THE EFFECT OF IMPLEMENTING A MODIFIED EARLY WARNING SCORE ON
PATIENT OUTCOMES IN AN INPATIENT CARDIOLOGY WARD

by

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Abstract

**Background:** The Modified Early Warning System (MEWS) was implemented on an in-patient cardiology unit with the aim of improving patient safety, increasing efficiency of transfer of unstable patients to critical care, more timely physician interventions, decreasing code blue calls, and improved communication between nurses and physicians.

**Objective:** To investigate the association between the implementation of a Modified Early Warning System (MEWS) on a cardiology unit with patient outcomes: proportion of code blue calls and in-hospital mortality and mean lengths of hospital stay.

**Method:** This study used a quasi-experimental design. Data sources included: discharge separation files and archived cardiac arrest data. Interrupted time series analysis was used to compare trends before and after MEWS implementation.

**Results:** Results from the generalized least-squares model reveal that there was an increase of 1.04 in the code blue rate following the implementation of the MEWS; however, this was not statistically significant (95% CI -0.0158-2.0991, p = 0.0671). There was a sustained significant increase in the trend of 0.33 of code blues called per month (95% CI 0.1932-0.4658, p = 0.0001). There was a decrease of 0.05 (95% CI -1.2328-1.3328, p = 0.94) of in-hospital mortality and a decrease of the in-hospital mortality trend of 0.16 per month (95% CI -0.0207-0.3374, p = 0.098) following the implementation of the MEWS, however, neither were statistically significant. A decrease of 0.07 in the mean length of stay (95% CI -1.6784-1.5322, p = 0.93) and a decrease in the trend of about 0.18 per month in the mean length of stay (95% CI -0.0429-0.4052, p = 0.13) following the implementation of the MEWS was found, but neither was statistically significant.

**Conclusion:** This study provides evidence that the use of a MEWS may not be associated with patient outcomes. Recommendations for future research and implications to nursing practice are
addressed. Interrupted time series analysis was a strong study design for examining the use of the MEWS and patient outcomes; It is a method that should be utilized in nursing research.
Lay Summary

The modified early warning system (MEWS) is a bedside tool used to identify patients at risk of deterioration while in hospital by assigning points according to vital sign measurements. This study aimed at examining the impact of implementing a MEWS during routine patient assessment on a cardiology unit. This study was a novel contribution to understanding the association of the use of a MEWS with patient outcomes, such as code blue calls, in-hospital mortality, and length of stay in hospital. No evidence of association between the use of the MEWS and a decrease in adverse patient outcomes was found. It may be that the use of a MEWS does not have the intended impact on overall patient outcomes and may not be a good investment without having a rapid response team available. These findings highlight the importance of evaluating quality improvement initiatives to determine if desired outcomes are being met.
Preface

Ethics approval was granted by the University of British Columbia Providence Health Care Research Ethics Boards (REB) with certificate number UBC-PHC H14-00396. Permission to use data was obtained from the Program Director for the Acute and Access Services Program at the hospital where the study took place. I designed this study, conducted a literature review to inform my study, and performed all parts of this research including analysis of data and interpretation of findings.
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<tbody>
<tr>
<td>ACF</td>
<td>Autocorrelation function</td>
</tr>
<tr>
<td>APACHE II</td>
<td>Acute Physiology and Chronic Health Evaluation II</td>
</tr>
<tr>
<td>AR</td>
<td>Autoregressive</td>
</tr>
<tr>
<td>ARMA</td>
<td>Autoregressive-Moving Average</td>
</tr>
<tr>
<td>AVPU</td>
<td>Alert, reacting to voice, reacting to pain, or unresponsive</td>
</tr>
<tr>
<td>CI</td>
<td>Confidence interval</td>
</tr>
<tr>
<td>DNAR</td>
<td>Do not attempt resuscitation</td>
</tr>
<tr>
<td>ID</td>
<td>Identifier</td>
</tr>
<tr>
<td>IHI</td>
<td>Institute of Healthcare Improvement</td>
</tr>
<tr>
<td>IOM</td>
<td>Institute of Medicine</td>
</tr>
<tr>
<td>MA</td>
<td>Moving average</td>
</tr>
<tr>
<td>MEWS</td>
<td>Modified Early Warning System</td>
</tr>
<tr>
<td>OD</td>
<td>Odds ratio</td>
</tr>
<tr>
<td>PHCREB</td>
<td>Providence Health Care Research Ethics Board</td>
</tr>
<tr>
<td>RRT</td>
<td>Rapid Response Team</td>
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<tr>
<td>SD</td>
<td>Standard deviation</td>
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<tr>
<td>SPSS</td>
<td>Statistical Package for the Social Sciences</td>
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<tr>
<td>UBC</td>
<td>University of British Columbia</td>
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</tbody>
</table>
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It is with gratitude that I recognize the many individuals who supported me through this journey. Thank you to my thesis committee chair, Dr. Sabrina Wong, for her dedication and guidance throughout this thesis. Her expertise and passion for research provided a strong foundation for my learning.

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Many thanks to Lucy Cheng, Dr. J. Sutherland, and Joseph Puyat for their statistical advice and expanding my knowledge of the analytical methods available to promote further nursing research.

On a personal note, special thanks are owed to my father Gino, my husband Ray, friends, and colleagues whose encouragement and support has meant so much.
Dedication

This thesis is dedicated to my mother Ann - my number one supporter always.
Chapter 1: Introduction

Patient safety has been a priority of hospital care following the release of a report by the Institute of Medicine (IOM), To Err is Human: Building a Safer Health System in 1999 (IOM, 1999). Patient safety includes the aim to prevent harm to patients wherever possible. The severity of harm in the hospital setting can range from additional monitoring to death. The Institute of Healthcare Improvement (IHI) suggests that there up to 50 incidents of harm for every 100 patients admitted to acute care hospitals (McCannon, Hackbarth, & Griffin, 2007). An indicator of harm is the rate of adverse events among hospital inpatients. Adverse events are unintended injuries or complications that arise from health care management and result in disability, prolonged hospital stay, or death. Past work has found that thousands of deaths each year are associated with adverse events that could have been prevented (Baker et al., 2004). The rate of adverse events is often used as an indicator of patient safety.

The IHI launched an initiative to reduce preventable in-hospital deaths in the United States. The 100,000 Lives Campaign initiated by the IHI in early 2006 included the use of Rapid Response Teams (RRT) to save the lives of patients who might experience cardiac arrest and die in hospital. Rapid Response Teams can initiate changes in care that prevent arrest or facilitate patient transport to a critical care unit where fast resuscitation after a cardiac arrest may have a higher likelihood of being successful (Berwick et al, 2006). Rapid response teams bring expert, critical-care personnel to the bedside with the aim of reducing life-threatening events on general medical-surgical floors by triaging and treating patients who are deteriorating. The IHI reported that the implementation of the six strategies put forward in the 100,000 Lives Campaign, RRTs being one, saved an estimated 122,300 lives in an 18-month period, produced positive clinical results, and improved hospital organizational culture (IHI, 2006; IHI, 2007). Indeed, a systematic
A review of RRTs found that their use was associated with a 33.3% reduction in adult rates of cardiopulmonary arrest outside the intensive care unit (ICU) (Chan, 2010).

As a way of triggering RRTs to prevent harm through increased observation and early intervention the IHI launched the 5 Million Lives Campaign in 2006 which recommended the use of early warning systems. The IHI promoted the use of early warning systems to decrease a phenomenon known as “failure to rescue”. Critically ill patients are often identified when there is a significant change in any single vital sign; however, a system that weighs multiple parameters at the same time can help identify at-risk patients at the first sign of even a subtle change in vital signs. Thus, an early warning system could provide a signal of early decline for unexpected, potentially life-threatening events (IHI, 2006).

An early warning system is a physiological “track and trigger” system that uses periodic observation of select vital signs with some predetermined criteria that prompt the notification of more specialized staff (Gao et al., 2007). An early warning scoring system can yield benefits for patients and hospitals by identifying deteriorating patients earlier, prior to adverse events occurring (Institute of Healthcare Improvement, 2006). Patients in hospitals often show signs of physiological deterioration in the hours preceding a cardiopulmonary arrest (Chan, 2010). Studies have suggested that 66%–84% of in-hospital cardiac arrests are preceded as much as 24 hours prior by at least one abnormal clinical observation, such as changes in vital signs or mental status (Buist, 2004; Franklin & Mathew, 1994). Many hospitals have adopted some form of early warning system to prevent “failure to rescue” or failure to prevent a serious adverse event, such as death, due to complications of an underlying illness or medical care (Maupin et al., 2009). Patient deterioration is potentially preventable in the in-hospital setting, however recognizing critical illness is a complex task (Smith, 2010).
Problem Statement

The implementation of a modified early warning system (MEWS) on a specialized cardiology unit in September 2011 was evaluated through surveys of nursing satisfaction (Talusan et al., 2012). However, the extent to which the goals of increased patient safety such as timelier transfer of unstable patients to critical care, timelier physician interventions, and decreased rate of adverse events, has been achieved has yet to be evaluated.

Significance of the Study

Nurses are primarily responsible for the on-going monitoring of patients and coordinating their care. Nurses often have the first opportunity to intervene and prevent complications from adversely affecting their patients. The failure of bedside nurses to recognize abnormal observations, due to lack of in depth knowledge or poor understanding, and the failure to communicate documented abnormal observations to a physician who can initiate treatment, due to lack of confidence or nurses feeling subordinate to physicians, can cause a delay in treatment (Subbe et al., 2003). This can all lead to an increase in potentially preventable adverse events. In line with the IHI recommendations to increase patient safety, the cardiology unit which is the focus of this study has implemented the use of a Modified Early Warning System (MEWS) by nurses. Of note, this hospital currently does not have a rapid response team or critical care outreach service available.

The impact of using a MEWS without access to a rapid response team has not been well documented and its use on a cardiac specific in-patient unit has yet to be evaluated statistically. Most studies (De Meester, Das, et al., 2013; Gardner-Thorpe et al., 2006; Ghanem-Zoubi et al., 2011) have evaluated a MEWS in a surgical or internal medicine unit setting. Findings from studies evaluating a MEWS in a general medical or surgical setting should be generalizable to
the cardiac setting, however one may wonder if the tendency for cardiac patients to have unpredictable arrhythmias and a higher number of cardiopulmonary arrests may decrease the potential positive impact of using a MEWS. The findings from this study will help determine the effectiveness of implementing a MEWS as a tool to help nurses in early detection of deterioration of patients in a cardiac in-patient setting, despite the lack of a RRT to offer support. Examining the impact of a MEWS on patient outcomes, such as cardiac arrests and in-hospital mortality, could provide information on its ability to increase patient safety. These findings may inform further improvements in the safety of hospitalized patients.

**Statement of Purpose**

The primary purpose of this study is to examine the effect of implementing MEWS within a cardiology in-patient unit on the patient outcomes including number of code blue calls, and in-hospital mortality, and length of stay in hospital.

**Research Questions**

1. On the cardiology unit is there a decline in the incidence of:
   a. code blue calls after the implementation of a MEWS by nurses during routine patient assessment?
   b. in-hospital mortality after the implementation of a MEWS by nurses during routine patient assessment?

2. Is there an association between hospital length of stay and implementation of a MEWS during routine patient assessment?

**Hypothesis**

The null hypotheses for this study are:
1. The use of a MEWS by nurses during routine patient assessment is not associated with decreased incidence of:
   a. code blue calls compared to prior to MEWS being implemented.
   b. in-hospital mortality compared to prior to MEWS being implemented.

2. There is no association between hospital length of stay and implementation of a MEWS during routine patient assessment.
Chapter 2: Literature Review

The purpose of this chapter is to review the published literature relating to the history of the development of the modified early warning score (MEWS) and its use in the clinical setting to improve patient safety. A review of the existing validation of MEWS will be provided and gaps in the literature will be identified. The literature review was limited to scholarly works published from the time of the first introduction of the Early Warning Scoring System in 1997 to 2015. The main objective of the literature review was to assess the existing knowledge on the use and benefits of a modified early warning score in the clinical inpatient ward setting.

The literature search was conducted using the electronic databases of PubMed, MEDLINE, the Cumulative Index of Nursing and Allied Health Literature (CINAHL), and Google Scholar. The following key words were used to search the literature: early warning scoring system, modified early warning scoring system, and modified early warning score. Articles that were in languages other than English were excluded due to researcher limitations. The literature review focused on articles that researched the use of a MEWS in adult inpatient settings. Many articles were found that discussed the use of a MEWS in the emergency department setting or in the community; however, these were excluded to focus on hospitalized patients suitable for an inpatient medical or surgical ward.

Table 1. Literature Search Findings

<table>
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<tr>
<th>Database</th>
<th>Citations Retrieved</th>
<th>Relevant Citations (excluding duplicates)</th>
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<td>Google Scholar</td>
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</table>
Patient Safety Framework

Patient safety is defined as the avoidance, prevention and amelioration of adverse outcomes or injuries stemming from the processes of health care (NPSF, 1999). Cronenwett et al. (2007) describe the nursing competency of safety as minimizing the risk of harm to patients through both individual performance and system effectiveness. The Canadian Patient Safety Institute’s (CPSI) Canadian Disclosure Guidelines (2008) define harm as “impairment of structure or function of the body and/or any deleterious effect arising there from” including “disease, injury, suffering, disability and death”. The terms adverse event and harm are often used interchangeably within the context of patient safety. Safety of the patient in hospital heavily relies on the individual performance of the bedside nurse. The Institute of Medicine (IOM) (2004) found that nursing actions are directly related to better patient outcomes and that nursing vigilance protects patients from harm. Therefore, it makes sense that an effective way to improve patient outcomes would be to improve nursing vigilance. Improving patient safety also involves system effectiveness in communication and collaboration. Nursing assessment, monitoring, and evaluation must often be communicated to other healthcare team members to allow collaboration between team members in developing appropriate plans of care. System effectiveness can be supported by a positive patient safety culture. Patient safety culture is a product of the values and beliefs concerning patient safety within a healthcare organization (Feng, 2008). A positive safety culture results when there is interdisciplinary agreement that patient safety is of the utmost priority. A more positive patient safety culture is linked to better patient outcomes as well as better patient perspectives on care (Ulrich & Kear, 2014). A positive patient safety culture aims to reduce human error but also recognizes that human error is not absolutely preventable and puts systems or protocols in place to reduce errors while maintaining patient safety.
Pronovost and colleagues (2006) have developed a four-question framework for measuring patient safety. Their framework can be divided into two subsets. The first two questions in the framework involve valid rates measures. These are a) “how often do we harm patients”; and b) “how often do we provide the interventions that patients should receive”? The last two questions in the framework involve non rate measures. These are a) “how we know we learned from mistakes”; and b) “how well we created a culture of safety” (Pronovost et al., 2006).

**Failure to Rescue**

It has been reported that patients can often show subtle signs of clinical deterioration as early as eight to twelve hours prior to an event (Albert & Huesmann, 2011). Early detection can help prevent significant clinical deterioration before it occurs and allow for preventative interventions to take place. Absence of a quick reaction to clinical deterioration or the appropriate escalation of care constitutes a “failure to rescue” and may result in a serious adverse event. Failure to rescue can result from numerous factors such as excessive lengths of time between vital sign measurements, incomplete vital sign measurements, nursing workload impacting the frequency of monitoring of patients, inadequate frequency of physicians’ assessments, and individual judgement regarding the accuracy and significance of abnormal findings (Jones, 2011). Jones has further broken down failure to rescue in to failure to monitor and failure to escalate. Failure to monitor involves insufficient patient monitoring and assessment such as vital signs not being monitored frequently enough or completely. Failure to escalate involves not recognizing the urgency of clinical symptoms or not seeking help where necessary. Rapid Response Teams were developed in an effort to address “failure to rescue” and are based on the belief that early intervention can improve patient outcomes. Early warning
systems can additionally address failure to rescue by directing the frequency and completeness of vital sign monitoring and documentation as well as providing guidance to the bedside nurse in taking steps to escalate care.

**Unstable Cardiac Patients**

The hospital where this study took place acts as a referral centre for many of British Columbia’s most acute cardiac patients. Common diagnoses of patients admitted to the cardiology unit include acute coronary syndrome, myocardial infarction, heart failure, arrhythmia, comorbid cardiac and obstetrical issues, and heart transplant. Given their complex cardiac conditions, these patients are at risk of experiencing in-hospital adverse effects such as sepsis, fluid overload, and arrhythmias. If not treated swiftly, these adverse effects can lead to cardiopulmonary arrest. A study by Peberdy et al. (2003) found that 41% of in-hospital cardiopulmonary resuscitation occurred in patients admitted to medical-cardiac services and the most frequent cause for cardiac arrest was a cardiac arrhythmia. About one third of in-hospital cardiopulmonary resuscitations occurred in patients with a diagnosis, during current or previous admission, of myocardial infarction or congestive heart failure (Peberdy et al., 2003). The cardiac setting is more likely to manage patients with diagnosed chronic diseases such as heart failure or arrhythmia compared to a surgical unit where the focus of care may be more rehabilitative.

The cardiology unit had one of the highest numbers of code blue responses in the hospital, excluding critical care areas, with up to six during a single month in 2011 (Talusan et al., 2012). In an effort to improve patient safety and quality of care, this unit implemented a modified early warning scoring system (MEWS) in 2012 to help nurses detect early deterioration of in-patients before cardiopulmonary arrest becomes imminent. A MEWS is a scoring tool used
to help nurses detect early deterioration of a patient by generating a score based on physiological parameters such as blood pressure, heart rate, respiratory rate, temperature, and level of consciousness (Talusan et al., 2012). Points are given to abnormal findings and increase with further deviation from normal parameters. A higher score indicates a higher risk for deterioration. The goals of implementing MEWS on this unit were to improve patient safety, increase efficiency and timeliness of transfer of unstable patients to critical care, provide timelier physician interventions, decrease the number of code blue calls, and improve communication between nurses and physicians (Talusan et al., 2012).

**History of the Early Warning Score**

“Track and trigger” warning systems, such as the Early Warning Scoring System, primarily developed as a means of alerting critical care outreach services in the United Kingdom and Australia before gaining momentum worldwide (Gao et al., 2007). The first early warning scoring system was developed in the United Kingdom during the late 1990s and was based on aggregate weighted scoring of physiological variables (Morgan, Williams, & Wright, 1997). Morgan and Wright (2007) state that the early warning score was designed to secure the timely presence of skilled clinical help at the bedside of patients exhibiting physiological signs compatible with impending clinical deterioration. The initial scoring system used physiological parameters such as systolic blood pressure, heart rate, respiratory rate, and temperature and assigned each parameter a numeric score. If a parameter was within normal range, it received a score of zero and values above or below what was considered normal received a score of 1 to 5, according to severity. When the individual scores were tallied, and the overall score was greater than or equal to a pre-determined cut-off score, this would trigger nurses to seek further assessments by other health care team members as outlined in an algorithm established by the
institution (Mapp, Davis, & Krowchuk, 2013). The original Early Warning Scoring System’s simplicity and ready access by nurses made it inexpensive and suitable for general hospital ward use (Wright, Stenhouse, & Morgan, 2000). Over the years, various modifications have been made to the early warning scoring system and fall under the umbrella of “track and trigger” systems. Track and trigger systems include criteria on various physiological components along with a predetermined threshold at which further assistance is sought. Health care facilities have often adapted early warning scoring systems to work within their organization or with a particular patient population. There is no clear evidence to indicate which track and trigger system is most effective. In fact, most track and trigger systems differ only in minor variations in the weightings for physiological instability and/or cut-off points between physiological weighting bands (Smith, Prytherch, Segmidt, & Featherstone, 2008).

**Modified Early Warning Scoring System**

One of the first modifications of the Early Warning Score was developed by Stenhouse, Coates, Tivey, Allsop, and Parker (2000) when they included urine output, made temperature deviations less sensitive, and measured systolic blood pressure as a percent deviation from the patient’s normal. MEWS has been validated for its ability to predict sudden adverse events such as death or unexpected transfer to critical care. Subbe et al. (2001) found that a MEWS score of 5 or greater was associated with an increased risk of death (OR 5.4, 95%CI 2.8-10.7), intensive care unit admission (OR 10.9, 95%CI 2.2-55.6), and high dependency unit admission (OR 3.3, 95%CI 1.2-9.2). Studies have also determined the accuracy of the MEWS using the area under the curve in predicting cardiac arrest, unexpected transfer to intensive care, and in-hospital mortality (Churpek et al., 2013; Ghanem-Zoubi et al., 2011).
Various hospital settings have used different modifiers specific to their patient populations and varying values for normal ranges (Table 2). For example, Albert and Huesman (2011) added white blood cell count, difficulty breathing, oxygen saturation, increased need for supplemental oxygen, decreased urine output, and new focal weakness in their MEWS calculations. Table 2 shows differences in the variables and specific parameters included in the MEWS amongst various studies in the literature.

<table>
<thead>
<tr>
<th>Article</th>
<th>Variables Used in MEWS Calculation and Normal value for score of 0 (if available)</th>
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<tbody>
<tr>
<td></td>
<td>Systolic blood pressure</td>
</tr>
<tr>
<td>MEWS at St. Paul's Hospital</td>
<td>101-159 mmHg</td>
</tr>
<tr>
<td>Albert &amp; Huesman (2011).</td>
<td>90-140 mmHg</td>
</tr>
<tr>
<td>Alvarez et al. (2013).</td>
<td>101-199 mmHg</td>
</tr>
<tr>
<td>Bleyer et al. (2011).</td>
<td>101-199 mmHg</td>
</tr>
<tr>
<td>Cooksley et al. (2012).</td>
<td>110-159 mmHg</td>
</tr>
<tr>
<td>De Meester, Das, et al. (2013).</td>
<td>*</td>
</tr>
<tr>
<td>De Meester, Haegdorens, et al. (2013).</td>
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<tr>
<td>Gardner-Thorpe et al. (2006).</td>
<td>101-199 mmHg</td>
</tr>
<tr>
<td>Ghanem-Zoubi et al. (2011).</td>
<td>101-199 mmHg</td>
</tr>
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### Variables Used in MEWS Calculation and Normal value for score of 0 (if available)

<table>
<thead>
<tr>
<th>Article</th>
<th>Variables Used in MEWS Calculation and Normal value for score of 0 (if available)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ludikhuize, Borgert, et al. (2014).</td>
<td>Systolic blood pressure 101-199 mmHg, Pulse rate 51-100 beats/min, Respiratory rate 9-14 resp/min, Temperature 35-38.4°C, Conscious Level (AVPU) Alert</td>
</tr>
<tr>
<td>Ludikhuize, de Jonge, &amp; Goosens (2011).</td>
<td>Systolic blood pressure 101-200 mmHg, Pulse rate 51-100 beats/min, Respiratory rate 9-14 resp/min, Temperature 36.6-37.5°C, Conscious Level (AVPU) Alert, Oxygen Saturation ≥90%, Urine output ≥75ml during previous 4 hours, Other No worry about patient’s condition</td>
</tr>
<tr>
<td>Ludikhuize, Smorenburg, et al. (2012).</td>
<td>Systolic blood pressure 101-200 mmHg, Pulse rate 51-100 beats/min, Respiratory rate 9-14 resp/min, Temperature 36.6-37.5°C, Conscious Level (AVPU) Alert, Oxygen Saturation ≥90%, Urine output ≥75ml during previous 4 hours</td>
</tr>
<tr>
<td>Maupin 2009.</td>
<td>Systolic blood pressure 101-199 mmHg, Pulse rate 51-100 beats/min, Respiratory rate 9-14 resp/min, Temperature 95-101.2°F (35-38.4°C), Conscious Level (AVPU) Alert</td>
</tr>
<tr>
<td>Moon et al. (2011).</td>
<td>Systolic blood pressure 101-180 mmHg, Pulse rate 51-100 beats/min, Respiratory rate 8-20 resp/min, Temperature 35.1-37.5°C, Conscious Level (AVPU) Alert, Oxygen Saturation 94-100%, Urine output ≥30 ml/hour, Other Absence of chest pain; Blood glucose 4-9.9 mmol/L</td>
</tr>
<tr>
<td>Page et al. (2008).</td>
<td>Systolic blood pressure 100-160 mmHg, Pulse rate 56-109 beats/min, Respiratory rate 9-19 resp/min, Temperature 35.5-374°C, Conscious Level (AVPU) Alert, Oxygen Saturation 90-100% on room air, Urine output ≥30 ml/hour</td>
</tr>
<tr>
<td>Stenhouse, et al. (2000).</td>
<td>Systolic blood pressure Normal for patient, Pulse rate 51-100 beats/min, Respiratory rate 9-14 resp/min, Temperature 35-38.4°C, Conscious Level (AVPU) Alert, Oxygen Saturation 1-3 ml/kg/hour</td>
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<td>Subbe, Davies, et al. (2003).</td>
<td>Systolic blood pressure 101-199 mmHg, Pulse rate 51-100 beats/min, Respiratory rate 9-14 resp/min, Temperature 35-38.4°C, Conscious Level (AVPU) Alert</td>
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<tr>
<td>Subbe, Kruger, et al. (2001).</td>
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</tr>
</tbody>
</table>

*Did not specify scoring values

### MEWS and Patient Safety

The majority of the research studies on MEWS have been prospective, quasi-experimental studies (Albert & Heusman, 2011; Alvarez et al., 2013; De Meester, Das, Hellemans, Verbrugghe, Jorens, Verpooten et al., 2013; Gardner-Thorpe et al., 2006; Ghanem-Zoubi et al., 2011; Ludikhuize, Borgert, et al., 2014; Maupin et al., 2009; Subbe, Davies et al., 2003; Subbe, Kruger et al., 2001). A few of the studies did include a retrospective analysis of previously documented data (Bleyer et al., 2011; Cooksley et al., 2012; Ludikhuize, Smorenburg
et al., 2012; Moon, 2011) and a couple reports were quality improvement projects (Albert & Huesman; Page et al., 2008). Some studies focused on validating a MEWS in its ability to predict sudden adverse events, while others looked at the effects of implementing a MEWS in practice. Studies have shown that using a MEWS can improve patient safety through improved nursing vigilance and improved patient outcomes as well as contribute to a positive patient safety culture.

Implementation of a MEWS as a part of standardized observation protocols in the clinical setting is a way to promote patient safety and prevent failure to monitor through increased patient observation and vital signs measurement (De Meester, Das, et al., 2013; De Meester K, Haegdorens F, Monsieurs KG, Verpooten GA, Holvoet A & Van Bogaert P., 2013). Implementing a MEWS on inpatient units could improve patient safety by simply increasing the frequency of measuring vital signs, either as single vital signs or as a set. McBride, Knight, Piper, & Smith (2005) found that the rate of recording respiratory rate measurements on hospital wards increased after the introduction of the MEWS. A study by De Meester, Haegdorens, et al. (2013) found that not only did nursing observations of patients increase, but so did the completeness of vital signs measurement during these observations. They specifically found that the measurements of patient’s oxygen saturation, consciousness, and respiratory rate increased following the implementation of a MEWS.

The use of the MEWS can contribute to a positive patient safety culture by increasing nurses’ confidence and supporting interdisciplinary communication. Maupin (2009) found that the use of the MEWS was associated with nurses feeling more confident when contacting physicians. Page et al. (2008) found that nurses reported high satisfaction and increased confidence following implementation of a MEWS, and physicians reported the use of the MEWS enhanced consultation with them. Physicians specifically appreciated that misleading calls were
decreased and that when nurses did decide to call physicians, they could provide sound evidence for concern (Page et al.). One study found that nurses educated on the use of a MEWS could identify deteriorating patients and react more appropriately when presented with case scenarios of deteriorating patients compared to nurses who had not received this education (Ludikhuize, de Jonge, et al., 2011).

The use of a MEWS has been shown to be associated with earlier transfer to intensive care units where lifesaving treatment is more readily available. When Stenhouse et al. (2000) implemented their MEWS, they found the use of the system was associated with earlier referral to the intensive care unit compared to not using any track and trigger system during patient assessments. This was evidenced by lower mean APACHE II scores, a measure of severity of illness, among patients admitted to intensive who had also been monitored using a MEWS. Subbe, Davies, Williams, Rutherford, and Gemmell (2003) also found a trend towards earlier intensive care unit admission with the use of a MEWS, as evidenced by significantly lower APACHE II scores on intensive care admission and a tendency towards being admitted earlier during their hospital stay.

The use of a MEWS has also been shown to increase collaboration with RRTs or critical care outreach services. This may increase patient safety as activation of a RRT has been shown to be associated with a decreased incidence of adverse events (Ludikhuize, Borgert, et al., 2014). Increases in number of activations of the RRTs were found when using a MEWS (Albert & Heusman, 2011; Moon, Cosgrove, Lea, Fairs, & Cresse, 2011; Maupin et al., 2009). Albert and Heusman found that, with the implementation of a MEWS, the number of calls to the RRT increased by 50%. Maupin et al. found that RRT calls increased by 110% with the implementation of the MEWS. Ludikhuize, Borgert, et al., (2014) found that regular use of the
MEWS, with a minimum of three times daily, increased calls to the RRT compared to using the MEWS only when clinically indicated.

Implementation of a MEWS in practice can affect patient safety outcomes such as cardiac arrests, code blue calls, and in-hospital mortality (Albert & Heusman, 2011; De Meester, Das, et al., 2013; De Meester, Haegordens, et al., 2013; Moon et al., 2011; Maupin, 2009). While Albert and Heusman found that calls to a Rapid Response Team increased, calls to their code blue team decreased by over 33%. Maupin et al. (2009) also found a 50% decrease in code blue calls along with both overall in-hospital mortality and death rates per cardiac arrest call reductions with the implementation of a MEWS. Neither study detailed the statistical methods used for analysis nor comment on statistical significance. Moon et al. (2011) found that cardiac arrest calls as proportions of adult admissions significantly reduced with the implementation of the MEWS, however, they implemented the MEWS simultaneously with a new critical care outreach service. De Meester, Haegordens, et al. (2013) found mortality, re-operation, and hospital length of stay decreased following the implementation of a MEWS as part of a standardized observation protocol in postoperative patients; however, none of their findings were statistically significant.

**Gaps in Knowledge**

Most of the studies on MEWS have focused on particular units within a given hospital or a specific patient population admitted to hospital. A few studies (De Meester, Das, et al., 2013; Ludikhuize, Smorenburg, de Rooij SE, & de Jonge, 2012) have looked at the use of a MEWS over multiple in-patient units. There is limited evidence of the use of MEWS across an entire hospital’s in-patient acute care units and there does not appear to be any evidence on the implementation of MEWS throughout an entire health organization.
Gao et al. (2007) completed a systematic review of various track and trigger systems which included MEWS in addition to twenty-four other distinct systems. Their literature search identified thirty-six articles, of which only five were research studies, and noted that none of the included studies met all methodological quality standards (Gao et al., 2007). The authors concluded that available data was insufficient to identify the best track and trigger system. No randomized controlled trial of any MEWS has been conducted, as finding two groups appropriate for direct comparison would be difficult given the many factors that can affect a unit’s patient safety outcomes such as unit safety culture, staff mix, workload, and patient population. Indeed, Subbe, Davies, et al. (2003) discussed the technical difficulty of randomization within units. Most studies that aimed to validate the use of a MEWS faced limitations in the differences between their control and study groups, such as the control group being a historic control, or the control groups being located on different units with different staff and possibly a different mix of patients. A randomized controlled trial may also not have been conducted given the subjective positive effects often seen following implementation of an early warning system, therefore making a true control group unethical.

Hospitals and individual inpatient units have adapted a MEWS to their liking when putting the system into implementation. The MEWS used often varies in the inclusion of certain measures such as urine output and oxygen saturation, as outlined in Table 2. Also, the variation in the criteria used for triggering escalation demonstrates a lack of understanding as to what aggregate criteria are truly meaningful in identifying patients at risk of deterioration in hospital. Although many MEWS employ some common, some MEWS use varying parameters to define normal values or what warrants a score elevation. Hospitals have also varied in the implementation of a MEWS from “only when clinically indicated” to its use in standardized
observation protocols. Only a handful of the studies evaluated the implementation of a MEWS where nurses had received education regarding how the MEWS was to be used and its benefits.

There is also minimal evidence on the use of MEWS as a tool to guide the bedside nurse and enhance communication between nurses and physician without triggering response from a designated team such as a Rapid Response Team. The cardiology unit providing the focus of this study differs from those that have previously been researched in the current literature given the specialized cardiology services provided, multiple Most Responsible Physicians (MRPs) attending on the unit according to cardiac sub-specialty, and the lack of any specified team to respond to elevated MEWS scores such as a formal Rapid Response Team or Outreach Team.

Although many studies have shown an association between high MEWS scores and adverse events, few have studied the use of a MEWS in practice and its ability to affect patient safety outcomes such as cardiac arrest and in-hospital mortality (De Meester, Das, et al., 2013; De Meester, Haegordens, et al., 2013; Maupin et al., 2009; Moon, 2011). Only one study appears to have studied the effect of using a MEWS on the patient safety indicator of length of stay in hospital (De Meester, Haegorden, et al., 2013). However, the authors admitted it was unclear what caused the decrease in length of stay and the actual association between length of stay and use of a MEWS remains uncertain. Another evaluation of various track and trigger systems has shown that the performance of most systems tested was poor when used to discriminate between survivors and non-survivors (Smith, Prytherch, Schmidt, Featherstone, & Higgins, 2008). This study will address the gaps of knowledge on the effect of using a MEWS, without a Rapid Response Team, on patient outcomes such as code blue calls, in-hospital mortality, and hospital length of stay.
Chapter 3: Methods

This thesis focused on the first question of Pronovost and colleagues (2006) framework for measuring patient safety: “how often do we harm patients”? Outcome measures that reflect harm by quantifying the occurrence of adverse events were examined. Specifically, the adverse events of code blue calls, in-hospital mortality, and increased length of stay were evaluated. Adverse events may result from errors of commission or errors of omission. Errors of commission are errors that occur from an action taken such as the administration of the wrong drug. Errors of omission are errors that occur from an action not taken such as failure to diagnosis or treat where necessary. The MEWS is a tool that may help prevent errors of omission by guiding the bedside nurse in monitoring patients’ conditions and communicating with other health care team members to ensure that changes in condition are identified early and treatment is initiated as necessary.

Research Design

In this study a quasi-experimental, retrospective interrupted time series design was employed (Polit & Beck, 2012). A retrospective design was necessary given the fact that the MEWS had already been implemented. Interrupted time series (ITS) is one of the strongest quasi-experimental research designs particularly when the investigator does not have control over the implementation of an intervention or the ability to obtain suitable randomization (Penfold & Zhang, 2015). An ITS design was suitable since a randomized controlled trial of the MEWS would have been difficult as finding two equal comparison groups would have been challenging given the specialized nature of the unit involved in the study. A randomized controlled trial might have also been problematic due to the possibility of subjective positive
effects as reported following implementation of the MEWS in previous studies, therefore making a true control group unethical.

**Setting**

This study was conducted using data from patients discharged from the in-patient cardiology unit at a quartenary-level hospital located in Vancouver, British Columbia. The cardiology unit is within a cardiac program which provides the full spectrum of care for British Columbians with all kinds of heart disease. The 25-bed unit admits patients with all non-surgical cardiac diagnoses, including acute myocardial infarction, unstable angina, heart failure, complex arrhythmias, pre- and post-transplant patients, and patients requiring mechanical circulatory support. Many, but not all, of these patients will have been cared for in the cardiac intensive care unit before being transferred to the cardiology unit. The unit provides telemetry monitoring and other specialized nursing care. A MEWS was implemented on this unit in September 2011.

To provide further background, environmental factors that may be associated with the study outcome variables were requested from the cardiology unit Operations Leader and the hospital’s Human Resources Department. If available, the information requested would have included baseline staffing levels and Registered Nurse position vacancy rates for the two periods of time before and after implementation of a MEWS.

**Sample**

The sample for this study consisted of electronic health records for all patients discharged from the cardiology unit from: September 2010 to September 2011 and September 2011 to September 2012. These time periods account for 12 months prior to the implementation of a Modified Early Warning System (MEWS) and 12 months following the implementation of a MEWS. Patients discharged from the cardiology unit during these time periods were identified
by the Health Records Department. Off-service patients (e.g. patients admitted to the cardiology unit but not under the care of a cardiologist or cardiac surgeon) were included given the difficulty in extracting information on the most responsible physician and given that off-service patient charts were still expected to be assessed according to the MEWS protocol. To provide further context for the post-MEWS implementation period as to the acceptance of the MEWS in practice, a sample of patient charts was audited. A random sampling of two patients discharged per month in the post-MEWS implementation period, from September 2011 to September 2012, were selected for a chart audit to review the consistency of the MEWS use in practice.

**Data Sources**

Upon obtaining ethics approval from the UBC/Providence Health Care Research Ethics Board, patients discharged from the cardiology unit between September 2010 and September 2012 were identified by health records. A data set from the hospital’s electronic discharge separation files was extracted by the Health Records department. This data set contained information on age, sex, most responsible diagnosis, presence of Do Not Attempt Resuscitation orders, hospital length of stay, and in-hospital mortality. The number of code blue calls and details of the cardiac arrest resuscitation were gathered through archived files obtained from the hospital’s Cardiac Arrest Database. This archived database included information on the type of arrest, procedures done during the code blue, and the outcome of the code blue event. Data obtained from the hospital’s Cardiac Arrest Committee that included any patient identifiers were encrypted and stored in a password protected computer. Code blue data was then stripped of patient identifiers prior to data analysis.

Two patients discharged each month following MEWS implementation were randomly selected for a chart audit (Appendix C) to review the utilization of the MEWS in practice. The
scanned patient chart for each randomly selected subject was accessed through the hospital’s Sunrise Clinical Manager system. The standard of care for the MEWS is that the components are assessed with each set of vital signs and recorded on the 24-hour clinical flowsheet. Repeat MEWS assessments for a score of 2-3 should be completed within 4-6 hours and within 1 hour for a MEWS score ≥ 4. The 24-hour clinical flowsheets for the randomly selected subjects cardiology unit stay were reviewed for adequate MEWS documentation. Adequate use of the MEWS were defined as a MEWS score coinciding with each vital signs measurement documented in the 24 hour flowsheet and each elevated MEWS score followed by a documented repeated assessment as per the MEWS algorithm. Each 24 hour flowsheet with all expected MEWS documented as per the MEW algorithm guidelines was recorded as an adequate day. Any missing MEWS documentation within a 24-hour period reflected by the 24 hour clinical flowsheet was not counted as an adequate use of the MEWS for that day. The use of the MEWS is expressed as a percentage of 24 hour days with adequate MEWS use per total days the randomly selected patients were admitted on the cardiology unit.

**Variables of Interest**

**Independent Variables**

The independent variable of interest was the use of the MEWS. The modified early warning system (MEWS) used in this study is based on the physiological parameters of the original Early Warning System: systolic blood pressure, pulse rate, respiratory rate, temperature, and AVPU score (Alert, reacting to Voice, reacting to Pain, or Unresponsive) (Morgan, Williams, & Wright, 1997). The cardiology unit that provides the setting for this study has also added the parameter of non-surgical pain to their MEWS system (Talusan et al., 2012; Appendix A).
The following co-variates were also examined: age, sex, most responsible diagnosis, and Do Not Attempt Resuscitation (DNAR) order. Age was calculated from year of birth-discharge and sex was recorded as male or female.

**Dependent Variables**

The dependent variables examined in this study were the proportion of code blue calls initiated on the cardiology unit per in-patients discharged monthly, the proportion of in-hospital deaths of cardiology in-patients discharged monthly, and hospital length of stay. Code blue calls were recorded as the total number of code blue calls occurring each month and were converted into monthly rates per number of cardiology unit discharges for analysis. In-hospital mortality was recorded as the number of cardiology in-patient deaths that occur each month and were converted into monthly rates per number of monthly cardiology discharges for analysis. Length of stay was recorded as the total number of days from admission to discharge and converted into monthly averages for analysis.

**Code Blue Calls**

When cardiopulmonary arrest occurs, or appears imminent, health care team members call a “code blue” which triggers an immediate response of a dedicated code blue team. The code blue team consists of critical care nurses, respiratory therapists, and intensive care unit physicians who can administer advanced life-saving measures as required. For each code blue response, a cardiac arrest record is completed by a member of the code blue team. Copies of the cardiac arrest records are retained by the Intensive Care Unit nurse educator as well as in the patient’s permanent health record. During the period being examined for this study, information from the cardiac arrest records was entered into the Cardiac Arrest Database. These data have recently been archived by the Cardiac Arrest Committee, because a new platform has been
adopted. The archived data were available for review after necessary permissions were obtained from the responsible Program Director responsible.

For the purpose of this study, a code blue call was defined as any code blue called on the cardiology unit that resulted in documentation of the event on a cardiac arrest record. For this study, all cardiac arrest records for code blue calls initiated on the cardiology unit from September 2010 to September 2011 and September 2011 to September 2012 were reviewed. Information on the type of arrest (respiratory, cardiac, or other), whether a palpable pulse was present when the code blue was called, whether the patient was intubated during the code blue, their acute care admission diagnosis, and final outcome at the end of the code blue (successful, unsuccessful) were extracted from the cardiac arrest data files.

All data were collected by the investigator. Data remain in a password protected electronic file, on a password protected network, accessed on a St. Paul’s Hospital workstation computer. All electronic files including patient identifiers were also encrypted. A coding system was prepared, with all personal identifiers removed (e.g., Personal Health Number) and replaced with study participant identity numbers.

**Data Analysis**

Data stripped of any personal identifiers were entered in Statistical Package for the Social Sciences (SPSS), version 24, or R statistical software, version 3.2.5, and on occasion transferred to a password protected laptop for data analysis.

Differences in demographics and variations in diagnoses between the 12 months prior to MEWS implementation and the 12 months following MEWS implementation were analyzed using t-tests for continuous data and chi-square for categorical data. Descriptive statistics were used to describe the sample before and after MEWS implementation. Differences in the
characteristics of the code blue calls between the 12 months prior to MEWS implementation and the 12 months following MEWS implementation were also examined.

An interrupted time series model was fit to assess for changes in the level (step) and trend (slope) in code blue calls, in-hospital mortality, and mean length of stay in hospital for patients discharged from the cardiology unit before and after MEWS implementation. Interrupted time series is a quasi-experimental design that involves the collection of data over an extended time period, with multiple data collection points both prior to and after an intervention (Polit & Beck, 2008). The use of multiple data points in interrupted time series analysis allow for addressing maturation threat and change from secular trends and random fluctuations (Polit & Beck, 2008).

Raw data were prepared for time series analysis by adding the necessary variables of time, level, and trend. Outcome data were set up in Microsoft Excel to have rows for each observation period and columns for the month of observation, outcome, time, level, and trend. The outcome variable was a ratio of monthly code blue call rates, in-hospital mortality rates, or mean length of hospital stay divided by the number of patients discharged. A time variable was created which assigned each month of observation a time using increments of 1 to 25 for the total 25 months of data collected. The level variable assigned a 0 for observations that occurred before MEWS implementation and a 1 for observations that occurred following MEWS implementation. The trend variable then assigned a 0 to each observation before MEWS implementation and increments of 1 to 13 for the observation points following the MEWS implementation. Once data were setup for time series analysis they were imported into R studio and preliminary plots were created to show the outcome observations and allow for visual inspection of the collected data.
Monthly code blue call and in-hospital mortality rates were initially examined through visual analysis of plots to determine any changes in slope. Average hospital length of stay was determined per month. Length of stay was also examined through visual analysis of a time series plot to determine any changes in slope. Generalized least-squares models were used to examine probabilities of code blue calls, probabilities of in-hospital mortality, and differences in length of stay prior to and following the implementation of the MEWS adjusting for any autocorrelation over time. Results are reported in changes in level(step) and trend(slope) with 95% confidence intervals and p-values.

**Addressing Autocorrelation**

Potential autocorrelations between months were assessed for all dependent outcome variables. Autocorrelation is a relationship in data points over time and the correlation in the error terms. In time series analysis, autocorrelation that may exist is expressed in an autoregressive-moving average (ARMA) model which provides a description of existing processes of both autoregression and a moving average. The autoregressive (AR) portion involves identifying patterns where past values influence current values. A process considered AR(1) means that the current value is based on the immediately preceding value and an AR(2) process means the current value is based on the previous two values. The moving average (MA) portion involves identifying correlations of current values in a linear combination based on previous random disturbances. A process considered MA(1) would mean the current value is based on the previous random disturbance. The overall ARMA model is usually referred to as the ARMA($p,q$) model, where $p$ is the order of the autoregressive part and $q$ is the order of the moving average part. Preliminary ordinary least squares (OLS) regression models of each outcome were run in R Studio to assess these models for autocorrelation. The preliminary OLS
regression model for each outcome was checked for autocorrelation using three different methods, as follows.

First, a Durbin-Watson test was performed on each outcome OLS model in R Studio. A Durbin-Watson test is a formal test that tests for correlated residuals that exist at certain lags. A lag refers to a period between one event and another. The Durbin-Watson test was conducted using 12 time period lags to account for seasonal trends that may have existed in the monthly data that was collected. The results of the Durbin-Watson tests did not identify any significant autocorrelations. In addition, residual plots of the OLS models were created and visually inspected but showed no obvious patterns of autocorrelation.

Lastly, autocorrelation plots were created to assess for autoregressive and moving average processes. Two plots for each preliminary outcome OLS model were created: an autocorrelation plot and a partial autocorrelation plot. The autocorrelation plot is the relationship of a variable with itself over time and a partial correlation is similar but has the linear component removed. The residuals of each model should be random and within two standard deviations of the true mean of residuals (or zero). Observations nearer in time are more often strongly correlated which would be seen by exponential decay in one of the plots where the residuals get closer and closer to zero the further lags in time periods apart they are. Significant spikes outside the two-tailed range of two standard deviations indicate autocorrelation at that lag of time periods. Table 3 summarizes how autocorrelation plots (ACF) and partial autocorrelation plots (Partial ACF) are interpreted.
Table 3. Interpreting Autocorrelation and Partial Autocorrelation Plots

<table>
<thead>
<tr>
<th>Model</th>
<th>ACF plot finding</th>
<th>Partial ACF plot finding</th>
</tr>
</thead>
<tbody>
<tr>
<td>No autocorrelation</td>
<td>All zeroes</td>
<td>All zeroes</td>
</tr>
<tr>
<td>Autoregressive (p)</td>
<td>Exponential decay</td>
<td>p significant lags before dropping to zero</td>
</tr>
<tr>
<td>Moving average (q)</td>
<td>q significant lags before dropping to zero</td>
<td>Exponential decay</td>
</tr>
<tr>
<td>Both (p,q)</td>
<td>Decay after q&lt;sup&gt;th&lt;/sup&gt; lag</td>
<td>Decay after p&lt;sup&gt;th&lt;/sup&gt; lag</td>
</tr>
</tbody>
</table>


As assessing for and identifying autocorrelation can sometimes be difficult and open to interpretation, all three tests were performed to ensure their results aligned and were reviewed by a statistician for confirmation.

**Ethical Considerations**

Approval was obtained from the UBC/Providence Health Care Research Ethics Board (UBC-PHCREB). As this research involves a retrospective chart review and use of retrospective data, the study fulfilled the criteria for waiver of consent for the secondary use of information as outlined by Article 5.5 of the Tri-42 Council Policy Statement. Confidentiality was preserved by replacing all direct patient identifiers (IDs), such as PHN and date of birth, with unique and anonymous subject IDs on study records, for any data that was transferred from a hospital electronic workstation. Electronic versions of study data are password-protected and hard copies kept in a secure, locked location. As per UBC policy, data are stored for five years and then destroyed in a manner consistent with Research Ethics Board policy.
Chapter 4: Results

This chapter begins with a description of the study sample and a comparison of the demographics of the pre-MEWS implementation sample with the post-MEWS implementation sample. The remainder of the chapter focuses on inferential statistics applied to the research questions: *On the cardiology unit is there a decline in the incidence of 1a) code blue calls after the implementation of a MEWS by nurses during routine patient assessment? 1b) in-hospital mortality after the implementation of a MEWS by nurses during routine patient assessment? 2) Is there an association between hospital length of stay and implementation of a MEWS during routine patient assessment?* The results are based on interrupted time series analysis of patient outcomes of a code blue call, in-hospital mortality, and length of stay in hospital.

Study Sample

The study sample include all patients (n=3,046) who were discharged from the cardiology unit at St. Paul’s Hospital from: September 1, 2010 to September 30, 2012.

Adequacy of MEWS Implementation

A total of 26 charts were audited. Two of the audited charts belonged to patients requiring only temporary holding following outpatient procedures and did not require a formal chart. Therefore, 24 of the audited charts were eligible for analysis. Adequate use of the MEWS was documented in 86% of the total days (n= 124 days) these patients were in-patients on the cardiology unit.

Baseline Characteristics

Table 3 provides a summary comparison of the patients’ clinical and demographic characteristics for both before and after MEWS implementation. The average age of patients for the period before MEWS was implemented was 64.3 years ($SD = 15.9$, range: 17 to 96 years) and the average age of patients for the period after MEWS implementation was 65.8 years ($SD =
15.0, range 13 to 98 years), \( p = .006 \). Though the difference in mean age was statistically significant the difference of 1.5 years was not felt to be of clinical significance and therefore it was decided to not adjust for this in the final analysis of the outcome variables. The average proportion of female patients for each period were equal at 35.5%. The most responsible diagnoses for the periods before and after MEWS implementation are listed in Table 4. The proportion of patients discharged who had DNAR orders in place were similar at 4.9% pre-MEWS implementation and 5.2% post-MEWS and had no statistically significant difference.

### Table 4. Characteristics of Study Population Before and After MEWS Implementation

<table>
<thead>
<tr>
<th>Clinical Demographic Characteristics</th>
<th>Pre-MEWS (n = 1442)</th>
<th>Post MEWS (n = 1604)</th>
<th>p-value (if applicable)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, mean years (SD)</td>
<td>64.3 (15.9)</td>
<td>65.8 (15.0)</td>
<td>0.006</td>
</tr>
<tr>
<td>Females (%)</td>
<td>510 (35.5)</td>
<td>570 (35.5)</td>
<td>NS</td>
</tr>
<tr>
<td>Most Responsible Diagnosis (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Myocardial infarction/coronary artery disease</td>
<td>401 (27.8)</td>
<td>478 (29.8)</td>
<td>NS</td>
</tr>
<tr>
<td>• Arrhythmia/syncope</td>
<td>376 (26.1)</td>
<td>378 (23.6)</td>
<td></td>
</tr>
<tr>
<td>• Heart failure</td>
<td>220 (15.3)</td>
<td>254 (15.8)</td>
<td></td>
</tr>
<tr>
<td>• Chest pain/angina</td>
<td>198 (13.7)</td>
<td>189 (11.8)</td>
<td></td>
</tr>
<tr>
<td>• Valvular dysfunction</td>
<td>121 (8.4)</td>
<td>136 (8.5)</td>
<td></td>
</tr>
<tr>
<td>• Complication of cardiac surgery/device</td>
<td>33 (2.3)</td>
<td>53 (3.3)</td>
<td></td>
</tr>
<tr>
<td>• Other</td>
<td>93 (6.4)</td>
<td>116 (7.2)</td>
<td></td>
</tr>
<tr>
<td>DNAR order present (%)</td>
<td>71 (4.9)</td>
<td>83 (5.2)</td>
<td>NS</td>
</tr>
</tbody>
</table>

Environmental factors that may have been associated with the study outcome variables, such as baseline staffing levels and registered nurse position vacancy rates, for each of the two periods, were requested from the cardiology unit Operations Leader and the hospital’s Human Resources Department. However, this information was not currently available for during the study period.

Table 5 provides a summary comparison of the type of code blue calls before and after MEWS implementation.
Table 5. Characteristics of Code Blue calls Before and After MEWS Implementation

<table>
<thead>
<tr>
<th>Code Blue Characteristics</th>
<th>Pre-MEWS (n = 21)</th>
<th>Post MEWS (n = 34)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of Arrest (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Respiratory</td>
<td>10 (47.6)</td>
<td>22 (64.7)</td>
</tr>
<tr>
<td>• Cardiac</td>
<td>3 (14.3)</td>
<td>3 (8.8)</td>
</tr>
<tr>
<td>• Other</td>
<td>8 (38.1)</td>
<td>9 (26.5)</td>
</tr>
<tr>
<td>Palpable pulse present when Code Blue called (%)</td>
<td>12 (57.1)</td>
<td>23 (67.6)</td>
</tr>
<tr>
<td>Intubated during Code Blue (%)</td>
<td>8 (3.8)</td>
<td>6 (1.8)</td>
</tr>
<tr>
<td>Outcome of Code Blue (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Death</td>
<td>2 (1.0)</td>
<td>4 (1.2)</td>
</tr>
</tbody>
</table>

Preliminary Findings

Figures 1-3 show the preliminary visual plots that were created from the raw outcome data. The x-axis indicates the months both pre and post MEWS implementation and the y-axis indicates the outcome measure. Visual inspection of these plots found no obvious changes in slope or secular trends.
Figure 1. Proportion of Code Blues per Patients Discharged
Figure 2. Proportion of In-hospital Mortality per Patients Discharged
Preliminary analysis of the code blue calls indicated the existence of an autoregressive process suggesting that autocorrelation needed to be addressed in the final model. A slight exponential decay is seen in the autocorrelation plot with the residuals becoming more closely clustered towards zero over time, as well as a significant spike seen at a lag of 2 observation periods in the partial autocorrelation plot. The autocorrelation was addressed by including an
AR(2) process in the final time series model for code blue calls to adjust for the correlation of observations over time. Figure 4 shows the autocorrelation plots used to assess for autocorrelation of residuals in the model.

Figure 4. Autocorrelation and Partial Autocorrelation for Code Blue calls
Results from preliminary analysis of the in-hospital mortality and the mean length of stay in hospital indicated there were no autocorrelations in the observations of either outcome over time as seen in figures 5 and 6. Therefore, the final time series models for in-hospital mortality and mean length of stay in hospital were not adjusted for any autocorrelation.

---

2 standard deviations

*Figure 5. Autocorrelation and Partial Autocorrelation for In-hospital Mortality.*
Results from the generalized least-squares model reveal that there was an increase of 1.04 percentage points in the code blue rate following the implementation of the MEWS; however,
this was not statistically significant (95% CI -0.0158-2.0991, p = 0.0671). There was a sustained significant increase in the trend of 0.33 in the code blues per month (95% CI 0.1932-0.4658, p = 0.0001). There were no statistically significant differences in level for code blue calls. However, the differences for trend were statistically significant but in the opposite direction.

*Figure 7. Interrupted Time Series Model for Code Blue Calls*
In-hospital Mortality

Results from the generalized least-squares model reveal that there was an increase of 0.05 of in-hospital mortality following the implementation of the MEWS; however, this was not statistically significant (95% CI -1.2328-1.3328, p = 0.94). The in-hospital mortality trend increased about 0.16 percentage points per month (95% CI -0.0207-0.3374, p = 0.098). The differences in level and trend for in-hospital mortality were not statistically significant.

*Figure 8. Interrupted Time Series Model for In-hospital Mortality*
Length of Stay

The results from the generalized least-squares model reveals that there was a decrease of 0.07 in the mean length of stay following the implementation of the MEWS, but this was not statistically significant (95% CI -1.6784-1.5322, p = 0.93). There was an increase in the trend of about 0.18 per month in the mean length of stay (95% CI -0.0429-0.4052, p = 0.13). The differences in level and trend for mean length of stay in hospital were not statistically significant.

Figure 9. Interrupted Time Series Model for Mean Length of Stay in Hospital
Summary of Hypotheses

1. H0: There is no association between the use of a MEWS by nurses during routine patient assessment with decreased incidence of:
   
a. code blue calls compared to prior to MEWS being implemented.
   
   We reject the null hypothesis since the use of a MEWS by nurses during routine patient assessment was associated with an increased incidence of code blue calls compared to prior to MEWS being implemented.

   b. in-hospital mortality compared to prior to MEWS being implemented.
   
   We cannot reject the null hypothesis since there was no association between the use of a MEWS by nurses during routine patient assessment decreased in-hospital mortality.

2. H0: There is no association between hospital length of stay and implementation of a MEWS during routine patient assessment.

   We cannot reject the null hypothesis since there was no association between the use of a MEWS by nurses during routine patient assessment and decreased hospital length of stay.
Chapter 5: Discussion

In this retrospective, observational study, adequate use of the MEWS was found with 86% of in-hospital days reviewed having had correct documentation of the MEWS. This aligns with literature findings of the MEWS being associated with increased frequency and completeness of vital signs measurements (De Meester, Haegdorens, et al., 2013; McBride, et al., 2005). Overall, MEWS did not have an effect on patient outcomes (code blue calls, in-hospital mortality, hospital length of stay). There was no significant difference observed for in-hospital mortality or mean length of hospital stay before and after the implementation of the MEWS. The implementation of the MEWS does not appear to be associated with any decrease of in-hospital mortality or length of stay in hospital. There was a slight increase in the trend of code blue calls following the implementation of the MEWS.

This is the first study to examine the use of the MEWS in a cardiology specific in-patient setting. Previous evaluation in the couple months following MEWS implementation on this cardiology unit found that there was no impact on nursing workload, the MEWS worked for the patient population of the unit, and there was improved interdisciplinary communication (Talusan et al., 2012). Although previous qualitative research has shown some of the benefits of the MEWS on this unit, one would expect quantitative analysis to also show some improvement in patient outcomes. Interrupted time series design offered a strong method of analysis, not commonly used in nursing research, to evaluate patient outcomes following a quality improvement initiative of the implementation of the MEWS. Although many studies examined the association between high MEWS scores and adverse events, few have studied if the MEWS has an impact on patient safety outcomes and can prevent adverse events. This is also the first study with the objective of examining the impact of a MEWS, despite the lack of a RRT to offer
support, on patient outcomes, such as code blue calls, in-hospital mortality, and length of stay in hospital.

The findings of an increased proportion of code blue calls contradict previous research findings of the MEWS being associated with a decrease in code blue calls (Albert & Heusman, 2011; Maupin, et al., 2009). However, these studies did not explain the statistical methods used for analysis nor did they report the statistical significance. A possible explanation for the increase in code blue calls found in this study is that they were being made for more cautionary reasons. The use of the MEWS has been associated with an increase in nurses’ ability to identify deteriorating patients and react more appropriately. It is possible that nurses’ increased confidence in their assessments following the MEWS implementation may have led to more code blue calls due to recognition of impending hemodynamic decompression. Increased acuity might account for an increase in code blue calls but no acuity data were collected for this study and the overall outcomes of patients who had code blue calls was not examined.

The lack of a Rapid Response Team may also influence the frequency of code blue calls as follows. Given the MEWS was primarily designed to trigger a call to a RRT, it is possible that the increased proportion of code blue calls was due to there not being any alternative option for triggering an immediate response to early deterioration, identified using the MEWS. Although this unit has 24-hour physician coverage, the physician coverage is not always in-house, particularly at night, or immediately available due to the possibility of conflicting clinical demands elsewhere. There was no analysis done on the time of day at which code blue calls were made, nor any information collected on whether the code blue calls were preceded by elevated MEWS requiring intervention. Also, despite an increase in trend of code blue calls, it is possible that there were fewer transfers to critical care post-MEWS and interventions were instead being
initiated on the unit. Patients who were transferred to critical care and later required a code blue call in the critical care setting were also not included in the code blue data obtained. Although the code blue calls on the cardiology unit increased, there could have been fewer subsequent code blue calls in the critical care units for patients transferred from the cardiology unit, which may explain some of the differences found.

The MEWS was designed and validated to promote patient safety, increase monitoring, and decrease failure to rescue (De Meester, Das, et al., 2013; De Meester, Haegdorens, Monsieurs, Verpooten, Holvoet, & Van Bogaert, 2013). However, the findings of a slight increase in code blue calls following implementation of the MEWS could mean that the MEWS is not effective in identifying deteriorating patients early enough to prevent the adverse patient outcome of cardiac or respiratory arrest of hemodynamic decompensation. Given findings in the extant literature that activation of a RRT has been shown to be associated with a decreased incidence of adverse events, it could be the implementation of an RRT itself that is associated with patient outcomes rather than the system (such as the MEWS) used to trigger clinical intervention such as the MEWS (Ludikhuize, Borgert, et al., 2014). It is also possible that the use of the MEWS in the absence of a RRT may have little effect on decreasing the incidence of adverse patient outcomes.

Few studies have examined the effect of MEWS implementation on in-hospital mortality. Those that did find a decrease in in-hospital mortality either implemented the MEWS simultaneously with a critical care outreach service, did not explain the statistical methods used for analysis, or did not find statistical significance in their results (De Meester, Haegordens, et al., 2013; Moon et al., 2011; Maupin, 2009). Although the in-hospital mortality increased slightly in this study following MEWS implementation, this refers to deaths that occurred on the
cardiology unit and does not include patients who were transferred to critical care and subsequently died in the critical care setting. Although there were more deaths on the cardiology unit, there could have been fewer deaths in the critical care setting among patients transferred from the cardiology unit which may explain some of the differences in in-hospital mortality that were found. It is also possible that the findings of no significant difference in in-hospital mortality means that the MEWS is not effective in identifying deteriorating patients early enough to prevent the adverse patient outcome of mortality.

This study adds to the extant literature on the association between the use of the MEWS and length of stay in hospital. Only one study was found in the literature that examined this outcome and although they found a decrease in length of stay in post-operative patients they did not use time series analysis and therefore did not control for any possible secular trends that may have already existed (De Meester, Haegordens, et al., 2013). An increase in length of hospital stay could be related to an increase in the overall acuity and complexity of the population of that study, but as previously mentioned this study did not include any acuity data.

**Limitations**

This study had a number of limitations, which included sampling, selection of study variables, and study design. As this research drew on one hospital unit within one site, it was limited in its depth of sampling and generation of generalizable results (Polit & Beck, 2011). An interrupted time series design allowed for comparison of a population before and after implementation of the MEWS given that a randomized control group was not feasible. However, the inclusion of a non-equivalent comparison group could have strengthened the study design and decreased threats to internal validity, such as attrition and maturation. Transfers to critical
care, which have shown to occur earlier following MEWS implementation and may impact patient outcomes, were not measured in this study (Stenhouse et al., 2000; Subbe et al., 2003).

The lack of data on patient acuity is a limitation; if available, these data could have allowed for more sophisticated analysis. Although the demographics of the patients admitted to the cardiology unit were similar, there is no data to determine the acuity level of the patients admitted. If patients admitted to the cardiology unit had increasing acuity or complexity over time, this would certainly affect the patient outcomes of code blue calls, in-hospital mortality, and length of stay in hospital. Collecting data on patient acuity would likely involve obtaining detailed individual patient information, which was outside the feasibility for this study given the time that would have been needed for individual chart reviews of all 3046 patients in the study sample.

Another limitation of this study was the limited number of observed events and possibility of inadequate power and a type II error as suggested by the wide range of the 95% confidence intervals. Bernal, Cummins, et al (2017) suggest that studies with few time points or small effect sizes may be underpowered and should be interpreted with caution. Further data collection to obtain a larger sample size would have increased the power of this study. Although there is no true minimum of observations required for an interrupted time series analysis, power does increase with the number of data points collected (Bernal et al., 2017).

Additionally, some in-hospital deaths may not have been accounted for, because some of the patients that were admitted to the cardiology unit during the study period were not ultimately discharged from the unit. Only deaths that occurred on the cardiology unit were counted and therefore there were deaths unaccounted for of those transferred from the cardiology unit. Further data collection, including patients transferred to a critical care setting from the
cardiology unit, who did not then return to the cardiology unit prior to in-hospital mortality or discharge, could potentially yield different results.

Implications

Future Research

Findings from this study offer important possibilities for future research. Given the 86% rate of correct use of the MEWS protocol in the 24-chart audit, further assessment could be done to ensure that the MEWS protocol is in fact being followed correctly and consistently. It is possible that the new clinical documentation tool may not have been fully adopted by staff at the beginning of the study period, but rather the consistency of its use may have increased gradually over the time period covered by this study.

Additionally, more detailed investigation of code blue calls and outcomes could be done to examine in greater detail the differences in code blue calls, the acuity of the patients on whom they are called, and the specific patient outcomes they yield. The number of patient transfers to critical care from the cardiology unit could also be examined further to investigate the effect of the MEWS on transfers to critical care and determine the impact of including this data in the overall analysis. A trend towards earlier critical care transfers, if found on this unit, could positively impact overall patient outcomes as has been noted in previous studies (Stenhouse, et al., 2000; Subbe, et al., 2003).

Furthermore, there are opportunities to build on the findings of this study by conducting additional data collection. Bernal et al. (2017) explain that power in time series analysis increases with the number of time points. Further data collection to obtain an increased number of data points could be carried out in the future which would yield results with a higher level of statistical power. Although a true control group may not be feasible, a non-equivalent control
group could be found to collect similar data and conduct simultaneous interrupted time series analysis.

Interrupted time series is a statistical method used frequently in the evaluation of public health interventions and public policy changes but not common in the nursing literature. Time series analysis is particularly useful when a randomized trial is not feasible as it is suitable to routinely and retrospectively collected data, does not require a control group, and is inexpensive to carry out. Nurses should become more knowledgeable on the strengths and limitations of time series analysis as it is a simple but powerful tool used for evaluating the impact of a policy change or quality improvement programs (Penfold & Zhang, 2013). Interrupted time series provides easy-to-interpret graphical results which can be valuable tools in presenting administrators and policy makers with the effects of a policy change (Penfold & Zhang, 2013).

**Nursing Practice and Education**

Though the results of this study showed no statistically significant decrease in patient outcomes - code blue calls, in-hospital mortality, or mean length of stay following the implementation of a MEWS, this should not necessarily discredit the use of the MEWS in the clinical setting. As discussed in the literature review, many studies have found the MEWS to be associated with increased nurse confidence, increased awareness of the features of the deteriorating patient, and more effective communication among interdisciplinary team members. The implementation of an electronic medical record, which is planned for this hospital in the next few years, will create the ability to use the MEWS in a new capacity. Electronic documentation will allow a MEWS score to be calculated automatically from vital signs records, reducing human error, and possibly providing a trigger for immediate escalation of care. This would also mean the MEWS could be easily calculated without significant workload to bedside
nurses. The ease of use of the MEWS and its ability to improve nursing documentation, increase nursing confidence, and improve communication between nurses and physicians warrants the continued use of the MEWS in clinical practice.

Conclusion

To my knowledge, this is the first study aimed at examining the impact of implementing a bedside MEWS, without a Rapid Response Team, on a cardiology unit. Although this study encountered limitations such as sampling and study variables, this study makes a novel contribution to understanding the association of the use of a MEWS during routine patient assessment with patient outcomes, such as code blue calls, in-hospital mortality, and length of stay in hospital. Using an interrupted time series design, this study did not find evidence of an association between the use of the MEWS and a decrease in adverse patient outcomes. Given the increase in code blue calls found, the use of the MEWS without a RRT may not be a good investment in terms of nursing time or resources. However, recommendations for further research have been made to definitively determine if any differences may exist and to build upon the findings of this study.

Given the results of this study, it may be concluded that the use of a MEWS may not have an impact on overall patient outcomes. The use of the MEWS during routine patient assessment may do more to improve nurses’ confidence, nursing documentation, and interdisciplinary collaboration rather than have a direct effect on patient outcomes. These other potential benefits of the MEWS may still contribute to a positive safety culture and increased patient safety on a cardiology unit. These findings also highlight the importance of evaluating quality improvement initiatives to determine if desired outcomes are being met. Interrupted time series analysis was the strongest quasi-experimental approach for this study, given the inability
to conduct a randomized control trial, and is a method of analysis that may be useful in some nursing research in the future.
References


Institute for Healthcare Improvement: IHI Announces that Hospitals Participating in 100,000 Lives Campaign Have Saved an Estimated 122,300 Lives (press release).


Appendices

Appendix A. Modified Early Warning Score Algorithm

<table>
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<tr>
<th>Modified Early Warning System (MEWS - 5A)</th>
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<td>3</td>
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<tr>
<td>Resp rate per minute</td>
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<td>Heart rate per minute</td>
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<td>Systolic blood pressure</td>
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<td>Conscious Level (AVPU)</td>
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<td>Temperature</td>
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Modifier: For non surgical pain please add the following to your MEWS score:

<table>
<thead>
<tr>
<th>Ongoing pain unrelieved with intervention</th>
<th>Pain relieved with intervention but pain returns within 2 - 4 hours</th>
<th>Pain relieved with intervention but pain returns within 8 hours</th>
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<tbody>
<tr>
<td>ADD 3 points</td>
<td>ADD 2 points</td>
<td>ADD 1 point</td>
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Green = 0 - 1
Yellow = 2 - 3
Orange = 4 - 5
Red = ≥ 6

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<thead>
<tr>
<th>Color</th>
<th>Action</th>
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<tbody>
<tr>
<td>0-1 Green</td>
<td>Rescore with VS as per protocol</td>
</tr>
<tr>
<td>2-3 Yellow</td>
<td>Ensure accuracy and significance of findings Investigate cause and treat appropriately Notify Charge Nurse RN reassesses and rescores in 4 - 6 hrs (use clinical judgment) Notify MRP if patient scores 3 in any one single category</td>
</tr>
<tr>
<td>4-5 Orange</td>
<td>Ensure accuracy and significance of findings Investigate cause and treat appropriately Notify MRP Notify Charge Nurse Page Clinical Resource Nurse RN monitors and rescores q1hr until improvement in patient’s condition - if no improvement after 2 hrs, notify MRP for reassessment and plan - 5A CN to notify Critical Care CN of patient’s condition When stable reassess and rescore depending on most recent score</td>
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<tr>
<td>6+ Red</td>
<td>Ensure accuracy and significance of findings Investigate cause and treat appropriately Notify MRP Notify Charge Nurse – CN to notify Critical Care CN of patient’s condition Page Clinical Resource Nurse RN monitors and rescores q1hr until improvement in patient’s condition - If no improvement after 1 hr, notify MRP for reassessment and plan</td>
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## Appendix B. MEWS Chart Audit Form

<table>
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<tr>
<th>Study Chart ID</th>
<th>LOS in hospital (days)</th>
<th>Total # of flowsheets reviewed</th>
<th>Total flowsheets w/ MEWS accurate</th>
<th>Percentage of accurate flowsheets for MEWS</th>
<th>Comments</th>
<th>MEWS used per Protocol - Day 1 (y,n)</th>
<th>Day 2</th>
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Appendix C. R Code for Final ITS Models

**ITS model for “Code Blue calls”**

```r
install.packages("car")
library(car)
library(nlme)

# A preliminary OLS regression
model_ols <- lm(codeblues ~ time + level + trend, data=data)
summary(model_ols)

# Fit the GLS regression model
model <- gls(codeblues ~ time + level + trend, data=data,
correlation=corARMA(p=2, form=~time),
method="ML")
summary(model)
confint(model)

# Produce final ITS plot
plot(data$time, data$codeblues,
ylim=c(0, 8),
ylab="Percent Code Blue Calls per Patients Discharged",
xlab="Month & Year",
pch=20,
col="pink",
xaxt="n")
axis(1, at=1:25, labels=data$month)

# Add line indicating MEWS implementation
abline(v=12.5, lty="dotted")
lines(data$time[1:12], fitted(model)[1:12], col="red", lwd=2)
lines(data$time[13:25], fitted(model)[13:25], col="red", lwd=2)
segments(1,
model$coef[1]+model$coef[2],
25,
model$coef[1]+model$coef[2]*25,
lty=2,
lwd=2,
col="red")
```

**ITS model for “In-hospital Deaths”**

```r
library(car)
library(nlme)

# A preliminary OLS regression
model_ols <- lm(deaths ~ time + level + trend, data=data1)
summary(model_ols)

# Fit the GLS regression model
model <- gls(deaths ~ time + level + trend, data=data1, correlation=NULL, method="ML")
summary(model)
confint(model)

# Produce final ITS plot
plot(data1$time, data1$deaths,
ylim=c(0, 4),
ylab="Percent In-hospital Deaths per Patients Discharged",
xlab="Month & Year",
pch=20,
col="pink",
```
ITS model for outcome “Length of Stay”:

```r
library(car)
library(nlme)

model_ols <- lm(LOS ~ time + level + trend, data=data2)
summary(model_ols)

# Fit the GLS regression model
model <- gls(LOS ~ time + level + trend, data=data2, correlation=NULL, method="ML")
summary(model)
confint(model)

# Produce final ITS plot
plot(data2$time, data2$LOS,
     ylim=c(3,10),
     ylab="Mean Length of Stay in Hospital (days)",
     xlab="Month & Year",
     pch=20,
     col="pink",
     xaxt="n")
axis(1, at=1:25, labels=data2$month)
abline(v=12.5, lty="dotted")
lines(data2$time[1:12], fitted(model)[1:12], col="red", lwd=2)
lines(data2$time[13:25], fitted(model)[13:25], col="red", lwd=2)
segments(1,
          model$coef[1]+model$coef[2],
          25,
          model$coef[1]+model$coef[2]*25,
          lty=2,
          lwd=2,
          col='red')
```

```