as the second-most influential domain with a value of (0.228). This suggests that risk managers and policymakers should promote morale and staff engagement to gain major benefits from the reporting practice.

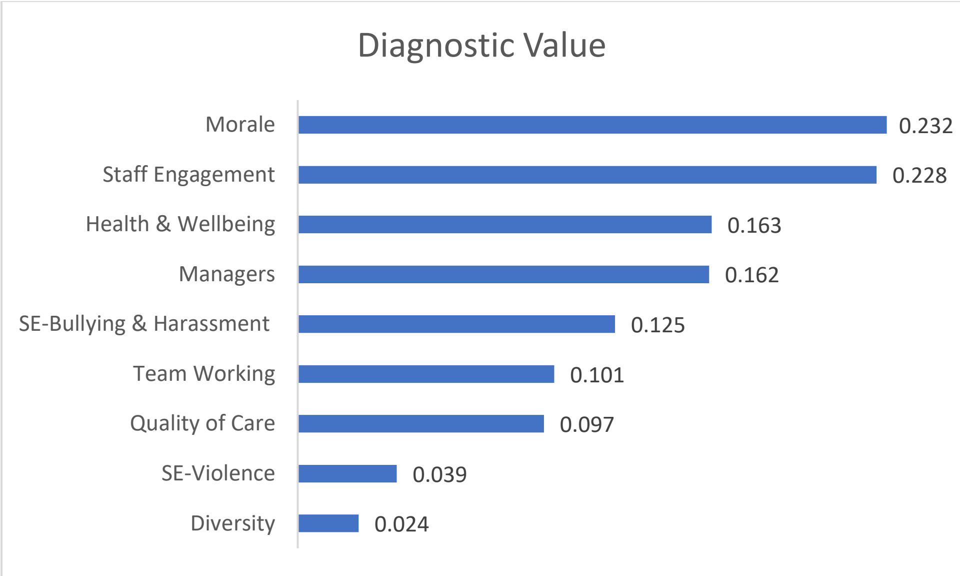

Figure 8: Diagnostic values of organizational factors

5.3.2 Forward Propagation

Forward propagation analysis is used to examine the propagation of one or more variables and measure their effects on the target node. It is simply a cause-and-effect analysis. We analyzed three different scenarios using forward propagation.

Scenario 1 has *morale* in its high state (State 1) because this variable is the most influential organizational factor that impacts incident reporting practice. This gave us a chance to see how the morale factor will affect our class variable (incident reporting) as well as its effect on other factors. Figure 9 shows that the target node State 1 had increased from 55% to 80%.

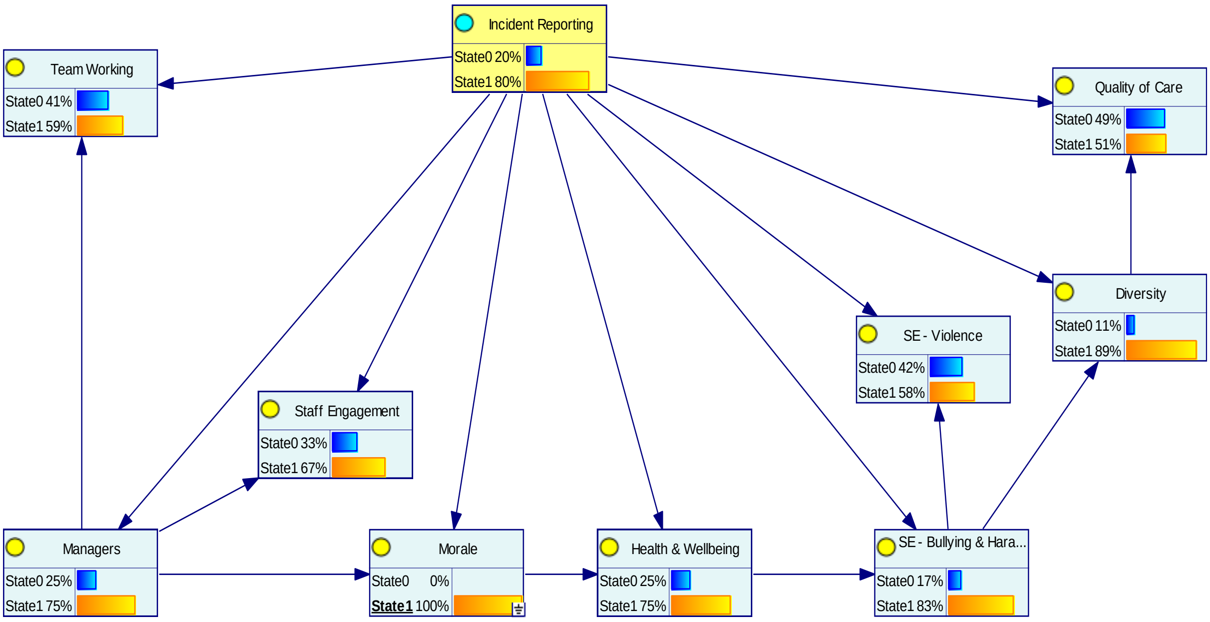

Figure 9: Incident reporting once the high state of the most influential variable (morale) is established

Scenario 2 has the *staff engagement* at high state (state 1), knowing that this variable is one of the most influential organizational factors that impacts the *incident reporting* practice. Figure 10 shows that the target node state 1 had increased from 55% to 83%.

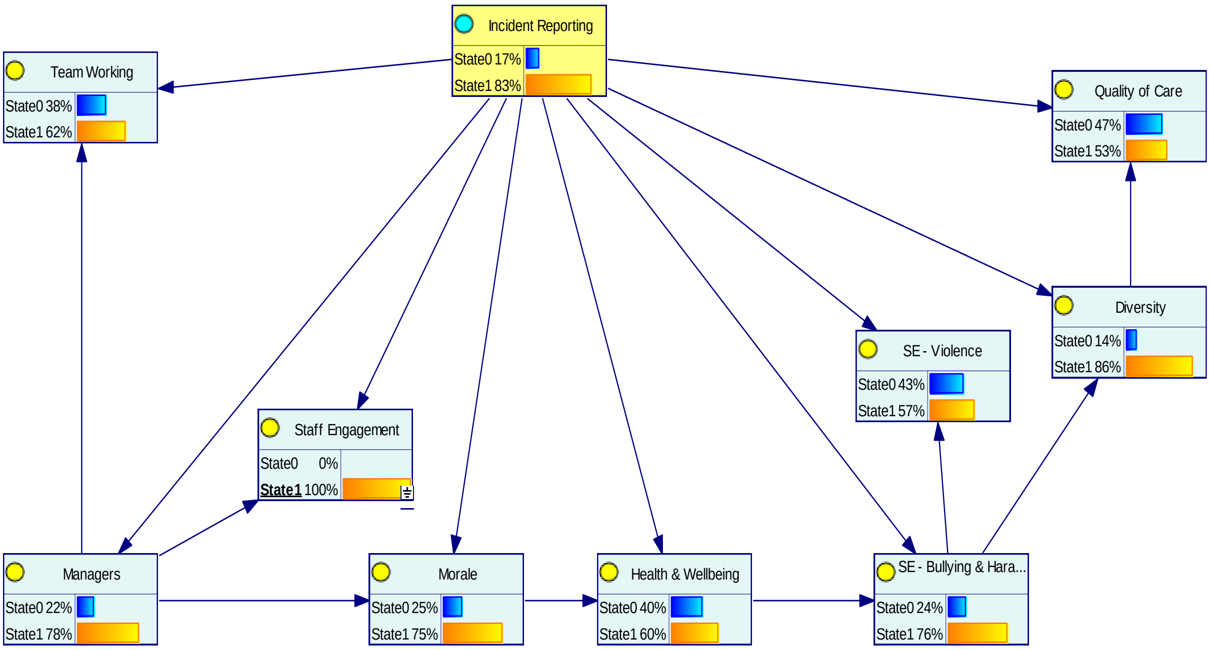

Figure 10: Incident reporting once the high state of (staff engagement) is established

Scenario 3 has both *morale* and *staff engagement* at high state (state 1), knowing that these variables are the two most influential organizational factors that impact the *incident reporting* practice. Figure 11 shows that the target node state 1 had increased from 55% to 92%.

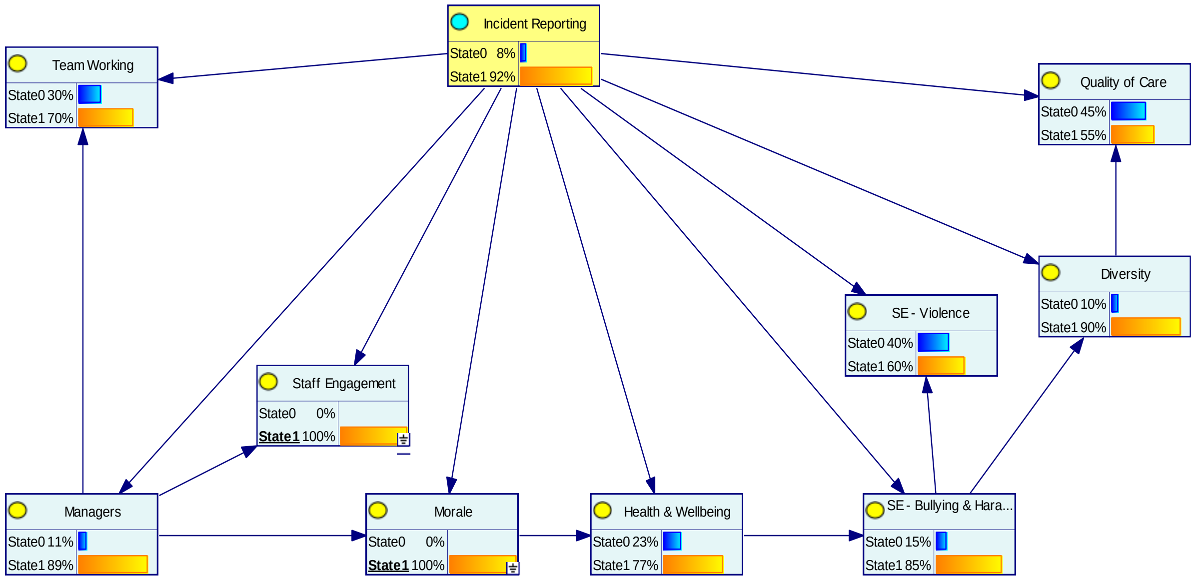

Figure 11: Incident reporting once the high state of morale and staff engagement is established

The relative impact of each variable was also determined by analyzing the change in the probability distribution of the target variable (incident reporting) as a result of each factor's extreme states. As seen in Figure 12, staff engagement was identified as the most essential factor concerning its influence on incident reporting because it resulted in the highest increase in likelihood (28%) related to the target variable.

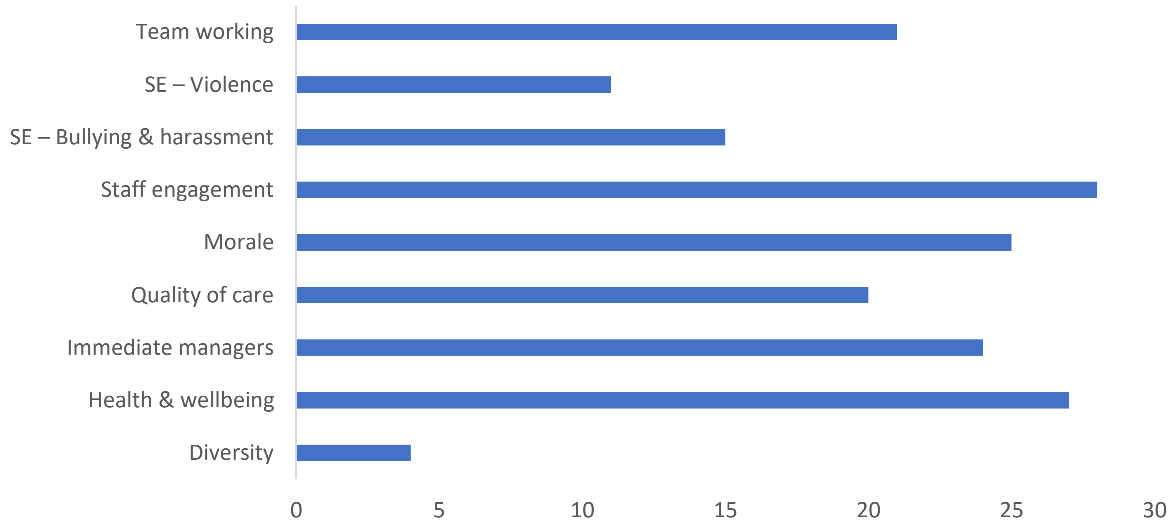

Figure 12: Impact of individual factors on the incident reporting relative to their high state "s1"

5.4 Chapter Summary

This chapter contains a description of the selection of the BBN algorithm based on the prediction accuracy found in GeNIe. Different approaches in GeNIe, such as diagnostic and scenario analysis, were used to identify the main drivers that influence incident reporting.

Chapter 6. Discussion

6.1 Chapter Introduction

In this chapter, a detailed discussion of the results described in the previous chapter is provided, along with supporting evidence from the literature.

6.2 Discussion

There are many organizational factors that may affect incident reporting practice, which is one of the factors that have a great impact on healthcare organizations. The following nine organizational factors from the NHS were analyzed concerning their impacts on reporting practice: (X1) Equality, diversity & inclusion; (X2) Health & wellbeing; (X3) Immediate managers; (X4) Morale; (X5) Quality of care; (X6) Safe environment – Bullying & harassment; (X7) Safe environment – Violence; (X8) Staff engagement; (X9) Team working. The results show that these factors have a great impact on reporting practice. A BBN model was used to explore the factors and identify their interdependencies and relative impacts on incident reporting practice. The most influential drivers in our models were found to be the *morale* and *staff engagement* factors, which were identified using diagnostic analysis in GeNIe. As a result, we were able to achieve our research purpose by identifying the main organizational factors that influence reporting practice.

These factors have been recognized in the literature as factors that contribute to safety risks in a variety of areas, including healthcare. The morale of healthcare professionals is widely perceived as an important factor in safety and quality of care. According to Sabotiva et al. (2020), healthcare providers with positive job morale are more likely than others to deliver high-quality care to patients. In addition, they link job morale with enhanced job performance and improved retention among medical professionals (Sabitova et al., 2020). Similarly, Sania et al. (2015) argued that workers with positive morale were happy, productive, creative, satisfied with their jobs, and committed to attaining organizational objectives instead of personal goals. Furthermore, in a study on the relationship between patient safety and incident reporting, Kelly et al. (2016) identified a link between employee optimism and patient experiences. In their study, they discovered that employees with positive morale shared effective practices, inspired and facilitated quality improvement, valued safe prescribing practices, and supported innovations (Kelly et al., 2016). Notably, these outcomes improve patient safety. Thus, improved morale benefits healthcare organizations by enhancing staff performance, employee retention, and patient safety.

There exists a positive correlation between near misses and incident reporting and morale. For example, Kelly et al. (2016) suggested a new approach to incident reporting that enabled healthcare organizations to recognize and capture learning from events of peer-reported excellence. Upon evaluating the proposed system—the learning for excellence model—the authors discovered that it positively influenced team learning, patient care, and staff morale. Arguably, reporting near misses and incidents helps capture valuable workarounds and adaptations, promotes excellence in practice, and advances staff competencies through medical training and professional development, leading to improved morale.

Successful healthcare leaders are aware of the organizational benefits of staff engagement. According to Kruse (2015), employee engagement increases people's emotional commitment to an organization. For example, the author argued that engaged workers are more likely to care about their institutions, colleagues, and patients than their disengaged counterparts (Kruse, 2015). In addition, Vidal (2019) argued that engagement makes employees feel worthwhile and useful, motivating them to infuse empathy into their clinical care and invest their mental, physical, and emotional energies into job performance. Moreover, Vidal (2019) reported that engaged staff are attentive to details and connected to organizational missions, purposes, and people. As a result, they are committed to meaningfully contributing toward improving job performance, which encompasses patient safety outcomes. Hence, staff engagement increases staff commitment toward attaining organizational goals and objectives, including patient safety.

Staff engagement directly impacts near-miss and incident reporting. For example, Ashcroft (2006) reported that employees who were less engaged with incident reporting systems were less likely to report adverse events than others because they felt that reporting was statistically insignificant. In addition, Macrae (2016) argued that the lack of staff engagement could make employees perceive incident reporting as simply logging problems and waiting for solutions instead of an opportunity for learning and sharing insights. Furthermore, organizations that do not recognize the significance of staff engagement may appear to provide insufficient, meaningless, or no feedback to workers after reporting adverse events (Macrae, 2016). Notably, feedback is instrumental in demonstrating the value of incident reporting and informing people about actions taken and lessons learned. Thus, the lack of staff engagement impedes near-miss and incident reporting.

According to our findings, healthcare organizations should support better staff experience to prevent incidents and near misses that may harm patients and staff. Although all nine themes had statistically significant relations with incident reporting, the results also presented important insights and suggestions on the relative impact of the factors. As a result, morale and staff engagement may require additional attention for new safety improvements to be realized.

6.3 Chapter Summary

This chapter contains a summary of findings of this study in a brief discussion along with supporting evidence from the literature. Morale and staff engagement were identified as the most influential factors on our target variable (incident reporting).

Chapter 7. Conclusion

7.1 Chapter Introduction

This chapter brings the investigation to a close. The research's key findings and primary contributions are discussed in this chapter. The limitations of this study are also presented, along with suggestions for future research.

7.2 Key Findings and Contributions

This study introduced a comprehensive framework for understanding and mapping the causes of incident reporting by identifying the main independent variables that impact this reporting practice. A variety of related empirical studies were reviewed to emphasize the importance of incident reporting practices. Current related literature contains a gap concerning what factors most influence incident reporting practices and how are they connected to other organizational factors. Moreover, because the researchers of previous studies in this context have failed to use new methodologies, the framework established in this study includes unique analysis tools with which to clarify the relationships between the studied organizational factors. Python and GeNIe were used to come up with a BBN with which to examine the influence of several organizational factors on incident reporting practices. The study was applied to the *NHS Staff Survey*, which included 371 responses from staff members at different hospitals around the UK. The key findings of the implemented analysis are presented below:

- After discretizing the data and testing three different BBN algorithms, we found that TAN had the highest prediction accuracy. Therefore, it was used in this study to adopt a BBN network in GeNIe.
- The leading factors that impact incident reporting practices based on the scenario and diagnostic analysis were *morale* and *staff engagement*.
- In addition to the relationships between the target variable and each of the factors, we identified eight interdependencies, while the *managers* variable was the only independent variable that solely depends on incident reporting practice.

This study's main contribution is the identification of the main factors that influence incident reporting practices. The study used a data-driven BBN to assess the relative importance of several organizational factors and their impacts on incident reporting practices. The graphical model supports our understanding of the influence of various organizational factors on our target variable. The results can provide hospitals with important insights into the various organizational factors that influence incident reporting. Furthermore, our findings might help healthcare institutes and hospitals prioritize their resources and focus on the specific aspect or aspects that are causing problems.

7.3 Limitations and Future Work

This study has some limitations. The data had to be discretized before the BBN could be applied in GeNIe. Another typical concern in the medical field, particularly in survey studies, is the issue of missing data. This research is based on hospital-level aggregate data. Therefore, unique hospitals' relative importance rankings of organizational factors may differ. Finally, because the data is limited to UK hospitals, the generalizability and transferability of the findings to other countries may be limited, and the relationships between staff experience and errors that affect patient and staff safety may differ.

Future research may benefit from the consideration of other factors and features that may affect healthcare reporting practices. Using the same methodology in a specific organization might help future researchers. Furthermore, substantial information might be gained by developing the model with local (UAE) survey data. In addition to comparing local outcomes to those from other regions of the world. We can start by implementing the same methodology to the UAE local data, while also considering more domains such as culture context and environment. Alternative discretization methods or machine learning methodologies may be evaluated and integrated further in studies to compare prediction abilities and potential discrepancies in the relative importance of organizational aspects. It would be useful to collect data from patients as well to explore how their experiences relate to safety results. Moreover, even though NHS resources ("Data quality Improvement," 2020) states that they have conducted validation tests, they did not explicitly present a specific methodology for it. Future research might look at hospital-level data to investigate opportunities for the validation of the survey further.

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Appendices

Appendix A: Survey Questions

Survey Question
1. Equality, diversity & inclusion
Q14 - “Does your organization act fairly with regard to career progression / promotion, regardless of ethnic background, gender, religion, sexual orientation, disability or age?” Q15a - “In the last 12 months have you personally experienced discrimination at work from patients / service users, their relatives or other members of the public?” Q15b - “In the last 12 months have you personally experienced discrimination at work from a manager / team leader or other colleagues?” Q26b - “Has your employer made adequate adjustment(s) to enable you to carry out your work?"
2. Health & wellbeing
Q5h - "The opportunities for flexible working patterns."
Q11a - “Does your organization take positive action on health and well-being?”
Q11b - “In the last 12 months have you experienced musculoskeletal problems (MSK) as a result of work activities?”
Q11c - “During the last 12 months have you felt unwell as a result of work related stress?”
Q11d - “In the last three months have you ever come to work despite not feeling well enough to perform your duties?”
3. Immediate managers
Q5b - “The support I get from my immediate manager.”
Q8c - “My immediate manager gives me clear feedback on my work.”
Q8d - “My immediate manager asks for my opinion before making decisions that affect my work."
Q8f - “My immediate manager takes a positive interest in my health and well-being.”
Q8g - “My immediate manager values my work.”
4. Morale
Q4c - “I am involved in deciding on changes introduced that affect my work area / team / department.”
Q4c - “I am involved in deciding on changes introduced that affect my work area / team / department.”
Q6a - “I have unrealistic time pressures.”
Q6b - “I have a choice in deciding how to do my work.”
Q6c - “Relationships at work are strained.”
Q8a - “My immediate manager encourages me at work.”
Q19a - “I often think about leaving this organization.”
Q19b - “I will probably look for a job at a new organization in the next 12 months.”
Q19c - “As soon as I can find another job, I will leave this organization.”
5. Quality of care
Q7a - “I am satisfied with the quality of care I give to patients / service users.”
Q7b - “I feel that my role makes a difference to patients / service users.”
Q7c - “I am able to deliver the care I aspire to.”
6. Safe environment - Bullying & harassment
Q13a - “In the last 12 months how many times have you personally experienced harassment, bullying or abuse at work from patients / service users, their relatives or other members of the public?” Q13b - “In the last 12 months how many times have you personally experienced harassment, bullying or abuse at work from managers?” Q13c - “In the last 12 months how many times have you personally experienced harassment, bullying or abuse at work from other colleagues?”
7. Safe environment - Violence
Q12a - “In the last 12 months how many times have you personally experienced physical violence at work from patients / service users, their relatives or other members of the public?”

Q12b - “In the last 12 months how many times have you personally experienced physical violence at work from managers?”

Q12c - “In the last 12 months how many times have you personally experienced physical violence at work from other colleagues?”

8. Safety culture

Q16a - “My organization treats staff who are involved in an error, near miss or incident fairly.”

Q16c - “When errors, near misses or incidents are reported, my organization takes action to ensure that they do not happen again.”

Q16d - “We are given feedback about changes made in response to reported errors, near misses and incidents.”

Q17b - “I would feel secure raising concerns about unsafe clinical practice.”

Q17c - “I am confident that my organization would address my concern.”

Q18b - “My organization acts on concerns raised by patients / service users.”

9. Staff engagement

Q2a - “I look forward to going to work.”

Q2b - “I am enthusiastic about my job.”

Q2c - “Time passes quickly when I am working.”

Q4a - “There are frequent opportunities for me to show initiative in my role.”

Q4b - “I am able to make suggestions to improve the work of my team / department.”

Q4d - “I am able to make improvements happen in my area of work.”

Q18a - “Care of patients / service users is my organization’s top priority.”

Q18c - “I would recommend my organization as a place to work.”

Q18d - “If a friend or relative needed treatment I would be happy with the standard of care provided by this organization.”

10. Team working

Q4h - “The team I work in has a set of shared objectives.”

Q4i - “The team I work in often meets to discuss the team’s effectiveness.”