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A Framework for Quantifying and Managing Overcrowding in Healthcare Facilities

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A FRAMEWORK FOR QUANTIFYING AND MANAGING OVERCROWDING IN HEALTHCARE FACILITIES

by

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ABSTRACT

Emergency Departments (EDs) represent a crucial component of any healthcare infrastructure. In today's world, healthcare systems face growing challenges in delivering efficient and time-sensitive emergency care services to communities. Overcrowding within EDs represents one of the most significant challenges for healthcare quality that adversely impacts clinical outcomes, patient safety, and overall satisfaction. Research in this area has resulted in creating several ED crowding indices, such as National Emergency Department Overcrowding Scale (NEDOCS) and Emergency Department Work Index (EDWIN) that have been developed to provide measures aimed at mitigating overcrowding. Recently, efforts made by researchers to examine the validity and reproducibility of these indices have shown that they are not reliable in accurately assessing overcrowding in regions beyond their original design settings. The shortcomings of such indices stem from their reliance upon the perspective and feedback of only clinical staff and the exclusion of other stakeholders. These limited perspectives introduce bias in the results of ED overcrowding indices.

This study starts with confirming the inaccuracy of such crowding indices through examining their validity within a new healthcare system. To overcome the shortcomings of previous indices, the study presents a novel framework for quantifying and managing overcrowding based on emulating human reasoning in overcrowding perception. The framework of the proposed study takes into consideration emergency operational and clinical factors such as patient demand, patient complexity, staffing level, clinician workload, and boarding status when defining the crowding level. The hierarchical fuzzy logic approach is utilized to accomplish the

goals of this framework by combining a diverse pool of healthcare expert perspectives while addressing the complexity of the overcrowding issue. The innovative design of the developed framework reduces bias in the assessment of ED crowding by developing a knowledge-base from the perspectives of multiple experts, and allows for its implementation in a variety of healthcare settings. Statistical analysis of results indicate that the developed index outperform previous indices in reflecting expert subjective assessments of overcrowding.

To the memory of my late father

***Sayed* Mohammed Albar**

Your tales have been, and will always be, my source of inspiration.

To my beloved mother

Fatima Aljohani

Your sacrifice, patience, prayer, and support were immeasurable and will never be forgotten.

To my beloved sister

Taiba Albar

I could not ask for a better sister. I respect you and love you.

To my beloved brother

Omar Albar

You always make me proud of you.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS AND ABBREVIATIONS

ACEP	American College of Emergency Physicians
AHA	American Hospital Association
ED	Emergency Department
EDWIN	Emergency Department Work Index
ESI	Emergency Severity Index
EMTALA	Emergency Medical Treatment and Labor Act
FLS	Fuzzy Logic System
GAO	United States Government Accountability Office
GIEDOC	Global Index for Emergency Department Overcrowding
HFS	Hierarchical fuzzy system
LOS	Length of Stay
LWBS	Left Without Being Seen
MOH	Ministry of Health
NEDOCS	National Emergency Department Overcrowding Score
READI	Real-time Emergency Analysis of Demand Indicators
IOM	Institute of Medicine
IRB	Institutional Review Board
WHO	World Health Organization

CHAPTER 1 INTRODUCTION

1.1 Introduction

Hospital-based emergency departments (EDs) are a crucial component of any healthcare infrastructure. EDs provide emergency and urgent care services to patients, in addition to providing acute care to uninsured people, serving as “the safety net of the safety net” (IOM, 2007). However, in today’s complex world, healthcare systems face growing challenges in delivering efficient and time-sensitive emergency care services to communities. Healthcare expenditures continue to increase, and at the same time, several difficulties exist relating to community or individual access to proper care. Such issues continue to impact healthcare systems of a multitude of nations, prompting governments to take action both politically and academically to identify and assess problems. For instance, the American College of Emergency Physicians’ (ACEP) 2014 report card revealed that the USA’s emergency care environment is worsening, as it barely passed ACEP’s assessment with a D-Plus grade. The report asserted that the issues regarding access to EDs play a critical role in any effort to improve ED services. Other countries, including Saudi Arabia, Canada, France, China, Spain, Italy, Iran, United Kingdom, India, Australia, and Germany, have suffered from increasing demands on EDs, which has led to a congestion of patients in such EDs. Generally, due to growing demands and limited resources, EDs globally face serious issues related to potential patients’ access to emergency care, the ability to deliver needed services, as well as concerns with EDs congestion.

EDs crowding, which, as stated by the ACEP, *"... occurs when the identified need for emergency services exceeds available resources for patient care in the emergency department (ED), hospital, or both"* (Lin, Taira, Promes, & Regan, 2011), is a multidimensional dilemma (Crane, Zhou, Sun, Lin, & Schneider, 2014) facing healthcare legislators and healthcare decision and policy makers around the world. The ED crowding phenomenon adversely impacts patient safety, clinical care outcomes, and patient and staff satisfaction as well as the reputation of healthcare institutions. In a recent published report, the United States Government Accountability Office claimed that "emergency departments crowding continues to occur, and some patients wait longer than recommended time frames." (GAO, 2009). To cope with this concern, interdisciplinary efforts have focused on reaching a consensus on a definition for the problem, developing measures of ED crowding, and investigating its influence on EDs' operational and clinical outcomes.

When an ED is crowded, decisions have to be made in a variety of areas to assure the ability of delivering safe emergency care services such as decisions regarding ambulance diversion and ED staffing. To evaluate an ED's level of crowding, there had been a need for a quantitative instrument that determines ED overcrowding status. As a result, four ED crowding measurement scales were developed. Those scales are Emergency Analysis of Demand Indicators (READI) (Reeder & Garrison, 2001), Emergency Department Work Index (EDWIN) (Bernstein, Verghese, Leung, Lunney, & Perez, 2003), National Emergency Department Overcrowding Score (NEDOCS) (Steven J. Weiss et al., 2004), and Work Score (Epstein & Tian, 2006). Lately, research efforts have moved towards examining the reproducibility, reliability, and validity of such indices within different healthcare systems. Unfortunately, most of those efforts show that the existing ED overcrowding measurement systems are not accurate in assessing overcrowding outside the settings where there were originally developed.

In addition to these inaccuracies, it has been noticed that most of these ED measurement scales rely mainly on the perspective and feedback of physicians and nurses, for the subjective assessment of crowding, who represent only one type of ED stakeholder. Thus, those indices are biased toward healthcare giver perspective leaving researchers lacking a quantitative tool for assessing ED crowding that takes into consideration the other stakeholder's perspectives, such as patients, and hospital administrators as well as healthcare experts.

1.2 Emergency Care System: An Overview

Hospital-based emergency departments (EDs), first emerging after World War II, are a relatively recent healthcare phenomenon (Morganti et al., 2013). By the early 1970's, emergency care services had developed in many ways, such as changes in ED staffing from existing as part-time community physicians to being full-time emergency physicians (IOM, 2007). Since then, the demand on emergency care has increased dramatically, and the quality of emergency services has been negatively impacted.

As Figure 1-1 illustrates, the conditions in EDs continues to worsen. The number of emergency department visits in the US reached 130 million visits in 2011, which is a 46% increase from 88.5 million visits two decades ago. Simultaneously, the number of emergency departments decreased by 12.7 % from 5,108 to 4,461. Moreover, the ED visits per 1000 persons increased from 351 to 415, as shown in Figure 1-2, which indicates a growing demand on emergency care services.

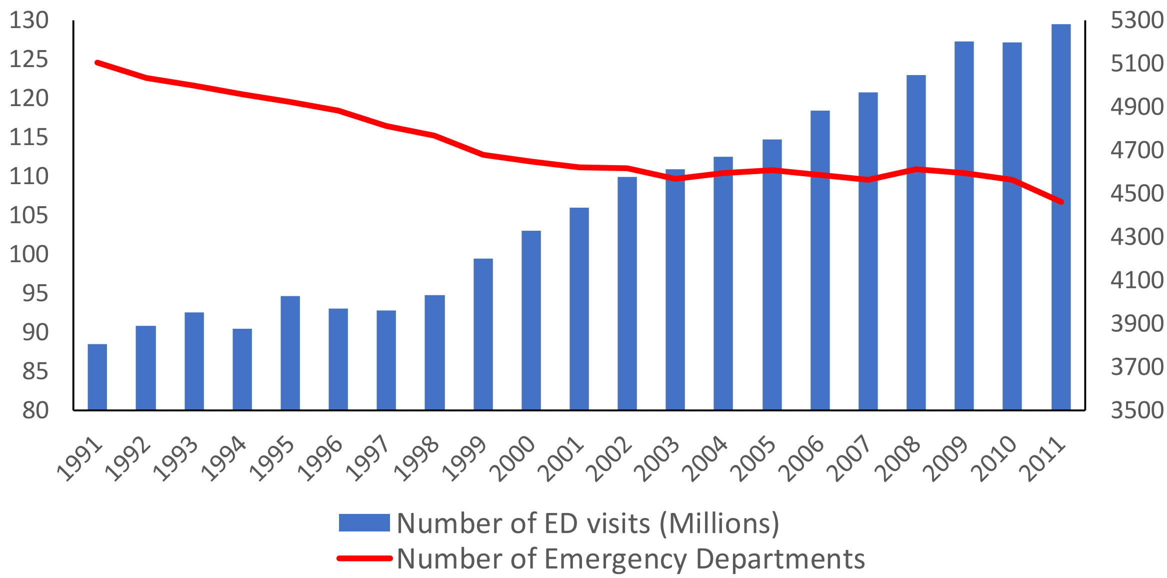

Figure 1-1: Number of ED visits and emergency departments in the USA, 1991-2011

Source: U.S. Department of Health and Human Services.

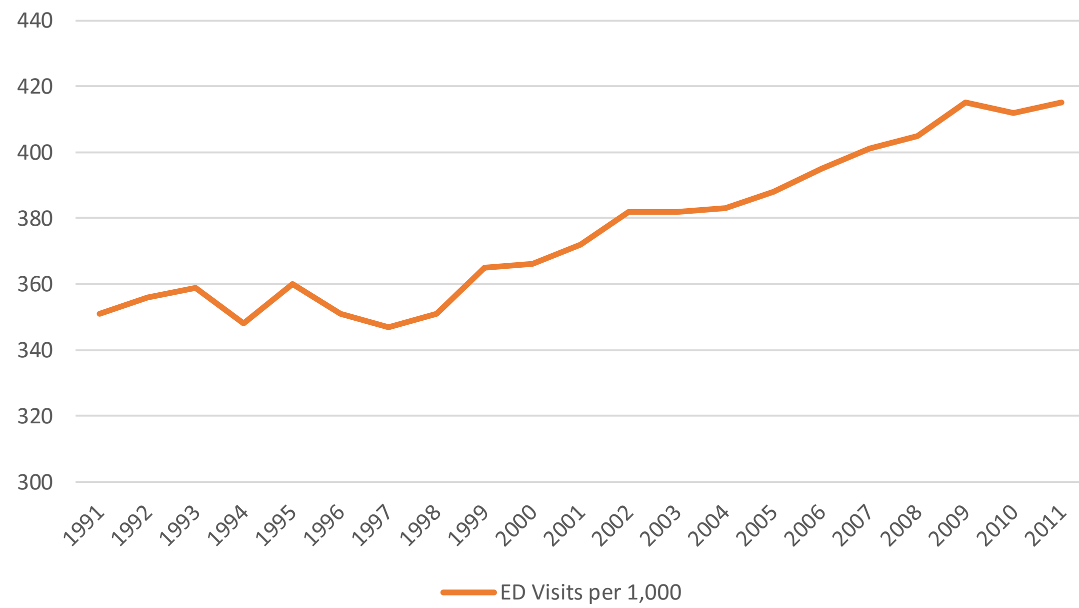

Figure 1-2: US emergency department visits per 1,000 persons

Source: U.S. Department of Health and Human Services

Every five years, the American College of Emergency Physicians (ACEP) reviews the emergency care environment and publishes a report card that provides more comprehensive information about the status quo of the emergency care services in the USA. The report card is divided into five categories and includes 136 objective measures. The categories, as illustrated in Table 1-1, include access to emergency care, quality and patient safety environment, medical liability environment, public health and injury prevention, and disaster preparedness. The report card evaluates the emergency care environment for each state. In addition, it evaluates the emergency care for the nation as a whole. The report card presents one grade for each of the five categories and an overall grade.

According to the most recent report card, released in 2014, the USA’s emergency care received a D-plus. It also revealed that the emergency care system in the USA has worsened since the last assessment in 2009, when it earned a C-minus. Access to emergency care, which represents 30% of the overall grade, is a vital factor in the evaluation. The overall grade for this factor is a D-minus in both 2009 and 2014 (ACEP, 2014).

If the grade is broken down by state, however, as presented in Figure 1-3, it can be seen that the situation has worsened in that more states received a grade of F in 2014 compared to the number of states in 2009. The number of states that received a B or C decreased by 6 and 5 states, respectively. It is obvious that these results agree with the tenor of the 2009’s report of the United States Accountability office titled “Hospital Emergency Departments: crowding continues to occur, and some patients wait longer than recommended time frames.” (GAO, 2009).

Table 1-1: Emergency care environment's report card

Source: American College for Emergency Physicians (ACEP)

Category	Weight	2009 Grade	2014 Grade
Access to emergency care	30 Percent	D-	D-
Quality and patient safety environment	20 Percent	C+	C
Medical liability environment	20 Percent	C-	C-
Public health and injury prevention	15 Percent	C	C
Disaster preparedness	15 Percent	C+	C-
Overall grade	100 Percent	C-	D+

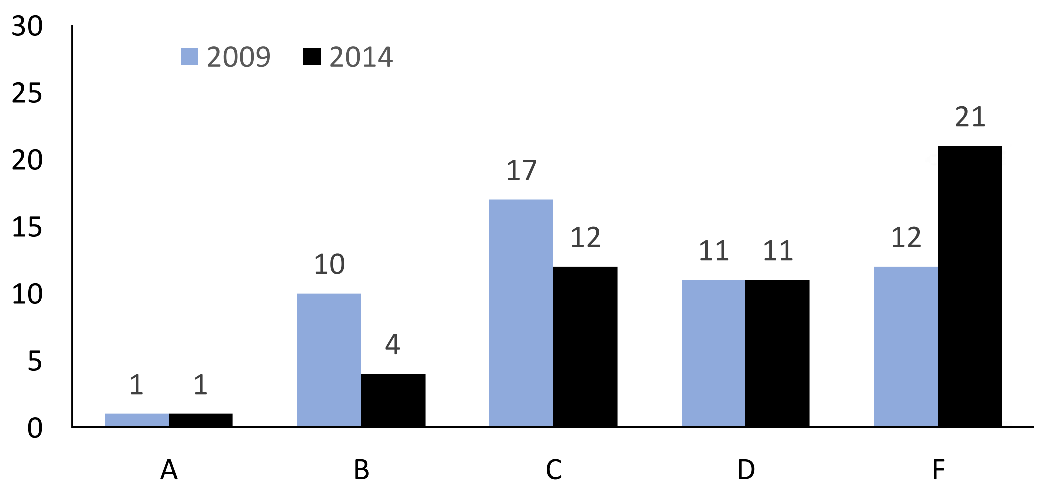

Figure 1-3: Grades received by states (access to emergency care)

Source: American College for Emergency Physicians (ACEP)

The Institute of Medicine's (IOM) 2001 report "'Crossing the Quality Chasm'' revealed that the healthcare system of the United States faces serious issues. To begin coping with such issues, six aims for healthcare improvement were proposed as follows:

- Safety: avoiding risk of harming patients from care service
- Effectiveness: avoiding overuse and underuse of care delivery.
- Patient-centeredness: respecting patient choices and taking into account patient values.
- Timeliness: reducing wait time for patients and care providers.
- Efficiency: reducing waste associated with care provided to patients.
- Equity: providing care to patients regardless of their racial or ethnic characteristics.

1.3 Testing NEDOCS and EDWIN Reliability: a Preliminary Study

1.3.1 Introduction

Crowding presents serious issues to EDs in any healthcare system, negatively impacting patient safety and clinical outcomes. Measurement tools play a critical role in addressing overcrowding by quantifying it and informing decision makers, however it is also important that they produce reliable results for multiple environments. Indices developed to quantify crowding vary in that they rely on unique perspectives from one type of stakeholder, in addition to utilizing different assessment approaches.

Based on a preliminary review of academic research on ED overcrowding, two assessment approaches were identified, including identification of measures and indicators for ED overcrowding, and the development of multidimensional indices for quantifying overcrowding. Additionally, seventy-one ED crowding measures, indicators, and indices were identified among the related research, and their applications were studied. Among these measures, four multidimensional ED overcrowding indices were identified, which are the Real-time Emergency Analysis of Demand Indicators (READI) (Reeder & Garrison, 2001), the Emergency Department Work Index (EDWIN) (Bernstein et al., 2003), the National Emergency Department Overcrowding Score (NEDOCS) (Steven J. Weiss et al., 2004), and the Work Score (Epstein & Tian, 2006).

The preliminary review of literature indicated that the reliability and validity of NEDOCS and EDWIN indices vary from one healthcare system to another. For instance, in some emergency care settings, the indices showed acceptable levels of accuracy in evaluating ED crowding, while in other settings they were ineffective in determining crowding status. These ED overcrowding indices needed to be examined in a new healthcare system where they have not been validated yet to test their usefulness across different ED contexts. Research shows that the validity and accuracy of the existing ED overcrowding indices have not been examined in the region of Middle East, where patient congestion in EDs is a serious issue. Therefore, a preliminary study was conducted in Saudi Arabia to help fill the knowledge gap in the studied region. Hence, the preliminary study will entail evaluating the reliability and validity of NEDOCS and EDWIN in Saudi Arabian healthcare organizations, where no ED crowding measurement systems have been previously implemented.

The objective of the preliminary study is to examine the accuracy and reproducibility of the National Emergency Department Overcrowding Scale (NEDOCS) and the Emergency Department Work Index (EDWIN) within the Saudi Arabian healthcare system.

Specifically, this preliminary study aims to answer the following questions:

- Is the National Emergency Department Overcrowding Scale (NEDOCS) valid and reliable in quantifying ED crowding within Saudi Arabian healthcare settings?
- Is the Emergency Department Work Index (EDWIN) valid and reliable in quantifying ED crowding within Saudi Arabian healthcare settings?

The collected data will be analyzed to quantitatively examine the validity and reproducibility of NEDOCS and EDWIN within Saudi Arabian emergency care settings.

1.3.2 Method

Two hypotheses were developed to be tested in this preliminary study, and are as follows:

- *Hypothesis one: the National Emergency Department Overcrowding Scale (NEDOCS) cannot accurately quantify the ED overcrowding levels within Saudi Arabian emergency care settings.*
- *Hypothesis Two: the Emergency Department Work Index (EDWIN) cannot accurately quantify the ED overcrowding levels within Saudi Arabian emergency care settings.*

Whether or not the NEDOCS index (Equation 6) is valid and reliable in Saudi Arabian emergency care settings will be examined. Both subjective and objective data will be collected from a distributed survey (seen in Appendix E) and analyzed to test hypothesis one. The qualitative section will involve collecting the opinions of physicians and nurses who work in the emergency department regarding the degree of overcrowding and about their feelings of being in rush at a given time. The quantitative section involves collecting information on five variables designed to count the number of patients and time of patient flow through the ED at a given time. In addition, the quantitative section takes into consideration two constants: the capacity of the hospital, and that of emergency department. The process of collecting the data will take place four times a day, seven days a week, for four weeks. Table1-2 illustrates the eligibility criteria for participation, the sample size, and timeline of the NEDOCS study.

Table 1-2: Eligibility criteria and timeline for NEDOCS and EDWIN study

	Physician Survey	**Nurse Survey**	**Quantitative Section**
Eligibility Criteria for Participation	ED Physician	ED Nurse	ED administrator, ED Nurse, or ED Physician
The duration of an individual subject's participation in the study	One minute	One minute	Five minutes
Number of participants	180	180	90
Duration of the study	Four weeks		

In a similar manner, subjective and objective data from distributed surveys in appendix F will be used to analyze and test hypothesis two, to ultimately determine the validity and reliability of the EDWIN index in the same ED setting. In the qualitative section of the survey, the opinion of physicians and nurses is collected regarding the ED busyness level at a given time. The quantitative section will collect information on four variables designed to determine both the number of patients in each triage category and the total number of patients at a given time. Data will be collected four times a day, seven days a week, and the study will last for four weeks. Table 1-2 illustrates the eligibility criteria for participation, the sample size, and timeline of the EDWIN study.

Samples that do not follow the eligibility criteria shown in table 1-2, and surveys which are not completely filled out by participants will be excluded from the final results.

The EDWIN score will be calculated using Equation 5, and the EDWIN Clinician Subjective Assessment (CSA) score will be determined using a five-point Likert scale as shown in Appendix F. The NEDOCS score will be calculated using Equation 6, and its CSA will be determined using a six-level Likert scale as shown in Appendix E.

The reliability of the EDWIN and NEDOCS index will be measured by testing the agreement levels between the objective scores of the indices and their CSA subjective scores. Kappa statistics is a suitable method for evaluating such reliability. Cohen's Kappa can be calculated using the following formula:

$$\kappa = \frac{\mathrm{Pr}(a) - \mathrm{Pr}(\mathrm{e})}{1 - \mathrm{Pr}(e)} \tag{1}$$

Where Pr(a) is the proportion of observations in agreement and Pr(e) is the proportion in agreement due to chance.

1.3.3 Results and Discussion

The preliminary study was conducted in the emergency department of a major public hospital in Saudi Arabia, which treats approximately 100,000 patients per year, and features 450 inpatient beds and 42 emergency care beds. The purpose of this section of this preliminary study was to test the objective scores from NEDOCS against the subjective assessment of clinicians on their perception of crowding in order to determine its accuracy in reflecting the level of ED crowding. Over the course of four weeks, 90 observations were randomly taken. Observations were conducted randomly to take measurements that correspond to the variables of the NEDOCS equation, including the number of admitted patients, the number of hospital beds, the waiting time for the last patient placed in an ED bed, the longest time among boarding patients since registration, and the number of occupied respirators. Simultaneously, surveys were distributed to two physicians who were available during an observation period, asking them to rate the degree of crowding in the ED, as well as their feeling of being rushed, on a Likert scale of 1 to 6. Two available nurses were also asked to rate the degree of crowding in the ED in each observation period.

As similar in the study by Steven J. Weiss et al. (2004), the Likert scale was assigned to six descriptive categories found in the NEDOCS scale, and was converted to a scale from 0 to 200, where 0 corresponded to "not busy", 40 was "busy", 80 was "extremely busy but not overcrowded", 120 was "overcrowded", 160 was "severely overcrowded", and 200 was "dangerously overcrowded". This would allow for the use of kappa statistics to determine the reliability and absolute agreement of the average of the six assessments taken.

The results from the observation period in Appendix H were analyzed to determine the reliability for subjective evaluations provided by both physicians and nurses, and finally the averaged assessments were compared to the NEDCOS scores. The inter-rater reliability between physician assessments of the level of crowding was 0.297, with a 95% confidence interval of

[0.175, 0.419], showing fair agreement. Appendix H also includes the cross-tabulation of the two physicians' responses, showing their agreement in each provided assessment. Among the 90 observations made on the six point Likert scale, only 43% of the physician responses were in agreement. The most common score for the first physician was a score of five, provided 24 times, while the second physician responded most frequently with a score of four, doing so 32 times. When physicians were asked about their feeling of being rushed, the inter-rater reliability between physician responses was 0.179 with a 95% confidence interval of [0.063, 0.295], indicating poor agreement. In the cross-tabulation of responses from Appendix H, physician assessments for their feeling of being rushed agreed only 34% of the time, and no scores of "1" were issued by the second physician among the 90 observations. The first physician issued a score of "3" most frequently at 25 times, while the second physician issued a score of "4" most frequently, at 32 times. For the agreement among nurse assessments of crowding, the inter-rater reliability was 0.253 with a 95% confidence interval of [0.130, 0.376], showing fair agreement. The cross-tabulated results from the nurse assessments show that nurse assessments agreed 39% of the time when issuing scores. The first responding nurse most frequently assigned a score of "5" at 22 times, while the second nurse issued a score of "2" most often for 22 assessments.

The agreement between the average physician response and average nurse response for the assessment of crowding was also found. The inter-rater reliability between the average clinician response on crowding was 0.204, with a 95% confidence interval of [0.073, 0.335], showing fair agreement. It was found that the averaged clinician responses resulted in no assessments issued in the first NEDOCS descriptive category of "not busy". The cross-tabulation of these responses show that the average clinician response was in agreement 30% of the time. The average nurse assessment most frequently assigned a score of “4” at 28 times. Similarly, the average physician response was most often “4” for 31 assessments. After calculating the objective scores from NEDOCS, it was found that the average was 132 on the 200 point scale.

To determine if NEDOCS accurately reflected the subjective assessment of clinicians, the averaged clinician assessments were compared to the objective NEDOCS scores across the six different descriptive categories using kappa statistics (Appendix H). It was found that among the 90 observations, NEDCOS assessed the crowding level to be “not busy” 11% of the time, while providing evaluations of “busy” 19% of the time, “extremely busy but not overcrowded” 33% of the time, “overcrowded” 22% of the time, “severely overcrowded” 13% of the time, and “dangerously overcrowded” only 1% of the time. In comparison, the average clinician evaluation of crowding for the 90 observations consisted of 12% “busy”, 24% “extremely busy but not overcrowded”, 38% “overcrowded”, 21% “severely overcrowded”, and 4% “dangerously overcrowded”. Furthermore, the objective scores issued by NEDOCS agreed with the average clinician subjective assessment only 43% of the time, with no agreement occurring in the first and last descriptive classes. The inter-rater reliability for the NEDOCS scores and the average clinician assessment was 0.276 [95% CI (0.156, 0.395)], indicating fair agreement. These findings indicate that NEDOCS is ineffective in accurately reflecting the subjective clinician perception of ED crowding in Saudi Arabia ED settings.

A similar methodology for the assessment of NEDOCS was carried out to determine accuracy of the EDWIN in reflecting the subjective assessment of crowding by clinicians. The findings in this section represent the second half of the preliminary study aimed at assessing the reliability and reproducibility of the mentioned indices. Data was collected for the testing of the

EDWIN index in the same hospital emergency department in Saudi Arabia in which the NEDOCS data was collected, during the same observational period of four weeks. In each observation, the recorded data included the number of patients in each triage category using the emergency severity index, the number of present physicians, the capacity of the ED, and the number of boarded patients. Simultaneously, subjective assessments were provided by two available physicians and two available nurses who rated crowding on a five point Likert scale. The clinicians were asked to rate the level of busyness in the ED, with one being the least crowded, and five being the most crowded.

When all observations were completed, the average subjective scores were compared to the EDWIN objective scores. In accordance to the methods by Bernstein et al. (2003), the average of the four clinicians' responses was determined, and assigned to the Likert scale, where three descriptive classes were assigned to three intervals on this scale to describe the average response. In keeping with Bernstein et al. (2003), the EDWIN scale similarly contained three descriptive classes on three intervals, where for scores between of 0 and 1.5, the ED crowding level corresponded to the class "active, but manageable". For scores between 1.5 and 2, the ED was considered "busy", and for scores higher than 2, the ED was "crowded". Similarly, the Likert scale on which the subjective responses were provided was assigned these same classes on three intervals. An average subjective assessment between 1 and 2 would correspond to "active, yet manageable", while an average assessment between 2 and 4 would be considered "busy", and an assessment between 4 and 5 would be "crowded". The average response from the four clinicians would then fall into one of these respective categories also used in the described EDWIN scale, to describe the average subjective assessment on crowding.

Reliability analysis (Appendix H) found that for the agreement among physician-physician assessments, the inter-rater reliability was 0.394, with a 95% confidence interval of [0.257, 0.531], indicating fair agreement. Among the cross-tabulation of the responses provided by physicians, it was found that physicians issued the same scores in 54% of their observations. The first responding physician in the observations issued scores of “4” most often, doing so for 34 such observations. The second responding physician also assigned a score of “4” on the five point Likert scale most frequently, doing so 28 times. The inter-rater reliability between nurses’ subjective assessment was 0.572, with a 95% confidence interval of [0.447, 0.697], which indicates moderate agreement. In the cross-tabulated results of the nurse assessments, it was found that nurses agreed in their evaluations 68% of the time. The first responding nurse assigned a score of “3” most often, doing so 31 times, while the second responding nurse also issued a score of “3” most often in 32 assessments. The agreement between average subjective responses of physicians and nurses was also analyzed. The inter-rater reliability for the average clinician responses was 0.239, with a 95% confidence interval of [0.108, 0.370], indicating fair agreement. Among the cross-tabulation of results from the average clinician response, it was found that the average physician assessment assigned a score of “4” most often 37 times, while the average nurse assessment assigned a score of “3” at 34 times. The calculated EDWIN scores resulted in an average score of 1.87.

Next, the subjective assessments of the clinicians was compared to the objective EDWIN scores in each of the three descriptive categories through the use of kappa statistics in order to determine if EDWIN accurately reflects the subjective assessments of clinicians. When EDWIN provided an assessment in the first category (active, but manageable), clinicians responded with 4 assessments in the same category, 11 assessments in the second category (busy), and 4 in the third category (crowded). In total, clinicians provided 19 assessments for this EDWIN category, 15 of which were higher than EDWIN's assessment, indicating clinicians overestimate the level of crowding. When EDWIN provided an assessment in the second category, clinicians responded with 57 assessments. 35 of these assessments were assigned to the second category, indicating agreement with EDWIN, while 1 assessment was assigned to the first class, and 21 were assigned to the third class. In total, 22 provided assessments were higher or lower than EDWIN's assessment in this category. When EDWIN assessed crowding as category three, clinicians provided assessments in the same category 11 times, while 3 assessments were provided in the second category. Out of the 14 assessments clinicians provided in this EDWIN category, only 3 were lower than EDWIN's assessment. The overall measure of agreement was k=0.235 [95% C.I. (0.080, 0.390), indicating fair agreement between the EDWIN scores and those of clinicians (Appendix H). This reveals that EDWIN is inaccurate in reflecting the clinician subjective perception of ED crowding.

The analysis of the results from the study carried out on the National Emergency Department Overcrowding Study and the Emergency Department Work Index shows that they were not accurate in assessing emergency department crowding in the Saudi Arabian healthcare setting. The shortcomings of these indices may be a result of their exclusion of important crowding indicators and stakeholder perspectives. For instance, NEDOCS does not consider the staffing level when evaluating crowding, and similarly EDWIN does not consider the nurse staffing level in its assessment. It can also be noted that the overall agreement for NEDOCS and the average clinician assessment within the studied Saudi Arabian ED (k=0.276) is comparable to the results of Raj, Baker, Brierley, and Murray (2006), who studied the accuracy of NEDOCS in an Australian

ED (k=0.31). The findings of this preliminary study confirm the inaccuracies in implementing the studied indices to measure ED overcrowding in settings outside their regions they were originally developed in.

1.4 Research Problem Statement

The demand on healthcare services continues to grow, and lack of access to care services has become a dilemma due to the limited capacity and inefficient use of resources in healthcare. This supply-demand imbalance and resulting access block is causing overcrowding in healthcare facilities, one type of which is emergency departments. These essential healthcare centers serve as a hospital's front door and provide emergency care service to patients regardless of their ability to pay. According to the American Hospital Association (AHA) annual survey, the visits to emergency departments in the USA exceeded 130 million in 2011 (AHA, 2014). In Saudi Arabia, the Ministry of Health (MoH) reported nearly 21 million visits in 2012 (MOH, 2014). With this massive demand on emergency care services, emergency departments mostly operate over capacity and sometimes report ambulance diversion.

When ED crowding started to become a phenomenon, a need appeared to quantify the problem as a way to offer support in making emergency care operational decisions. As a result, four ED crowding measurement scales were developed which are Emergency Analysis of Demand Indicators (READI) (Reeder & Garrison, 2001), Emergency Department Work Index (EDWIN) (Bernstein et al., 2003), National Emergency Department Overcrowding Score (NEDOCS) (Steven J. Weiss et al., 2004), and Work Score (Epstein & Tian, 2006). However, many criticized the reliability, reproducibility, and validity of these crowding measurement scales when implemented in emergency settings outside of the regions they were originally developed in. Moreover, their efficiency has been a concern, especially with regards to their dependency solely on emergency physicians' and nurses' perspectives.

1.5 Research Objectives

ED crowding has become a serious issue in many healthcare organizations. It affects both operational and clinical aspects of emergency care systems. To evaluate such an issue, healthcare decision makers should be provided with a robust quantitative tool that measures the problem and aids in ED operational decision making. To achieve this, the proposed study aims to:

- Develop a quantitative measurement tool of evaluating ED crowding that captures healthcare experts' opinions and other ED stakeholder perspectives and has the ability to be applied in variety of healthcare systems.

1.6 Research Questions

This research aims to answer the following question:

- What is an appropriate quantitative instrument to assess ED crowding which has the capability to be reproduced within different healthcare contexts?

1.7 Research Contributions

This study will contribute to the existing knowledge of the field of quality systems engineering by proposing a robust framework for assessing crowding in healthcare facilities. The proposed research is unique in its application of fuzzy logic, which has the ability create a logical quantitative measurement tool founded upon the perspective of multiple subject matter experts and recognize patterns of bias. This will allow the developed index to overcome the problems associated with the indices founded upon singular stakeholder perspectives. An index created from the developed framework can be used by leading stakeholders to better assess crowding in EDs, and ultimately make better informed decisions when mitigating overcrowding. Moreover, the implementation of such an index developed from this research could contribute to achieving care providers' overall goals of offering safe and timely care in ED settings. In addition to the benefits this study would offer to practitioners, researchers could additionally benefit from the creation of a robust quantitative instrument when studying the impact of ED overcrowding on a variety of operational and clinical outcomes. The developed index may also be utilized by researchers seeking to measure the effectiveness of patient flow for related improvement projects and initiatives in healthcare settings.

1.8 Organization of the Dissertation

The following is a description of the organization and content for the remaining elements of this dissertation. Chapter two reviews relevant literature on the subject of emergency department overcrowding, and presents the existing conceptual and quantitative approaches for understanding and measuring ED overcrowding. Moreover, this chapter sheds light on the subject of fuzzy logic and its applications in performance management. Chapter three describes the adapted research methodology, which encompasses the preliminary fuzzy logic framework for evaluating overcrowding in EDs. Chapter four describes the theory behind all conceptual and technical aspects of the proposed framework that are related to its design. It includes the architecture of the hierarchical fuzzy logic system, its mechanism, the methods of eliciting expert assessment, the procedures of expert knowledge acquisition, and the development of the proposed fuzzy system. Chapter five documents the construction of the knowledge base, where results from the inclusion of expert knowledge are analyzed. Additionally, the implementation and initial validation steps are discussed, and some reflections are made based upon analysis of the entire chapter. Finally, Chapter six concludes the dissertation by reviewing the background of the research topic, summarizing the implications of previous research on the defined research problem, and discussing the results from the novel index created in response to the research problem. This chapter additionally defines the success of the designed framework by assessing its ability to achieve its design goals. Lastly, limitations of the research are discussed, and recommendations are made for future research related to this study.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

Healthcare systems today face a variety of challenges. Limited resources and growing demands on healthcare services as well as increasing costs have exacerbated the delivery of such services to communities. Crowding within hospital-based emergency department (EDs) is a growing challenge faced by healthcare systems worldwide. This phenomenon negatively impacts patient outcomes and satisfaction. Moreover, crowding can financially affects hospitals because it creates an environment where medical errors are more likely to occur. The World Health Organization (WHO) states that it is a priority for healthcare systems to concentrate on decreasing crowding levels in their facilities in order to minimize effects that crowding has on its patients, clinicians, and other stakeholders (WHO, 2014).

This chapter reviews relevant literature on emergency department overcrowding, its operational definitions, and its impact on quality of care, patient safety and outcomes, patient and clinician satisfaction, and clinician workload. It also sheds light on the conceptual frameworks that have been developed to facilitate the understanding of the phenomenon of ED overcrowding as well as its root causes or determinants. In addition, this chapter reviews in detail the existing measures for assessing overcrowding, and their relation to each other and to clinician perspectives of overcrowding. Moreover, this chapter further reviews available approaches of assessing the status of overcrowding in emergency departments, as well as the applicability, reliability, and validity of these approaches. Finally, chapter two includes a section that provides background on the fuzzy logic approach and its applications in management aspects.

2.2 Definitions of Emergency Department Crowding

Due to the seriousness of the problem of overcrowding and its adverse impact on both providers and seekers of health services, many definitions for emergency department crowding have been proposed in the literature. Nevertheless, there is no consensus on a standard universal definition for crowding in EDs (Anneveld, van der Linden, Grootendorst, & Galli-Leslie, 2013; Asplin, 2006; Asplin et al., 2003; Beniuk, Boyle, & Clarkson, 2012; Bernstein et al., 2003; Casalino et al., 2013; Eitel, Rudkin, Malvehy, Killeen, & Pines, 2010; Epstein & Tian, 2006; Green, Dawber, Masso, & Eagar, 2014; N. R. Hoot, Zhou, Jones, & Aronsky, 2007; Hwang & Concato, 2004; Hwang et al., 2011; Johnson & Winkelman, 2011; Morris, Boyle, Beniuk, & Robinson, 2012; Moskop, Sklar, Geiderman, Schears, & Bookman, 2009; Steven J. Weiss et al., 2004; S. J. Weiss, Ernst, & Nick, 2006; Wiler, Griffey, & Olsen, 2011).

The U.S Government Accountability Office's (GAO) 2003 report on ED crowding reveals the complexity of the issue, and how challenge measuring the problem is, although, hospital officials report that "they know it [crowding] when they see it" (GAO, 2003). The American College of Emergency Physicians (ACEP) reports that "crowding occurs when the identified need for emergency services exceeds available resources for patient care in the emergency department (ED), hospital, or both" (Lin et al., 2011). This general definition, which has been adopted in many studies, simply views the issue as a typical imbalance between supply and demand that widely occurs in many growing markets.

Michael J. Schull, Slaughter, and Redelmeier (2002) consider ambulance diversion as a reasonable operational definition for urban ED crowding; however, this definition might not be generally accepted since ambulance diversion policies differ from one healthcare organization to another, and some healthcare policies do not allow initiation of ambulance diversion. Jessie M. Pines (2007) considers EDs are crowded "when inadequate resources to meet patient care demands lead to a reduction in the quality of care." Yet, this definition encounters challenges when considering how to measure quality of care in such an environment, where patients needs differ. Pines cleverly illustrates the problem of EDs crowding by describing it as "the elephant standing in the room; it is just very difficult to describe how heavy he is, how bad he smells, and just when the floor might give."

2.3 Consequences of Emergency Department Crowding

Emergency department crowding is a multidimensional problem. The complexity of this phenomenon arises from the unique nature of the workflow in emergency departments. Unlike other service providers, emergency departments face increasing, and unstable demand resulting in overcrowded environment.

The effects of ED crowding have been widely studied in related literature, both clinically and operationally. Many ED stakeholders are impacted by the overcrowding such as patients, physicians, nurses, administrators, and wards employees. It also affects the quality of care that is provided within the emergency room. During overcrowding episodes, patients receive inferior care (Johnson & Winkelman, 2011), their safety and outcomes are adversely impacted, and patient satisfaction decreases (Johnson & Winkelman, 2011). In addition, satisfaction among physicians and nurses decreases.

2.3.1 Crowding and Patient Safety and Outcomes

Overcrowding in emergency departments negatively affects care seeker safety and outcomes (Johnson & Winkelman, 2011). It causes delays in vital interventions such as cardiac intervention (Kulstad & Kelley, 2009; J. M. Pines, Hollander, Localio, & Metlay, 2006; Michael J. Schull, Vermeulen, Slaughter, Morrison, & Daly, 2004), antibiotic administration, and analgesia use (Fee, Weber, Maak, & Bacchetti, 2007; J. M. Pines et al., 2006; J. M. Pines, Localio, et al., 2007). Moreover, the literature shows that long wait times for emergency care is significantly associated with poor pain management (Hwang et al., 2008; Hwang, Richardson, Sonuyi, & Morrison, 2006; Johnson & Winkelman, 2011; Mills, Shofer, Chen, Hollander, & Pines, 2009; J. M. Pines & Hollander, 2008; J. M. Pines, Shofer, Isserman, Abbuhl, & Mills, 2010).

Mortality is a common measure for patient outcome and is a good indicator for evaluating the quality of care (Kane, Scalcucci, Hohmann, Johnson, & Behal, 2013). Chalfin, Trzeciak, Likourezos, Baumann, and Dellinger (2007); Diercks et al. (2007); Fatovich (2005); Miró et al. (1999); Richardson (2006); Shenoi et al. (2009); and Sprivulis, Da Silva, Jacobs, Frazer, and Jelinek (2006) all studied the effects of overcrowding on mortality. Although each study use a different method to measure ED overcrowding, their results agree that a strong correlation exists between ED overcrowding and increased mortality.

Beniuk et al. (2012) investigated the effects of ED crowding on admitted patients. They found that patients admitted to inpatient wards through the emergency department on days of crowding as measured by ambulance diversion periods, were negatively impacted. Specifically, the likelihood of inpatient death and the length of patient stay increased under such conditions by 5%, and 8%, respectively.

According to another study by Epstein et al. (2012), when an ED experiences high levels of crowding, the risk of preventable medical errors increases. In yet another study, Watts, Nasim, Sweis, Sikka, and Kulstad (2013) assert that there exists a linear association between ED overcrowding and an increased number of medical errors arising from a disruption in physician focus, administrative mistakes, and physician miscommunication with patients. Within the same context, Epstein et al. (2012) found that frequency of medical errors positively correlates with ED overcrowding. The medical errors they found include prescribing incorrect medication doses, durations, frequencies or routes as well as giving patients contraindicated medications. Such medical errors directly affect the quality of care, patient safety and outcomes, and the reputation of the healthcare institution.

2.3.2 Crowding and Patient Satisfaction

To assess, manage, and improve the quality of emergency care services, it is important to investigate the impact of overcrowding on patients' perceptions of the service. Patient satisfaction is a critical indicator of the quality of emergency care because it captures patients experience (Hall, 1996).

Benjamin C. Sun et al. (2000) identified determinant factors of patient satisfaction within the emergency care context and patients' willingness to return to the same emergency service provider. Their study concludes that perception of waiting time is negatively associated with patient satisfaction. When patients leave the emergency department without being seen by physicians, it is an indicator of ED crowding and poor patient satisfaction (Johnson & Winkelman, 2011). McMullan and Veser (2004) list the department-dependent factors that patients report as reasons for their decision to leave, which include total hospital admissions through the ED, ED volume, the waiting room time, and the total resuscitations in the ED. Moreover, patients' psychological distress and their perception of ED busyness are among the factors that increase the rate of patients who leave without being seen or treated.

In another study, Vieth and Rhodes (2006) confirm the adverse impact of ED crowding on patient satisfaction. They state that patient satisfaction decreases significantly when the perceived wait time exceeds one hour, and is very low if a patient waits more than four hours. The results of this study indicate that even if patients were satisfied with the medical care, their overall visit satisfaction dropped when the wait time was excessively long. The study also investigated the reasons for patients leaving without being treated. The outcomes of the investigation reveal that when patients are too sick to wait, the wait is too long, or they feel mistreated by the ED staff, they leave the ED before receiving care.

Another study examined physicians, nurses, and patients perceptions on the association between ED crowding and the quality of care. In this study, all of these ED stakeholders report that crowding significantly impacts the quality of emergency care (J. M. Pines, Garson, et al., 2007). In a relevant study, J. M. Pines et al. (2008) conclude that wait time and ED crowding are associated with lower patient satisfaction. In addition, they stated that the long wait time for boarding patients after care negatively impacts patient overall assessment of the hospital services.

Recently, Tekwani, Kerem, Mistry, Sayger, and Kulstad (2013) studied the effect of ED crowding on discharged patients from emergency departments. The researchers used the EDWIN Index and ED occupancy rate to measure crowding while using Press-Ganey surveys to assess patient satisfaction. The results show that the patient satisfaction significantly decreases with higher EDWIN scores and ED occupancy rates. Moreover, it was found that patient satisfaction also slightly decreases in ambulance diversion episodes.

Boarding patients in the emergency department contributes to the ED crowding because it is the responsibility of ED staff to continue providing them with adequate care until they move to appropriate wards. A recent study state that boarded patients prefer to stay in an inpatient hallway than emergency hallway (Viccellio et al., 2013). Viccellio et al. (2013) add that these findings could be considered as an indicator of decreased patient satisfaction among emergency boarding patients.

2.3.3 Crowding and Clinician Workload and Satisfaction

Like patients, clinicians are impacted by ED overcrowding but in a different way. Coles (2010) tested whether ED overcrowding affects provider workload or not. The study used the EDWIN index and occupancy rate as two different objective methods to measure crowding and the National Aeronautics and Space Administration Task Load Index (NASA-TLX) to measure provider subjective workload. The results of this study reveal that ED crowding is significantly associated with variation in provider workload when using occupancy rate as a crowding measure, and is mildly correlated with workload when using the EDWIN index. Another study found a strong association between the number of boarded patients and decreased nurse job satisfaction (Bornemann-Shepherd et al., 2015). In general, patient congestion in EDs affects the staff workload, and clinician satisfaction. It creates an environment where medical errors could occur which threatens clinician job security (Epstein et al., 2012).

2.4 Conceptual Emergency Department Crowding Models

In the literature, there currently exist only two conceptual models to describe the ED crowding phenomenon. The first and the most accepted one is the input-throughput-output model which divides patients flow in EDs into three stages. The other is the cardiac analogy model, which illustrates the problem by drawing an analogy to the cardiac system and compares ED overcrowding to a stroke, which limits its use to medical professionals. This section describes these conceptual models and their contribution to understanding the issue of ED crowding.

2.4.1 Emergency Department Input-Throughput-Output Model

In order to comprehend ED crowding, Asplin et al. (2003) developed a framework that divides emergency care processes into three interdependent phases: input, throughput and output (Figure 2-1).

The Input component is described as including any element or event that adds to the demand of emergency care service. The sources of demand on ED service are classified into three channels: emergency care, which includes patients from the community with serious conditions and referrals with emergency conditions; unscheduled urgent care; and safety net care, such as treatment of uninsured patients who have the right to receive emergency care services as a result of the Emergency Medical Treatment and Labor Act (EMTALA).

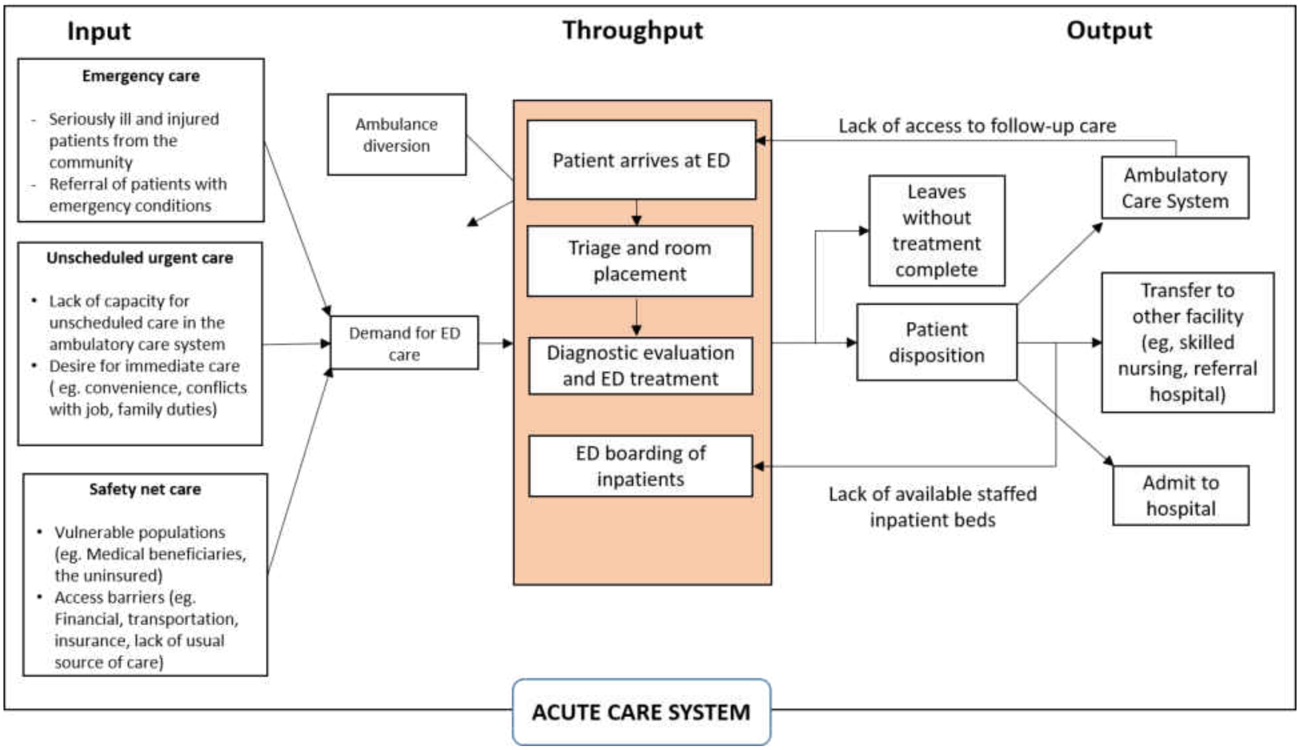

Figure 2-1: Asplin's conceptual model for emergency department crowding

Adopted from (Asplin et al., 2003)

The throughput component includes two major stages. The first stage includes patient arrival, the triage process, room placement, and the initial treatment. The second stage is the diagnostic evaluation, which involves performing diagnostic tests and communication with different departments such as laboratories. In addition, patients boarded in EDs who are defined by the ACEP as "a patient who remains in the emergency department after the patient has been admitted to the facility, but has not been transferred to an inpatient unit" (Griffin et al., 2016), acquire more ED resources and their stay time affects throughput stage. The throughput component includes all internal processes that take place in the emergency department. Therefore, in order to improve the efficiency of the ED, efforts should focus on this stage, which would reduce waiting time, and improve patient flow.

The last stage in this model, the output stage, includes admitting patients to the hospital, transferring patients to other healthcare facilities, or transferring patients to ambulatory care providers. The output stage also includes patients who leave without being seen or treated. Typically, when a patient is admitted to the hospital, if there is an available bed, the patient move immediately; otherwise, the patient is boarded in the ED, which contributes to the ED overcrowding level. Moreover, if a patient is advised to visit an ambulatory care provider, and there is a lack of access to such service, the patient may return to the ED, which adds unnecessary workload to the ED. Finally, in cases where a patient is transferred to another healthcare facility, typically the patient needs an ambulance pick-up. The wait time for an ambulance would contribute to the overcrowding level, according to this model.

2.4.2 Cardiac Analogy Model

Laskowski-Jones (2005) first created the cardiac analogy model to illustrate ED crowding. In terms of the heart, when preload increases, so does cardiac output up to a certain level, "beyond which the myocardial fibers are overstretched and any further increase leads to a decrease in cardiac output."

When applying the cardiac analogy model, cardiac output is comparable to overall ED system performance, which includes total ED throughput, patient and staff safety and satisfaction, and quality of emergency care. Heart rate is comparable to the speed at which service is delivered, which is related to the availability of staff members and their experience, knowledge, and efficiency. Stroke volume is comparable to the amount of total productivity in a given period. The stroke volume depends on preload, afterload, and contractility. Preload reflects the demand for ED services. Preload can be viewed as the resistance to ED outflow. Contractility is analogous to the flexibility and readiness of the ED staff to respond to unstable working conditions (Laskowski-Jones, 2005).

Although this model is useful in conceptualizing the phenomenon of ED crowding, it has not been widely used due to the medical concepts implements. They limit the understanding to people of medical expertise, who are familiar with the heart failure pathophysiology (Bellow & Gillespie, 2014).

2.4.3 Determinants of ED crowding

Michael J. Schull et al. (2002) proposed four determinates of crowding in urban emergency departments related to characteristics of the community, the patients, the emergency department itself, and of its respective hospital.

The community is an external factor that affects the emergency departments. The availability of home care services, availability of alternative choices for ER patients such as community-based care, and ambulance diversion that occurs in local EDs are among the community factors. This determinant is essential to consider when ED crowding is analyzed from a macro-level point of view. Interestingly, none of the existing ED crowding measurement indices has adopted any community factor.

The second of Schull's proposed determinants is the patient, which is considered as an external factor as well. Patients differ in age, urgency level, discharge diagnosis, time of arrival to the ED, and the day of the week they seek ED services. Because each patient has unique characteristics, not just clinically but also personally, the delivery of ED services becomes even more complex.

The internal factors are at the micro (emergency department level), or meso (hospital level). Emergency department factors such as number of admitted patients in the ED, number of arrivals (through ambulance or walk-in), physicians and nurses staffing, response time, policies, ED layout, and access to diagnostic tests, can be used to evaluated the ED crowding internally.

Moreover, hospital level factors such as number of beds (intensive critical unit beds, and acute beds), hospital occupancy rate, and inpatient length of stay, are significant in comprehensively analyzing the ED crowding issue.

2.5 Quantitative Emergency Department Crowding Models

Generally speaking, crowding is a problem that many industries experience. The factors that contribute to crowding in EDs are also contributing to crowding in other industries, which may include high demand, a lack of performance management, and limited systems capacity. The general impact of crowding ranges from physical damage to psychological effects on entities. The rail transportation industry (Mohd Mahudin, Cox, & Griffiths, 2012), retail (Mehta, 2013), parks and outdoor recreation centers (Manning, Valliere, Minteer, Wang, & Jacobi, 2000), and healthcare facilities (Moskop et al., 2009) are among the environments that experience crowding.

The crowding phenomenon has caught researchers' attention, leading them to explore its causes, consequences, impact on customers' behavior and influence on the quality of service and customer satisfaction. Research efforts also include the designing and developing of crowding measurement scales.

In the literature, there are two different approaches regarding ED crowding measurement. One is to identify and create ED crowding measures such as waiting time and ED occupancy rate. Those measures mainly reflect real time observations of emergency care processes and some of them are not quantifiable. The second measuring approach focuses on developing multidimensional crowding measurement scales such as Emergency Department Work Index (EDWIN) and National Emergency Department Overcrowding Score (NEDOCS) (Beniuk et al., 2012). The following sections extensively reviews these two approaches in the context of EDs crowding.

2.5.1 ED Crowding Measures

Ospina et al. (2007) identified the ten most important crowding indicators in Canadian emergency departments. The ten key indicators are as follows:

- Total number of ED patients
- Percentage of ED occupied by inpatients
- Total time in the ED
- Percentage of time spent in ED at or above stated capacity

- Overall bed occupancy
- Time from bed request to bed assignment
- Number of staffed acute care beds
- Time from triage to EP
- Time from bed ready to transfer to ward
- Emergency Physician satisfaction

In a recent comprehensive systematic review, Hwang et al. (2011) identified seventy one unique ED crowding measures. The author categorized those measures into clinician opinion of crowding, input measures, throughput measures, output measures, and multidimensional indices. The following section reviews the relevant literature on all identified measures of ED crowding.

2.5.1.1 Measures of Clinician Opinion of ED Overcrowding

Table 2-1 shows all measures of clinician opinions towards emergency department crowding. Five subjective measures were identified by (Hwang et al., 2011) namely, if physicians feel rushed, if nurses feel rushed, clinician opinion of crowding, clinician opinion of ED busyness, and emergency physicians satisfaction.

Table 2-1: Measures of clinician opinion on ED overcrowding.

Partially Adapted from (Hwang et al., 2011)

Measure Type	Measure
Clinician opinion	– Physicians feel rushed – Nurses feel rushed – Clinician opinion of crowding – Clinicians opinion of ED busyness – Emergency Physicians satisfaction

First, the physician perception of feeling rushed measure is a six-point Likert instrument that has been considered as a subjective measure of emergency department overcrowding, that was first used by (Derlet, Richards, & Kravitz, 2001; Richards, Navarro, & Derlet, 2000). Afterward, Steven J. Weiss et al. (2004) utilized this measure as a base when developing the NEDOCS scale. Currently, the physician's feeling of being rushed is used to examine the validity and reliability of the NEDOCS scale in different healthcare systems by measuring the agreement between the subjective perception of physicians about their feeling and the quantitative NEDOCS results (Anneveld et al., 2013; Raj et al., 2006; Wang et al., 2014). Hwang et al. (2011) state that the physicians' perception of feeling rushed is significantly associated with clinicians' assessment of overcrowding.

Second, the nurse perception of feeling rushed at a given time is another subjective measure of emergency crowding. It was used by (Anneveld et al., 2013), who tested its agreement with the measure "physicians feel rushed". They found a good intra-rater agreement (κ=0.73) between the two measures.

Third, to measure the subjective perception of clinicians' (emergency nurses and physicians) opinion of emergency department overcrowding, (Vieth & Rhodes, 2006) introduced a five-point Likert scale for observing the physicians and nurses assessment of crowding. (Steven J. Weiss et al., 2004) used a six-point Likert scale for the same purpose. (Hwang et al., 2011) claim that the clinician opinion of crowding shows significant association with the number of patients who leave the emergency department without being seen by physicians. (Bernstein et al., 2003) explored the same concept, but called it "clinicians' opinions of ED busyness" and used a five-point Likert scale.

Finally, because emergency department overcrowding increases the workload on emergency physicians, the job satisfaction level of physicians has been used as a measure that may reflect the level of crowding. Using the Delphi method, Ospina et al. (2007) identified ten key indicators of emergency department overcrowding in Canada, one of which was physician satisfaction, which supports the hypothesis of the association between the satisfaction of physicians and the physicians' assessment of emergency department crowding.

2.5.1.2 Input Measures

Table 2-2 encompasses all measures of crowding in the literature that are associated with the inputs of emergency department. The identified 17 identified Input measures address all emergency department events prior to emergency treatment (Hwang et al., 2011). These measures include factors such as the number of patients, their waiting times, and patient complexity and severity.

Wait time is a very significant measure that reflects the busyness of ED (Hwang et al., 2011). In a survey of emergency department directors, respondents claimed that waiting time is a common measure for overcrowding because long wait time is a result of overcrowding which directly affects patients' experience (Derlet et al., 2001; Richards et al., 2000). N. R. Hoot et al. (2008, 2009) used the wait time measures in a discrete event simulation model for forecasting ED overcrowding. It shows a good two-hour-ahead forecast for overcrowding but is relatively poor at forecasting eight hours ahead. Wait time has also been used as a measure in conjunction with other measures to evaluate the level of overcrowding when implementing ED expansion projects (Han et al., 2007; Mumma, McCue, Li, & Holmes, 2014). Furthermore, one study states that wait time is a factor related to the emergency department itself (Miro et al., 2003). On one hand, (Han et al., 2007) claimed that wait time does not correlate with ambulance diversion periods. Yet Gilligan et al. (2008) found that the number of patients who left without being seen was strongly correlated with the long wait time. Interestingly, among the four ED crowding measurement indices, NEDOCS is the only system that utilized wait time measures in the index development (see Table 2-6 for details).

A waiting room that becomes filled more than six hours in a day is another input measure for ED crowding. Richards et al. (2000); Vieth and Rhodes (2006) found that ED directors are suggesting using this measure when evaluating overcrowding. Moreover, it has been found that this measure significantly associates with clinician opinion of crowding (Hwang et al., 2011).

"time to physician" measure is an interval time for assessing patient flow in EDs. Ospina et al. (2007) defined the time to physician measure as "Time (min or h) from assignment of triage category to examination by an EP", and listed it among the ten important key indicators of ED overcrowding in Canadian healthcare settings. According to Asplin's input-throughput-output framework (Figure 2-1), time to physician measure should be listed under the throughput section. Bullard et al. (2009) in their study support this placement by considering the time to physician as a throughput measure. Gilligan et al. (2008) studied the impact of a large number of boarded patients on many crowding measures, one of which was the time to physician. They show that time to physician was not impacted by the boarding practice. Time to physician has been found, however, to be significantly associated with physician opinion of crowding (Johnson & Winkelman, 2011) and patients who Leave Without Being Seen (LWBS) (Gilligan et al., 2008).

Table 2-2: Input measures of ED overcrowding.

Adapted from (Hwang et al., 2011).

Measure Type	Measure
Input	– Waiting time – Waiting room filled more than 6 hours / day – Time to physicians – Number of arrivals – Number of patients in waiting room – Number of patients registered – Number or percentage of ambulance patients registered – Number of patients awaiting triage – Number of low-complexity patients – Number of patients at each acuity level – Average triage acuity level – Number of new patients by usual care – Percentage of open appointments in ambulatory care clinics – Left without being seen (LWBS) – Average or percentage of patients who leave without treatment complete – Ambulance diversion episodes – Average Emergency Medical Services (EMS) waiting time

The number of arrivals to ED, which is defined by Spencer S. Jones et al. (2009) as "count of patients arriving to the ED during a given hour," is a numerical count measure for evaluating the demand on emergency care services. Asaro, Lewis, and Boxerman (2007a) studied the factors that affect the rate of reneging (i.e. the rate of patient who leave without being seen by a physician). The study found that patient arrival rate is significantly associated with increased reneging rate. In another study, J. M. Pines, Localio, et al. (2007) investigated the impact of input and output factors on the throughput of EDs. They found that arrival rate significantly affected wait time, ED length of stay, and boarding time. In addition, the arrival rate has been found to be a key indicator of determining emergency department census, and the needed diagnostic resources. Interestingly, the READI index is the only ED crowding instrument that uses arrivals per hour in assessing overcrowding (see Table 2-6).

The number of patients in waiting room is another important numerical count measure used in ED crowding assessment. From the patient's perspective, the number of patients in the waiting room is the most evident indicator of ED crowding (N. R. Hoot et al., 2008). Some hospitals initiate ambulance diversion when all ED beds are occupied and the number of patients in the waiting room reaches 10 patients or more (N. R. Hoot et al., 2008). This measure has been used by different studies such as ones which developed an overcrowding sampling form (Steven J. Weiss et al., 2002), investigated variables of ED crowding (Steele & Kiss, 2008), and determined the effect of crowding on ED process outcomes (McCarthy et al., 2009). The number of patients in the waiting room has been found to be significantly associated with physician opinions of crowding (Derlet et al., 2001; Richards et al., 2000; Steven J. Weiss et al., 2002), waiting room time, ambulance diversion (Miro et al., 2003), and ED length of stay (McCarthy et al., 2009). Despite its importance in evaluating crowding, the Work Score index is the only crowding measurement system that uses the number of patients in the waiting room in assessing ED overcrowding status (see Table 2.6).

Number of registered patients is also a measure used in evaluating crowding. The total number of patients registered has been used in two studies which used it as a factor of ED crowding (Han et al., 2007; Steven J. Weiss et al., 2002). The percentage of ambulance patients registered has been identified as a potential measure of crowding (Solberg, Asplin, Weinick, & Magid, 2003).

Accordingly, Hwang et al. (2011) claim that these two measures associate significantly with clinician opinion of crowding. The number of patients awaiting triage is another potential measure for crowding, as Steven J. Weiss et al. (2002) found that it strongly correlates with clinician opinion of crowding.

The acuity level is a critical factor in determining the needed resources for emergency care services. For this reason, three measures were created in this context, including the number of low-complexity patients, the number of patients at each triage, and average triage acuity level (Hwang et al., 2011). The emergency nurses assign patients to the appropriate triage category and prioritize them based on their acuity level. Low-complexity patients spend a longer time in the waiting room in the presence of high severity patients.

M. J. Schull, Kiss, and Szalai (2007) studied the impact of the number of low-complexity patients on waiting times in emergency department. They found that the number of low-complexity patients in the ED slightly increases time until other patients are seen by physicians and the ED length of stay. The number of patients at each triage level is a very important measure used in assessing overcrowding. The EDWIN and READI indices both use the number of patients at each triage category as a measure in evaluating the overcrowding status (see Table 2-6). The acuity ratio is the average triage acuity level of all patients in the ED and it reflects the severity level and the needed resources for emergency patients (Solberg et al., 2003). The acuity ratio has been found to be significantly associated with physician opinion of crowding (Hwang et al., 2011).

The number of new patients by usual care and the percentage of available appointments in ambulatory clinics that serve ED patients have been suggested as to be potential measures for ED overcrowding (Solberg et al., 2003). However, there currently exists no study that has used these two measures in assessing overcrowding.

The measure of leaving (the ED) without being seen (LWBS), which reflects a group of patients who could not wait longer to be seen by a physician, has been reported as a serious problem internationally (Clarey & Cooke, 2012). As such, the number of patients who left without being seen is a common measure for ED crowding (Bullard et al., 2009; Han et al., 2007). The majority of studies on LWBS has been conducted within the United States healthcare system. These studies show that the rate of LWBS varies from 0.84% to 15% in different cases (Clarey & Cooke, 2012). The rate of LWBS has been found to be significantly associated with wait times in EDs (Clarey & Cooke, 2012). However, it has been found that no association exists between the LWBS and ambulance diversion (Hwang et al., 2011). Another suggested crowding measure related to LWBS is the rate or percentage of patients who leave the ED without complete treatment (Solberg et al., 2003), because it correlates with clinician opinion on crowding (Hwang et al., 2011). None of the existing ED measurement indices uses this measure in assessing overcrowding (see Table 2.6).

Periods of ambulance diversion has been suggested as a proxy measure for ED crowding, since it reflects working at overcapacity, and is an action taken as a direct result of ED overcrowding (Michael J. Schull et al., 2002; Solberg et al., 2003). Burt, McCaig, and Valverde (2006) state that about 501,000 ambulance diversions happened in 2003 in the United States, an average of one ambulance diversion per minute, making it a remarkable consequence of ED crowding. It has been noticed that ambulance diversion episodes are significantly associated with clinician opinion of crowding (Michael J. Schull et al., 2002). Solberg et al. (2003) suggest measuring the average emergency medical service (EMS) waiting time, defined as "total time at hospital for ambulances delivering patients to ED during a defined period", divided by the "number of ambulance deliveries within that period" which they claim reflects ED efficiency. Hwang et al. (2011) added that the average EMS wait time strongly correlates with clinician opinion of crowding.

2.5.1.3 Throughput Measures

Table 2-3 encompasses all measures of crowding in the literature that are associated with the throughput of an emergency department. The identified 22 unique throughput measures consider all emergency department events and processes after admitting patients (Hwang et al., 2011). This includes ED capacity, ED workforce, and ED efficiency.

ED beds fully occupied for more than 6 hours a day or hallway beds at capacity more than 6 hours indicate a crowded ED. Derlet et al. (2001); Richards et al. (2000) list these two measure among potential measures for ED crowding. In addition, Ospina et al. (2007) suggest adding the percentage of time an ED works at or more than stated capacity to the ED throughput measures. The number ED rooms at full capacity is another measure that has been used is evaluating overcrowding (Steven J. Weiss et al., 2002). Such measures are significantly associated with physician opinion of overcrowding (Hwang et al., 2011).

Counting the number of patients at different ED processes is a direct way to assess and manage patient flow and ED overcrowding. Total number of patients in an ED reflects the total workload within an ED. Bullard et al. (2009) assert that patient volume is an important variable when tracking ED overcrowding, in addition to taking into consideration the acuity and complexity of patients' health issue. The ED census has also been used as a critical factor in developing an ED forecasting model (Spencer S. Jones et al., 2009; S. S. Jones et al., 2008). In addition, Ospina et al. (2007) list total number of patients among key indicators of crowding. Flottemesch, Gordon, and Jones (2007) conclude that studying ED census patterns provides more insight about ED overcrowding, operational efficiency and daily surges. The total number of patients in an ED is strongly correlated with clinician opinion of crowding (Hwang et al., 2011). Despite the importance of this measure, Steele and Kiss (2008) state that ED patient volume encompasses many variables; therefore, counting patients in different emergency care stages provides clearer details than total ED volume in assessing overcrowding. The NEDOCS index is the only ED crowding measurement system that uses ED census as a key measure in assessing crowding level (see Table 2-6).

Another suggested patient count measure is the number of hallways patients which has been found to be significantly associated with physician opinion of crowding (Steven J. Weiss et al., 2002). In addition, the number of patients who are being treated are considered a crowding measure (Miro et al., 2003). McCarthy et al. (2009) found that increase in the number of patients being treated significantly increases treatment time and patient waiting time overall. When a patient arrives at the ED with a high-complexity case, a specialty consultant is required to provide a detailed diagnostic. The number of patients waiting for such a consultation are considered a measure for crowding because it is significantly associated with patient boarding time (Steele & Kiss, 2008). Moreover, the waiting time to consultation is a measure that can provide more insight about patient flow and ED overcrowding (Bullard et al., 2009).

ED occupancy rate, which is defined as "the total number of patients in ED beds divided by the number of licensed treatment beds" is widely used as an indicator of ED overcrowding (N. R. Hoot et al., 2008). In the early of 2000s, Solberg et al. (2003) suggested the use of ED occupancy rate as a clear and simple measure of overcrowding. Later on, another study reached consensus on the most important crowding measures, with one of them being ED occupancy rate (Ospina et al., 2007). Another study by McCarthy et al. (2008) compared the efficiency of ED occupancy rate as a crowding index with the EDWIN index, and concluded that occupancy rate is not an ideal overcrowding index, yet it can be used as a simple real-time assessment tool of ED busyness. By itself, ED occupancy rate has been found to be significantly associated with physicians assessment of crowding, LWBS, and ambulance diversion (Hwang et al., 2011), and continually has been a main variable in developing ED overcrowding forecasting models (N. R. Hoot et al., 2009; N. R. Hoot et al., 2007; Schweigler et al., 2009).

Table 2-3: Throughput measures of ED overcrowding.

Partially Adapted from (Hwang et al., 2011)

Measure Type	Measure
Throughput	– ED beds at capacity more than 6 hours or hallways filled more than 6 hours – Percentage of time ED at greater than or equal to stated capacity – Number of full rooms – Total number of patients in ED – ED occupancy rate – Number of hallway patients – Number of resuscitations in past 4 hours – Number of patients being treated – Number of patients waiting for specialty consult or disposition by consultant for more than 4 hours – Number of ED diagnostic orders – Number of patients awaiting test results – Number of nurses working – Number of physicians working – Patients treated by acuity per bed hours – Number of patients per physician or nurse – Number of patients admitted or discharged per physicians – Sum of patient care time per shift – ED ancillary service turnaround time – Time to consultation – Time to room placement – ED treatment time – ED length of stay (LOS)

The total number of resuscitations within a four hour observation period is another ED throughput measure that can be used in assessing ED overcrowding. This measure indicates the number of high-complexity patients that arrive in the ED during a given interval of time (Steele & Kiss, 2008). Another form of this measure is used by the NEDOCS index as a measure in assessing

ED overcrowding (see Table 2-6), which is the number of "vent patients" in the ED at a given time.

During the emergency diagnostic phase, many orders are sent to supporting departments, and the number of these diagnostic orders may be used as a measure for assessing the workload and overcrowding within EDs. This includes ED laboratory orders, ED radiography orders, and ED computer tomography orders (Spencer S. Jones et al., 2009). Moreover, the number of patients waiting for test results of such orders is considered to be another throughput measure that reflects the workflow within an ED (Miro et al., 2003). These measures are significantly associated with physician opinion of overcrowding (Hwang et al., 2011). In addition, turnaround time of ED ancillary time, which is the average time from placing the diagnostic order to the result report, has been suggested as another measure for use in evaluating ED throughput and overcrowding (Steven J. Weiss et al., 2002). (Solberg et al., 2003) found that this measure is associated with physician opinion of crowding.

ED staffing and the staff's productivity play a major role is the assessment quality of emergency care. The number of emergency nurses on duty is based upon many factors such as the size of the hospital, the capacity of the ED, and the daily volume of emergency care demand. The American Academy of Emergency Medicine suggests an appropriate nurse-to-patient ratio of 1:3 (AAEM, 2015). Due to their influence on ED outcomes, the number of nurses working in an ED has been used as a measure of assessing ED crowding in two previous studies (Bernstein et al., 2003; Steele & Kiss, 2008). Currently, the Work Score index is the only measurement instrument that uses number of nurses at a given time to assess ED overcrowding (see Table 2-6). The number of physicians is another factor that has determined the level of overcrowding in indices. The

EDWIN Index in one such measurement tool which uses the number of on duty emergency physicians in evaluating the ED overcrowding status (Steven J. Weiss et al., 2004) (See Table 2-6). Moreover, the number of patients per nurse and per physician can offer more insight about the workload, level of crowding and appropriate ED staffing strategies (Schneider, Gallery, Schafermeyer, & Zwemer, 2003; Solberg et al., 2003). Hwang et al. (2011) note that this measure is significantly associated with clinician perspective of overcrowding. Another suggested measure that relates to ED throughput is the number of patients who are admitted or discharged per physician (Solberg et al., 2003). Hwang et al. (2011) found that this measure correlates with physician opinion of overcrowding. In general, this measure indicates the productivity of emergency physicians. However, to assess the ED productivity of a given time which takes into consideration the productivity of all emergency staff, the total of patient care time in a given shift is an appropriate measure which could also be used in assessing overcrowding (Richardson, 2006).

The time from triage to room placement is another time interval measure that has been suggested for evaluating patient flow and ED overcrowding (Bullard et al., 2009; Solberg et al., 2003). Hwang et al. (2011) state that the time to room placement is associated with physician opinion of overcrowding. In addition, ED treatment time is another ED throughput measure that has been used in assessing overcrowding (Hwang et al., 2011). Solberg et al. (2003) also suggest using the number of patients treated, and considering their complexity level and bed hours as a potential measure of overcrowding. Hwang et al. (2011) state that this measure associates with physician opinion toward crowding.

Finally, the length of stay (LOS) in an ED has been used in many studies to evaluate the ED throughput and ED crowding. Ospina et al. (2007); Solberg et al. (2003) suggest LOS as a potential measure for crowding, and it is considered an important measure in constructing ED crowding forecasting models (N. R. Hoot et al., 2008, 2009). Han et al. (2007) studied impact of ED extension projects on overcrowding. Using LOS as an outcome measure of such a project. It has been found that LOS is associated with physician opinion of overcrowding (Hwang et al., 2011).

2.5.1.4 Output Measures

Table 2-4 includes all measures of crowding in the literature that are associated with the output of emergency departments. The identified 21 unique output measures are associated all emergency department events and processes after emergency treatment is completed (Hwang et al., 2011). Some important measures include boarding, hospital occupancy rate, in addition to hospital or transfers to another healthcare facility, and availability of other care options.

When emergency care is completed, patients are either discharged and recommended to receive ambulatory care, admitted to inpatient beds, or transferred to another appropriate healthcare facility (Asplin et al., 2003). The number or percentage of admissions is a common measure of ED output. Nearly half of hospital admissions in the USA come from the emergency department (Schuur & Venkatesh, 2012). Asaro et al. (2007a); Asaro, Lewis, and Boxerman (2007b) found that the number of admissions negatively influences ED throughput because the admitted patients usually result in an increase in the number of boarded patients, who typically occupy more emergency diagnostic and treatment resources, thereby affecting the ability of ED staff to meet of the needs of new arrival patients. In addition, they found that the number of admitted patients increases the wait time for new emergency patients. Other investigators found that the percentage of daily admitted patients positively correlated with ED LOS (Lucas et al., 2009), and the findings from Rathlev et al. (2007) agree. The number of admitted patients is also significantly associated with waiting room time (Asaro et al., 2007b), and LWBS (Asaro et al., 2007a).

In cases where a patient is admitted to the hospital and there is no available bed, the patient must stay in the ED and keep receiving care from the ED until a bed becomes available. This situation which Kishore, Abraham, and Sinfield (2011) express as "backpropagation of congestion within hospital wards", exhausts ED resources. Nolan et al. (2015) state that boarding in ED is a major cause of ED overcrowding. A number of studies have been conducted on of boarding at emergency departments and its effects on patient flow and overcrowding. Due to the negative impact of boarding, measurements such as the number of and average number of the percentage of boarding within the ED, and the length of boarding duration have been listed as among the important measures of ED overcrowding (Asaro et al., 2007b; Ospina et al., 2007; Solberg et al., 2003; Steven J. Weiss et al., 2002). In a crowding forecasting study, N. R. Hoot et al. (2008, 2009) used boarding count and boarding time with other operational measures to develop forecasting models finding that the forecasted overcrowding moderately correlated with the number of boarded patients and their boarding time. In another study, investigators found that the more patients become boarded in an ED, the longer a patient's LOS in the ED will be. Because longer boarding times negatively impact patient outcomes and satisfaction in addition to patient flow, Solberg et al. (2003) suggest breaking down the boarding time into the time for bed assignment, bed cleaning, and transfer arrival to evaluate the efficiency of each process, which would help in improving such processes. Hwang et al. (2011) state that the number of boarded patients is associated with ambulance diversion, waiting room time, LWBS, clinician opinion of overcrowding, boarding time, treatment time, and ED LOS. Moreover, they state that the boarding time is associated with ambulance diversion, clinician opinion of overcrowding, and the rate of LWBS.

When analyzing the causes of overcrowding, it is obvious that ED crowding is not just the responsibility of the emergency department. The healthcare system as a whole contributes to this dilemma, and fourteen measures that deal with external sources of ED overcrowding have been identified.

Two potential measures that are relevant to boarding time are time from bed request to bed assignment, and time from which the bed is ready to ward transfer (Ospina et al., 2007). These measures, which are also associated with physicians opinion of overcrowding (Hwang et al., 2011), reflect the efficiency of the hospital operational management.

Another non-ED related crowding factor is the number of patients who are waiting for ambulance pick-up (Miro et al., 2003). When high-complexity patients are transferred to another healthcare facility, they typically need an ambulance to move between facilities. The wait time for such a service is an additional load to the ED, as patients in waiting for transfer will impact the ED capacity for new patients. Therefore, counting the number of patients waiting for an ambulance may be useful as a measure for overcrowding. This measure is associated with physician opinion of overcrowding (Miro et al., 2003). Solberg et al. (2003) also suggest using the rate of ED transferred patients as a measure for evaluating overcrowding because it shows a significant association with clinician opinion of overcrowding.

In addition, Solberg et al. (2003) suggest six additional output measures that contribute to ED overcrowding, including observation unite census, hospital admission source, hospital supply-demand forecast, ratio of ED volume to inpatient bed capacity, number of inpatients ready for discharge, and inpatient processing times. According to Hwang et al. (2011), these six measures are significantly associated with physicians opinion of overcrowding.

Bed management plays a critical role in hospital operations. One of the significant measures that bed management decision makers consider is inpatient occupancy rate. High occupancy rate increases the chances that an ED will have to work to overcapacity (Asaro et al., 2007b). For this reason, it is suggested that occupancy rate be taken into consideration when assessing ED efficiency, in addition to the level of overcrowding (Spencer S. Jones et al., 2009; Lucas et al., 2009). Previous studies found that the hospital occupancy rate is significantly associated with LWBS (Asaro et al., 2007a), boarding and treatment time (Asaro et al., 2007b), clinician opinion of overcrowding (Solberg et al., 2003), and LOS in EDs (Lucas et al., 2009).

The number of staffed acute care beds is a critical measure of hospital capacity that may also be used in assessing the level of crowding (Ospina et al., 2007). The NEDOCS index is the only ED crowding measurement system that uses number of staffed acute care beds as a measure in assessing overcrowding status (see Table 2-6). Hwang et al. (2011) state that this measure is significantly associated with physician opinion of overcrowding. Another non-ED factor related to overcrowding is the number of inpatient radiology, laboratory, and computed tomography orders (Spencer S. Jones et al., 2009).

Table 2-4: Output measures of ED overcrowding.

Adapted from (Hwang et al., 2011)

Measure Type	Measure
Output	– Number or percentage of admissions – Number, mean number, or percentage of boarders – Boarding time – Boarding time components – Observation unit census – Number of patients awaiting discharge or ambulance pick-up – ED admission transfer rate – Hospital admission source – Inpatient occupancy level – Hospital supply/demand forecast – ED volume/inpatient bed capacity – Number of inpatients ready for discharge – Number of staffed acute care beds – Inpatient processing time – Inpatient laboratory, radiology, computed tomography (CT) orders – Time from request to bed assignment – Time from bed ready to ward transfer – Agency nursing expenditures – Local home care service availability – Alternate level of care bed availability – Nearby EDs diverting ambulances

J. M. Pines et al. (2011) reveal in their multi-country study that Scandinavian countries do not report overcrowding as a major problem. They state that such countries do not experience ED overcrowding because of the availability of alternative care centers outside of EDs. For this reason, the availability of local home care services, and availability of alternative level of care beds have been suggested as important indicators of ED overcrowding (Hwang et al., 2011). Michael J. Schull et al. (2002) found that these two indicators are significantly associated with ED clinician opinion of overcrowding.

Finally, when nearby EDs are experiencing ambulance diversion, it indicates a high demand on the ED within a specific urban area. This may delay ambulance pick-up for recently discharged patients and contribute more to overcrowding. Consequently, the number of nearby EDs which are on ambulance diversion episodes should be taken into consideration in assessing overcrowding (Michael J. Schull et al., 2002).

2.5.1.5 Prioritization of ED Overcrowding Measures

In a recent study, the previously identified 71 ED crowding measures were prioritized, using the Delphi method. The results show that the following eight measures are believed to provide a comprehensive view of the ED crowding status (Beniuk et al., 2012):

- Ability of ambulances to offload
- Number of patients who leave without being seen or treated
- Time until triage
- ED occupancy rate
- Patients' total length of stay in the ED
- Time to see a physician
- ED boarding time

- Number of patients boarding in the ED

2.5.2 ED Crowding Indices

Since thee ED crowding phenomenon has gained increased attention, there have been some initiatives to develop measurement scales to quantify it. The aim of such scales has been to evaluate whether an emergency department is overcrowded or not. Reeder and Garrison (2001) developed the Real-time Emergency Analysis of Demand Indicators (READI) model, a simple formula-based model, which is composed of three ratios to detect situations when demand exceeds supply. Bernstein et al. (2003) developed the Emergency Department Work Index (EDWIN) to measure emergency department busyness. Steven J. Weiss et al. (2004) also developed the National Emergency Department Overcrowding Score (NEDOCS), a simple linear regression model, to quantify ED crowding in academic medical centers. Epstein and Tian (2006) developed the Work Score, a regression-based model, to quantify ED crowding and staff workload. Table 2-5 includes all of existing developed and modified ED crowding related indices. This section reviews the literature on these four ED crowding scales, seeking to analyze them and provides more insight into their applicability, validity, and reliability.

Table 2-5: Multidimensional indices of ED overcrowding.

Adapted from (Hwang et al., 2011)

Measure Type	Measure
Multidimensional indices	– EDWIN – NEDOCS – Pediatric NEDOCS (PEDOCS) – READI – EDCS – ED Work score – Critical Bed Status (CBS) – System complexity – Overcrowding Hazard Scale

2.5.2.1 Real-time Emergency Analysis of Demand Indicators (READI)

The READI index was the first multidimensional index designed to measure ED crowding, composed of three parts that represent the ED fixed assets (beds), the current acuity level (triage category), and the efficiency of physicians.

The bed ratio (Equation 2) quantifies the availability of ED treatment spaces. The calculation of this ratio depends on four variables: the number of patients in the ED, the number of predicted arrivals, the number of predicted departures, and the total ED treatment spaces. The predictions are based on historical arrival and departure data. The bed ratio determines the availability of ED treatment spaces (Reeder & Garrison, 2001). A bed ratio of less than one indicates that the ED is not busy, while, a bed ratio of greater than one is a signal of ED overcrowding.

$$Bed\ Ratio\ (BR) = \frac{(number\ of\ patients\ in\ ED + predicted\ arrivals - predicted\ departures)}{ED\ spaces} \qquad (2)$$

The second part of the READI index analyzes the current acuity level. EDs use a triage system such as the Emergency Severity Index (ESI) to sort and prioritize patients (see Appendix H). Equation 3 consists of three ED crowding measures: the triage category, the number of patients in each category, and the number of patients in the ED (Reeder & Garrison, 2001). When using the ESI, which is a 5 points acuity scale, a score of 5 represents the most acute level, and 1 the least. The READI index assumes a 4-point triage system. Therefore, an acuity ratio closer to 4 is an indication of high acuity.

$$Acuity\ Ratio\ (AR) = \frac{\sum(triage\ category)(number\ of\ patients\ at\ each\ category)}{number\ of\ patients\ in\ ED} \qquad (3)$$

The third factor considered in the READI index, physician staffing, plays a critical role in efficient ED patient flow. Therefore, it is essential to consider the productivity of physicians in the process of evaluating ED crowding. The third component of the READI index is the Provider Ratio (Equation 4), which quantifies the relationship between physician productivity and patient arrival rate. Equation 4 is composed of two variables: patient arrivals per hour and the average number of patients treated by each physician. A provider rate of less than 1.5 expresses appropriate staffing, while a rate greater than 1.5 indicates inadequate staffing (Reeder & Garrison, 2001).

One shortcoming of the READI index is that it ignores the role of nurses as factor in evaluating the ED crowding (Reeder, Burleson, & Garrison, 2003).

$$Provider\ Ratio = \frac{arrivals\ per\ hour}{\sum average\ number\ of\ patients\ for\ each\ physician} \quad (4)$$

The READI Demand Value, or DV (Equation 5) measures the overall demand on an ED. The DV can be used to determine if the demand exceeds ED capacity, which is an indicator of potential crowding. The three ratios mentioned above -- the bed ratio, the provider ratio, and the acuity ratio -- are the main components of the DV. When the DV is greater than 7, the ED decision maker should investigate each ratio to detect the source of the ED supply-demand imbalance leading to congestion in the ED (Reeder & Garrison, 2001).

$$Demand\ Value\ (BV) = (Bed\ Ratio + Provider\ Ratio) \times Acuity\ Ratio \quad (5)$$

A study by (Reeder et al., 2003) demonstrates that the READI index may not correlate with the ED physicians and nurses' subjective assessment of crowding. However, S. S. Jones, Allen, Flottemesch, and Welch (2006) show that the bed ratio on its own can be used as an indicator for crowding since it yields a good results for predicting perceived crowding. As a crowding measurement scale, READI has a low discriminatory power for anticipating ambulance diversion (N. R. Hoot et al., 2007).

2.5.2.2 Emergency Department Work Index (EDWIN)

Bernstein et al. (2003) developed the EDWIN instrument, another quantitative tool for evaluating ED crowding. The main objective for designing this index was to quantify the crowding and busyness at EDs, where numbers could be used as a way to help affect quality improvement and inform administrative activities. This observational study was specially aimed at developing an index that would agrees with physicians and nurses subjective assessment of ED busyness. Equation 6 defines the EDWIN index.

$$EDWIN = \frac{\sum n_i t_i}{N_a(B_T - B_A)} \qquad (6)$$

Where:

n_i = the number of ED patients in triage category i.

t_i = the triage category (ESI, a five-point scale).

N_a= the number of ED physicians at a given time.

B_T = the number of available beds in the ED.

B_A= the number of admitted patients.

The developers of EDWIN suggest interpreting their index scores as follow: a score less than 1.5 indicates indicate an active but controllable ED; a score between 1.5 and 2.0 indicates a busy ED; a score more than 2.0 indicates a crowded ED (Bernstein et al., 2003).

The EDWIN index is significantly associated with physicians' and nurses' subjective assessment of crowding (Bernstein et al., 2003; S. S. Jones et al., 2006; S. J. Weiss et al., 2006). It also has been found that a correlation exists between EDWIN results and ambulance diversion status (Bernstein et al., 2003; N. Hoot & Aronsky, 2006; N. R. Hoot et al., 2007). However, the EDWIN's accuracy with respect to identifying diversion is only considered to be moderate (McCarthy et al., 2008). Moreover, the EDWIN can detect hours when patients leave without being seen with a moderate accuracy (McCarthy et al., 2008).

2.5.2.3 National Emergency Department Overcrowding Score (NEDOCS)

Steven J. Weiss et al. (2004) developed a multiple linear regression crowding measurement scale to quantify overcrowding in academic-based emergency centers. Like the EDWIN index, the NEDOCS objective scores mainly reflects the subjective assessment of ED physicians and nurses for ED crowding. The authors validated the index by comparing the objective scores with the subjective perspectives of the ED staff. Equation 7 defines the NEDOCS index as follows:

$$NEDOCS = 85.8 \times \frac{P_{bed}}{B_t} + 600 \times \frac{P_{admit}}{B_h} + 5.64 \times W_{time} + 0.93 \times A_{time} + 13.4 \times R_n - 20 \tag{7}$$

Where:

P_{bed} = number of patients in ED beds and other treatment spaces such as hallways beds.

B_t = number of ED treatment beds.

P_{admit} = number of admitted patients

B_h = number of licensed hospital beds

W_{time} = waiting time for last patient placed in an ED bed.

A_{time} = longest time among boarding patients since registration.

R_n = number of occupied respirators.

0 – 20 not busy	20-60 busy	60-100 Extremely busy but not overcrowded	100-140 overcrowded	140-180 severely overcrowded	180-200 dangerously overcrowded

Figure 2-2: NEDOCS scores.

Adapted from (Steven J. Weiss et al., 2004)

Attempts to test and validate the NEDOCS scale have been carried out in different ED settings within different countries. Raj et al. (2006) claim that NEDOCS is not a valid ED crowding index in some settings such as Australian EDs, adding that it is a good instrument, but needs refinement. On the other hand, a recent study found that the NEDOCS has acceptable agreement with the subjective physicians and nurses assessment of crowding in the Netherlands, but it has not been validated yet in a busy ED (Anneveld et al., 2013).

A problem with the NEDOCS formula is that it does not take into consideration triage category, which thus gives patients of different acuity level the same weight. To put it another way, suppose that five patients with triage category one, who usually acquire a massive amount of resources, arrive at an ED at the same time. In such a case, the NEDOCS will just consider them as if they are triage category five. Such a weakness is identified by researchers as worthy of more investigation (B. C. Sun et al., 2013). Moreover, in a recent study, (Wang et al., 2014) examined the reliability and validity of the NEDOCS tool in quantifying overcrowding in extremely high-volume EDs. The results show that the NEDCOS index is inaccurate in determining ED crowding in a high-volume ED setting.

2.5.2.4 Work Score

Epstein and Tian (2006) developed a quantitative instrument, the Work Score, to quantify ED crowding and to determine the root cause of crowding, that is, whether it is due to input, throughput, or output factors as laid out in Asplin's conceptual model for ED crowding (Figure 2-1). Equation 8 defines the Work Score.

$$Work\ Score = 3.23\ \frac{Patients\ in\ waiting\ room}{number\ of\ ED\ tratment\ areas} + 0.097\ \frac{\sum reversed\ ESI}{number\ of\ nurses} + 10.92\ \frac{boarders}{number\ of\ ED\ treatment\ areas} \tag{8}$$

The index consists of three major parts. Part one, representing the input factors of an ED, encompasses the ratio of the number of patients in the waiting room to the number of ED treatment areas. Part two, representing the throughput factors of an ED, is the ratio of the sum of patient-complexity level to the number of ED nurses. It can be noticed that this model does not take into consideration the number of ED physicians on duty, which is a critical factor in evaluating the efficiency of ED processes. Part three, representing ED output factors, includes the ratio of number of boarding patients in the ED to ED capacity. Ambulance diversion was chosen as a base for building the model, since when the ED department starts diverting ambulances it is considered crowded. Ambulance diversion episodes are initiated when a clinician decides that the ED is overcrowded (Epstein & Tian, 2006). Therefore, Work Score essentially depends on physicians and nurses perspectives of ED crowding.

Table 2-6 illustrates the components of all the above-mentioned ED crowding indices to provide a side-by-side comparison.

Table 2-6: Indicators of emergency department crowding indices

	Input						Resources				Throughput			Output		
Variables / ED crowding index	Predicted arrivals	Arrivals per hour	Number of patients in ED	Number of patients at each triage category	Number of patients in waiting room	Longest wait in waiting room	Number of ED beds	Number of physicians	Number of nurses	Number of hospital beds	Triage category	PPH for each physician	Number of vent patients in ED	Number of admitted patients (boarding)	Longest admit boarding time	Predicted departures
READI	x	x		x			x				x	x				x
EDWIN				x			x	x			x			x		
NEDOCS			x			x	x			x			x	x	x	
Work Score					x		x		x		x			x		

2.6 ED Crowding in Saudi Arabia

Since most of the ED crowding research has taken place in the United States, J. M. Pines et al. (2011) studied the extent of the ED crowding in fifteen other countries learn more facts about overcrowding from different healthcare systems and environments. One of the countries they examined is Saudi Arabia, where ED crowding has been identified as a major problem and a serious challenge to the Ministry of Health. According to this study, Saudi Arabia's public healthcare system recorded more than 15 million ED visits in 2006. With this massive demand on ED services, 70% of EDs reported greater than 100,000 annual ED visits. In a recent survey of administrators of 10 different EDs in Riyadh city conducted by J. M. Pines et al. (2011), 50% reported that their departments are always overcrowded, and 40% reported crowding was often a problem. According to Tashkandy, Gazzaz, Farooq, and Dhafar (2008), the primary causes of ED crowding in Saudi Arabia are delays in discharging patients, unavailability of inpatient beds, boarding patients in EDs, a growing demand on ED services, and delays in preparing disposition plan.

Data obtained from the King Faisal Specialist Hospital and Research Center reveal that more than 50% of admitted patients are boarded in the ED are present for over 6 hours, and 15% of patients wait more than 24 hours in total (J. M. Pines et al., 2011). According to the 2012 Statistics Report of the KSA Ministry of Health, EDs reported 20,881,477 visits (MOH, 2014). J. M. Pines et al. (2011) indicated that no initiatives to cope with ED crowding in Saudi Arabia were being developed.

2.7 Fuzzy Logic

Fuzzy logic is a reasoning system derived from the fuzzy sets theory. In the mid-1960s, Dr. Lotfi Zadeh introduced the concept of fuzzy sets; unlike traditional binary variables which can only take on true and false values, fuzzy sets consider classes and structures with uncertain boundaries (Zadeh, 1965). A Fuzzy Logic System (FLS) is a modeling approach that combines linguistic variables and a set of fuzzy rules utilizing fuzzy logic philosophies and fuzzy sets principles. It is the only approximation approach that can simultaneously handle linguistic and numerical data (Mendel, 1995). In general, a FLS consists of four main components: a fuzzifier, rules base, inference engine, and defuzzifier (Öztürk, 2013). Figure 2.3 illustrates the general structure and the main blocks of a fuzzy logic system.

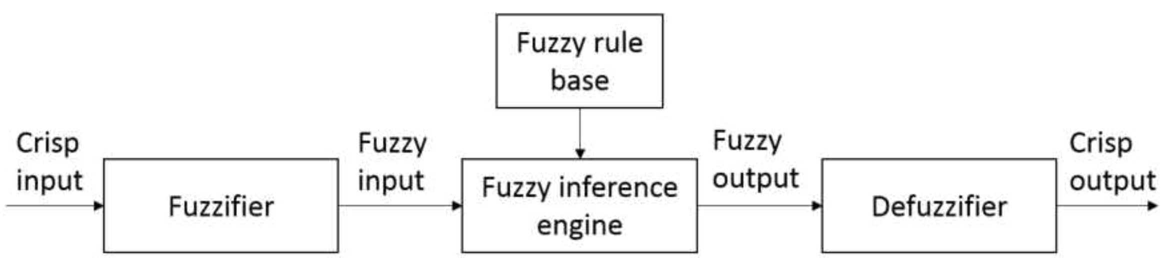

Figure 2-3: Structure of a fuzzy logic system.

Adapted from (Shin & Xu, 2009)

These fuzzy system components perform sequentially to achieve the designed goals of the system. First, the fuzzifier transforms numerical quantities of input parameters to fuzzy values (Shin & Xu, 2009). Fuzzy values are represented by linguistic terms, such as “busy”, “crowded”, “overcrowded” and so on, and the terms have a certain level of membership to fuzzy sets. Next, the fuzzifier feeds the fuzzy inference engine with membership values. A fuzzy inference engine is a tool that maps fuzzy inputs to fuzzy outputs using defined fuzzy rules. The fuzzy rule base works as a knowledge system that directs all procedures in the fuzzy inference engine. Finally, the defuzzifier converts the fuzzy values back into numerical values or crisp outputs.

The very real advantages of the fuzzy logic approach include its ability to deal with vague, imprecise, and missing information, its capability of converting ambiguous human judgments into mathematical models (Dotoli, Epicoco, Falagario, & Sciancalepore, 2015), and its use of linguistic variables (Singh, Kainthola, & Singh, 2012).

2.7.1 Applications of Fuzzy Logic in Industrial Engineering

Because of its ability to stimulate human reasoning, fuzzy logic systems have been used as a modeling approach for assessing and evaluating situations that involve subjective aspects. The fuzzy logic approach has been integrated with many analytical and decision methods. For example, Tsourveloudis and Phillis (1998), claiming that flexibility is a vague concept because human perception and belief are involved in its measurement process, used a neural network that utilized fuzzy logic in measuring manufacturing flexibility. Boninsegna, Coianiz, and Trentin (1997) also developed a neuro- fuzzy system for estimating the levels of crowding in a scene.

In the risk management domain, many studies have applied fuzzy logic concepts to evaluate the amount of risk in different fields. For instance, in their recent work, Aras, KarakaA, and Bicen (2014) introduced a novel fuzzy-logic-based risk management model that takes into consideration human factors such as attention and fatigue to assess risks. The fuzzy logic approach has also been used in maritime risk and safety research, with notable examples including its use to assess risk associated with loading and offloading liquefied natural gas at terminals (Elsayed, 2009), to evaluate risk and hazards on fishing vessels (Pillay & Wang, 2002), and to assess and manage the risks of port security (Ung, Williams, Bonsall, & Wang, 2009). Essentially, the fuzzy logic approach has been proven as a suitable method in the field of risk assessment (Aras et al., 2014). Moreover, in construction management, Marzouk and Amin (2013) utilized fuzzy logic and neural networks to develop a system that can accurately predict prices of construction materials.

2.8 Literature Review Summary

In review, this chapter has examined information from previous studies regarding definitions and impacts of ED overcrowding, conceptual models of patient flow within emergency centers, quantitative and qualitative measures and indicators that have been used or suggested in evaluating ED overcrowding levels, and the existing ED overcrowding measurements indices. In addition, the literature review presented related studies on the validity and reliability of the ED overcrowding measurement indices, within different healthcare systems and the criticisms of their reproducibility outside of settings where they were originally developed in. It ends with a review of the related literature on the fuzzy logic system and its practical applications in the field of industrial engineering such as risk measurement and management to show its ability as a quantitative tool in measuring vague situations.

2.9 Research Gap Analysis

Based on the literature review conducted, two existing crowding assessment approaches were identified, which include the identification of measures and indicators for ED overcrowding, and the development of multidimensional indices for quantifying crowding. After an extensive review of the related literature, sixty-five ED crowding measures and indicators were identified, and their uses were studied. In addition, four ED multidimensional overcrowding indices were identified. Those indices are the Real-time Emergency Analysis of Demand Indicators (READI) (Reeder & Garrison, 2001), the Emergency Department Work Index (EDWIN) (Bernstein et al., 2003), the National Emergency Department Overcrowding Score (NEDOCS) (Steven J. Weiss et al., 2004), and the Work Score (Epstein & Tian, 2006).

Two of the indices, the READI, and EDWIN index used simple mathematical equations, while the NEDOCS index used multiple linear regression, and the Work Score used logistic regression in the index development stage. The READI, EDWIN, and NEDOCS overcrowding indices were developed based on clinician opinion of crowding, while the Work Score index was developed based on ambulance diversion episodes (see Table 2-7). The dependence on the perspective and feedback of physicians, who are only one of the multiple EDs' stakeholders present in EDs, and upon nurses' perspectives and subjective assessment of crowding, make READI, EDWIN, and the NEDOCS index biased toward healthcare giver perspectives. Consequently, there is a lack of a proper quantitative tool for assessing ED crowding which takes into consideration other stakeholder's perspectives, such as patients, and hospital administrators as well as the opinion of healthcare experts.

The literature shows, however, that the reliability, reproducibility, and validity of these crowding measurement scales in other emergency care settings has been subject to much criticism. Four critical studies examined the validity of those indices in the United States, The Netherlands, and Australia. The results of these studies conclude that the NEDOCS and the EDWIN indices could not be validated outside the settings where they originally developed. The READI and the Work Score could not be applied in different healthcare systems due to the fact that the READI uses a four-level triage system which limits it use to healthcare systems that uses the same triage system, and the Work Score deals with ambulance diversion which limits its use to hospitals that allow ambulance diversion.

To bridge the gap between the needed effective quantitative tool for assessing ED crowding and existing ones, the intensive literature review shows that fuzzy logic is a robust approach for developing quantitative assessment tools due to its ability to deal with vague, imprecise, and missing information; and its use of linguistic variables. In addition, the fuzzy logic approach is capable of converting ambiguous human judgments into mathematical models. According to the author's knowledge, the fuzzy logic approach has not been utilized yet to develop a multidimensional ED overcrowding scale. Therefore, it is a potential approach for fulfilling the aims of this research.

Table 2-7: Gap analysis

Index (Author, year)	Method			Basis of the Index		
	Simple mathematical formula	Regression Model	Fuzzy Logic	Ambulance Diversion	Clinician Opinion	Expert opinion
READI (Reeder & Garrison, 2001)	X				x	
EDWIN (Bernstein et al., 2003)	X				x	
NEDOCS (Steven J. Weiss et al., 2004)		X			x	
Work Sore (Epstein & Tian, 2006)		x		x		

The identified research gap reveals that although there are several indices designed to quantify ED crowding, they are ineffective when implemented in some healthcare systems. Furthermore, this gap outlines the need for a more robust quantitative measurement tool which can measure ED crowding that produces consistent and reliable results in a variety of healthcare settings. The fuzzy logic approach was identified as a viable method for measuring ED crowding, as it is capable of using data provided form subjective human assessment and linguistic variables. This potential approach for quantifying crowding has properties identified in table 3-1 as being important to appropriately modeling the problem of overcrowding, given its interconnected nature and variables.

CHAPTER 3 RESEARCH METHODOLOGY

3.1 Introduction

The importance of research methodology in scientific research and investigation is highlighted by the role it plays in achieving objectives and aims. It sets forth a design plan for the course of the research, and can be compared to a production line which has to be appropriately designed and configured to manufacture the intended product. Therefore, this chapter describes the research methodology that is implemented in this dissertation to achieve the stated aims and objectives. It details all stages that must be completed in order to develop and validate a novel emergency department crowding measurement system. Additionally, this chapter provides more information on the proposed framework by providing a conceptual explanation of the proposed framework upon which chapter four will develop. The designed methods will ultimately guide the creation of the described ED crowding index, which would contribute to the fields of knowledge of quality systems engineering and healthcare systems engineering.

3.2 Research Methodology

The research methodology is illustrated in Figure 3-1. This research began with an inquiry on how the overcrowding in EDs could be objectively measured. The research idea has been influenced by insights from different sources of information, such as recent technical reports which reveal that emergency departments are facing growing demand while experiencing limitations in emergency care resources, leading an unbalanced relationship between supply and demand. After identifying the problem, the next step was to review the related literature on ED crowding in more detail, including the impacts crowding has on EDs, and how this phenomenon is being assessed. A review of research was essential to understand what studies have been conducted within the contexts of this problem to gain more insight about it and identify shortcomings and opportunities for development. In the review of literature, careful analysis is done through presenting and discussing the findings of studies that investigated the impact of ED crowding on the different ED stakeholders, proposed definitions of ED crowding, existing conceptual models, the different approaches to measuring ED crowding, and developed measurement systems. After this step, a gap analysis is performed to determine what research within the area of measuring ED crowding might have potential contributions to this research domain.

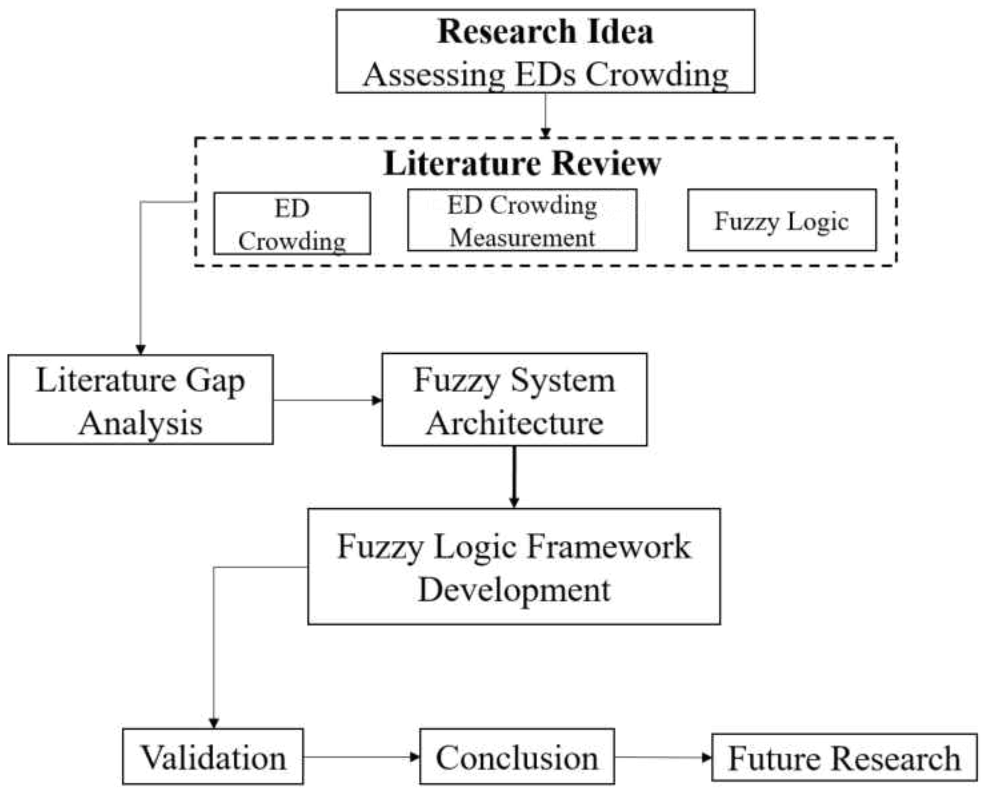

Figure 3-1: High level research methodology

The gap analysis showed that the existing ED overcrowding measurement scales have not been able to be reproduced outside the settings where they were originally developed. To further explore the cause of this and investigate an appropriate method for this study, more background information was required. Several requirements for studying the research problem were identified, and several quantitative approaches for modeling crowding in similar contexts were reviewed. The advantages and limitations between these studied approaches were analyzed, which include formula based approaches, regression modeling, queuing theory, discrete event simulation, and fuzzy logic. Fuzzy logic, which has been applied to similar problems such as measuring risk, appeared to be the most appropriate approach in modeling the problem, since it offers the ability to handle ambiguous human judgment and interconnected factors, in addition to its ability to provide scale based evaluations. After this review of modeling approaches, fuzzy logic was adapted to be included in the design of the proposed framework to measure ED crowding. In the next stage, the system architecture will be described in detail, which will identify the type of fuzzy system to be used, while addressing the organization of the subsystems architecture. In addition, the crisp inputs and outputs will be identified, and the interconnected nature of the identified crowding factors will be discussed.

Once all of the fuzzy system requirements are identified, the next step will include the process of developing the fuzzy system, consisting of four main components. The fuzzy system architecture will be discussed in detail, where the crisp inputs, inference engine, expert knowledge, and crisp outputs will be developed. In this stage, the knowledge base will be constructed through the elicitation of knowledge from experts to create both the membership functions and rule base for the fuzzy system. The elicitation method used to construct the knowledge base will also be described, including a discussion of identified elicitation methods. In addition, the fuzzification and defuzzification processes will be described. After constructing the framework, a validation study will be conducted in an ED to verify the accuracy of the proposed framework in quantifying the ED overcrowding status. Once its accuracy is determined, conclusions, recommendations, and future research opportunities will be presented.

3.3 Research Idea

Emergency departments and centers are a crucial component of any healthcare system. Many healthcare systems around the world are experiencing growing demands on emergency care services in the presence of limited resources. This increasing demand has led to an unbalanced relationship between resource supply and demand, resulting in overcrowding in EDs. As The United States Government Accountability Office recently reported, "Emergency Departments crowding continues to occur, and some patients wait longer than recommended time frames." Moreover, the World Health Organization recently revealed that it is a priority for healthcare systems to concentrate on decreasing crowding levels in healthcare facilities in order to mitigate or eliminate its adverse influence on both patients and clinicians. In addition, the American College of Emergency Physicians' (ACEP) 2014 report card revealed that the USA's emergency care environment is worsening, and barely passed ACEP's assessment with a D-minus grade. The report asserted that the issues regarding access to EDs play a critical role in any effort to improve ED services. These technical reports confirm the impact of growing demand on EDs, and outline the need for effective measures. These reports were the starting point for this research, and led to a review of scientific research based literature to enable a full investigation of the situation so as to gain a multitude of perspectives.

3.4 Literature Review

The review of literature conducted in this study covers academic works on emergency department overcrowding, including its operational definitions, and the impact it carries on quality of care, the satisfaction of patients and clients, patient safety and outcomes, and clinician workload. This section also sheds light on the conceptual frameworks that have been developed to facilitate the understanding of the phenomenon of ED overcrowding as well as on the determinants of the problem. In addition, it reviews the existing measures that have been used in assessing overcrowding in detail, explores their similarities of their results, and compares their results with clinician perspectives of overcrowding. It also reviews all approaches available to assess the status of overcrowding in emergency departments and examines their applicability, reliability, and validity. Based on the intensive literature review, a literature gap was identified, which is discussed in detail in the following section.

3.5 Literature Gap Analysis

The literature review started with a simple question: What approaches for measuring emergency department overcrowding are available? Two existing approaches were identified, namely identification of measures and indicators for ED overcrowding, and the development of multidimensional indices for quantifying crowding levels. The next question was: What ED overcrowding measures, indicators, and indices exist? After an extensive review of the related literature, sixty-five measures and indicators were identified, and their uses were studied. In addition, four ED multidimensional overcrowding indices were identified which are Emergency Analysis of Demand Indicators (READI) (Reeder & Garrison, 2001), Emergency Department Work Index (EDWIN) (Bernstein et al., 2003), National Emergency Department Overcrowding Score (NEDOCS) (Steven J. Weiss et al., 2004), and Work Score (Epstein & Tian, 2006). Next, the methods which were used in each of those models were identified, and the bases used for developing those indices were explored.

Among the former methods, two used simple mathematical equations; one used multiple linear regression, and one used logistic regression in developing the indices. For bases of development, the READI, EDWIN, and NEDOCS overcrowding indices were developed based on clinician opinion of crowding, while the Work Score index was developed based on ambulance diversion episodes.

The literature shows, however, that the reliability, reproducibility, and validity of these crowding measurement scales in other emergency care settings has been subject to much criticism. Four critical studies examined the validity of those indices in the USA, Netherlands and Australia. The results of these studies conclude that NEDOCS and EDWIN could not be validated outside the settings where they originally developed. In addition to these results, those of the preliminary study confirms the criticisms of these models. READI and Work Score could not be applied in different healthcare systems due to the fact that READI uses a four-level triage system, which limits it use to healthcare systems that uses the same triage system, and Work Score addresses ambulance diversion, which limits its use to hospitals that allow ambulance diversion.

At this point, the research gap was identified. The gap indicates that although many indices have been developed to measure ED crowding, they are not effective when implemented in some health care systems due to the described criticisms. Thus, there is a need for the development of an appropriate method that could be used to develop a measurement instrument for this situation in a variety of ED contexts.

The next critical question was: What approach that has the ability to deal with ambiguous human judgments can be utilized to develop a quantitative tool for assessing ED overcrowding? The literature review shows that fuzzy logic is a robust approach for developing quantitative assessment tools due to its ability to deal with vague, imprecise, and missing information; its capability of converting ambiguous human judgments into mathematical models and its use of linguistic variables. Moreover, the review of literature indicated that the fuzzy logic approach has not been utilized yet to develop a multidimensional ED overcrowding scale. Therefore, it is a potential approach for fulfilling the aims of this research. According to table 3-1, fuzzy logic possesses all properties which were identified as necessary for modeling the problem, which includes three properties that no other approach possessed. As such, fuzzy logic is identified as the most appropriate modeling approach.

Table 3-1: Comparison among modeling approaches

Properties \ Approach	Formula-based Method	Regression Modeling	Queuing Theory	Discrete-Event Simulation	Fuzzy Logic
Statistical basis		✔	✔	✔	✔
Expert Subjective Assessment		✔			✔
Linguistic variable		✔			✔
Dealing with ambiguous human judgments					✔
Interconnected factors					✔
Scalability					✔

3.6 Fuzzy Logic System Architecture

To construct the fuzzy system, the different components must be identified and defined. First, the inputs and outputs must be defined according to insights gained from the literature review, in addition to Asplin's conceptual model for overcrowding. This comprehensive definition of overcrowding from literature based sources will allow for a more effective application of fuzzy logic as it applies to a complex and subjective problem. Next, the method for implementing the fuzzy logic system will be identified, whether it be a standard fuzzy system, or hierarchical fuzzy system. The interconnectedness between the determinants of crowding will also be discussed to offer an effective system design. As each determinant affects other determinants in addition to the crowding level, it may become necessary to develop a logical structure of fuzzy subsystems to isolate the determinants and more accurately define inputs and outputs of the system.

Expert knowledge is another key part of the fuzzy system architecture, as the knowledge base will play a key role in obtaining outputs. The discussion of the knowledge base construction will include the defined fuzzy classes, the types of membership functions, and the fuzzy numbers. The completed architecture will accomplish the task of creating a logical system defined by the combination of the determinants of crowding, the designed inputs, and components built with expert knowledge.

3.7 Fuzzy Logic Framework Development

As shown in Figure 3-2, the proposed framework encompasses four components, including the crisp inputs, a fuzzy logic system, the expert knowledge, and crisp outputs. The figure further shows the relation between these components by showing the steps an input goes through to obtain an output. While a fuzzy system alone may be simple to design in general, what makes this framework novel is its integration of expert knowledge in the form of a knowledge base with the fuzzy system.

The crisp inputs include identified measures and indicators that reflect many ED and hospital operational aspects that affect ED crowding levels. The crisp inputs feed the second component of the framework, the fuzzy logic system, with numerical information. The fuzzy logic system includes the fuzzifier, fuzzy inference engine, knowledge base, and defuzzifier, at which the crisp ED crowding measures are converted to crisp output. Expert knowledge is used to construct knowledge base, consisting of the fuzzy rules and the database, which fuzzifies inputs, provides supporting decision making information to the inference engine, and defuzzifies outputs. The resulting crisp output reflects the level of overcrowding in the ED.

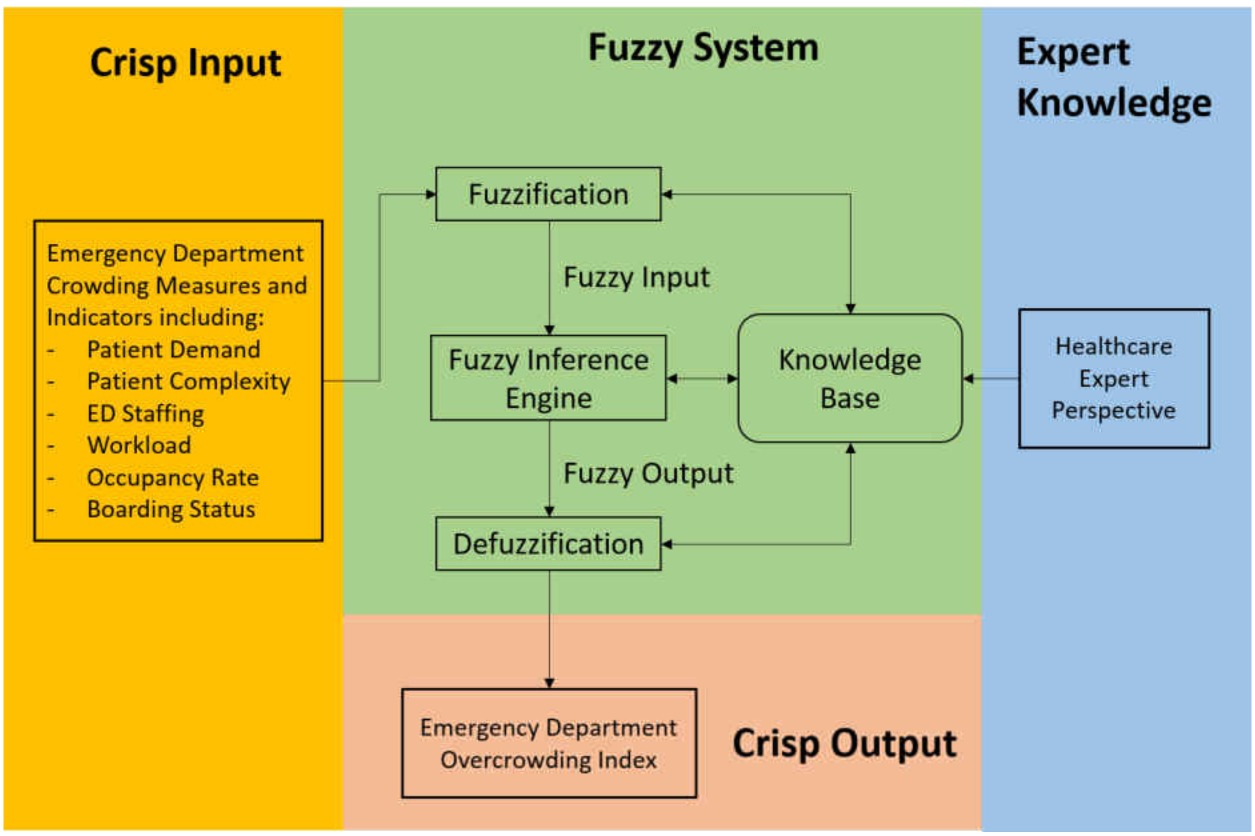

Figure 3-2: Proposed framework

The output of the framework is an index of ED overcrowding that aids in measuring patient congestion and patient flow within EDs. It is a quantitative instrument that evaluates the ED crowdedness based on the input of healthcare experts. The output can be utilized with a decision support system to inform and aid an ED in coping with ED crowding.

3.8 Validation

The purpose of the validation is to evaluate the accuracy and sensitivity of the proposed ED overcrowding measurement system in determining the levels of crowding. The proposed framework will be implemented at an ED in Saudi Arabia and the performance of the index will be monitored. From the data obtained from the implementation period, it will be possible to assess the impact of each observed input on the major operational scores and overall crowding. At the same time, the subjective perception of healthcare experts towards the level of crowding will be assessed using a subjective assessment tool.

The objective results of the index and the subjective assessment of the healthcare experts will be discussed in an analysis of the validity and accuracy of the proposed framework. Specifically, Kappa statistics will be utilized to perform this analysis.

The mentioned Kappa statistical analysis will be conducted specifically to evaluate the level of agreement between the index scores of the crowding level and the experts' perspective on the crowding level. The Kappa statistical analysis will be performed using equation 1. Finally, this Kappa score will be compared with the Kappa scores from the application of NEDOCS and EDWIN in Saudi Arabia from the preliminary study to further determine the accuracy of the prosed index. The determined accuracy of the proposed index will provide insight on its capability to emulate human reasoning in perceiving overcrowding.

3.9 Conclusion

The conclusion to the dissertation will recall patterns recognized in data from the analysis of the model, and draw upon them to make a conclusion on the constructed model. The discussion of these findings will aid in assessing the quality of the results from the framework development, in addition to contributing to the identification of bias in expert assessment.

Overall, the conclusion will review the research problem in its context and the framework developed in accordance to an identified need. With the discussion of the results, it will be possible to assess the developed overcrowding index, and its benefits to stakeholders can be highlighted. Any identified limitations will contribute to recommendations for future researchers.

3.10 Future Research

As a first research attempt to use a fuzzy logic system in assessing the vague crowding situations in healthcare facilities, the proposed framework will open up new research opportunities in the domain of patient flow studies and crowding measurement and improvement. A potential opportunity for future research could focus on linking and integrating the results of the scores of the proposed index to a decision making system. The implementation of the proposed index in other healthcare settings could be another potential research effort, which could further test the reproducibility of results from the index.

3.11 Summary

In review, chapter three explains the methodology that is followed in this research to achieve its stated objectives. It begins by introducing an overview on the origins of the research idea. Then, it describes the intensive literature that has been reviewed to lead the identification of the literature gap. The gap analysis was then discussed in detail, which led to an identified need within the context of EDs. The architecture of the proposed framework, designed in response to the identified literature gap, is then discussed. The components and technical aspects of the framework are explained in the discussion of the fuzzy logic framework development. This chapter also describes the design of the validation study and the statistical method that will be applied to examine the accuracy of the proposed model and its predecessors. The objectives for the conclusion are briefly discussed, and finally projections for future research are provided, which will conclude the dissertation.

The methodology section represents an accumulation of reviewed literature, information for the proposed framework, and its anticipated outcomes which will provide a basis for a several types of analysis. With the proposition of the fuzzy system sufficiently discussed, the next chapter will provide more discussion of the specified components, and detail all specific aspects of the system's design.

CHAPTER 4 FRAMEWORK DESIGN

4.1 Introduction

Chapter four of this dissertation describes the technical aspects of the proposed framework, expanding on the theory behind its construction, while showing the design process for the fuzzy systems. First, a conceptual comparison is drawn between the hierarchical and standard fuzzy logic systems, and the choice of utilizing a hierarchical fuzzy system in this research is justified. Next, the architecture of fuzzy logic is described, encompassing the overall system, the subsystems, and the components of each subsystem. The relation of the proposed fuzzy system and its inputs and outputs is elaborated upon in the four different subsystems. In another section, the procedure for developing the main components of each subsystem is described, starting with the knowledge base which contains the fuzzy rule base and database. The designed survey and assessment forms are also discussed, which are important instruments for constructing the knowledge base. Finally, the fuzzification and defuzzification processes and methods are presented.

4.2 Hierarchical Fuzzy System

Hierarchical fuzzy systems (HFSs) are implemented by researchers for two main purposes. First, they help in minimizing the total number of fuzzy rules in the knowledge base which feed into the fuzzy inference engine. Second, the HFSs are effective in building the logical relationship among different crisp input variables in complex systems, unlike Standard Fuzzy Systems (SFSs), which become exponentially complicated as the number of variables and their fuzzy sets' levels increase. Figure 4-1 and 4-2, where O_n stands for the crisp output of fuzzy subsystem n, and O_f stands for the crisp output of the main fuzzy system, illustrate the difference between applying traditional standard fuzzy logic approach versus applying hierarchical fuzzy logic approach to construct and determine the relationship between a fuzzy subsystem's crisp outputs and the main fuzzy system (Aly & Vrana, 2007).

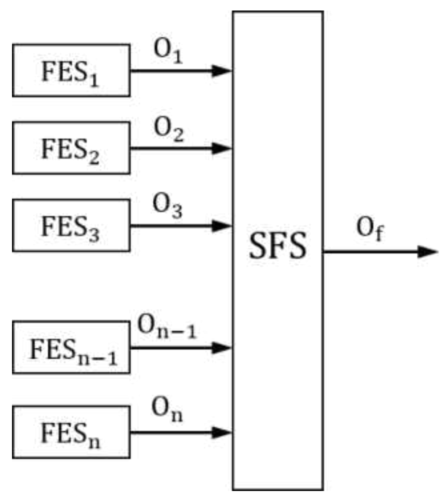

Figure 4-1: Standard fuzzy logic system.

Adapted from (Aly & Vrana, 2007).

In the case of SFSs, the total number of fuzzy rules related to the number of crisp inputs is exponentially proportional, whereas it is linearly proportional in HFSs. For instance, supposing that the number of crisp variables equal five, and each variable encompasses five fuzzy sets, then when utilizing a SFS, the total number of fuzzy rules for the whole fuzzy system is ($5^5 = 3125$ rules), whereas in a four-level HFS with four fuzzy subsystems, each encompassing two crisp inputs, the total number of fuzzy rules for the complete fuzzy system is ($5^2 = 100$ rules). It is clear that utilizing HFSs significantly reduces the total number of fuzzy rules necessary to construct the knowledge bases for the whole fuzzy system. Thus, utilizing HFSs in this study makes it possible to analyze the complicated nature of emergency health care systems, which if studied through SFSs, could involve too many fuzzy rules and computations for an effective analysis. It is also notable that using HFSs detailed in Figure 4-2, will help in determining the relationship between outputs of the fuzzy subsystems and the main fuzzy system, and in specifying the relationship among fuzzy subsystems as well.

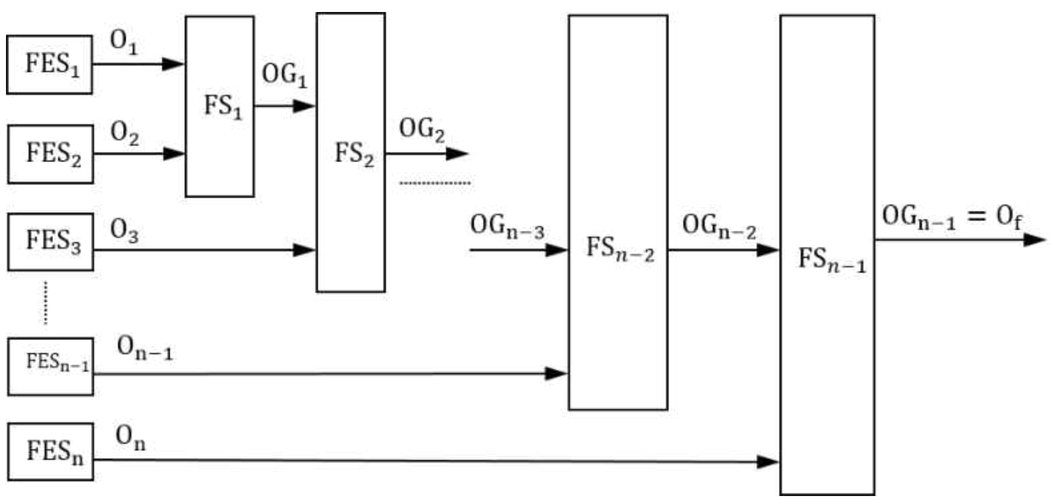

Figure 4-2: Hierarchical fuzzy systems.

Adapted from (Aly & Vrana, 2007).

4.3 Fuzzy System Architecture

In order to define the fuzzy subsystems, Asplin's comprehensive ED overcrowding conceptual model (Figure 2-1) was utilized, which divides emergency care processes into three interdependent phases: input, throughput and output. Each phase in Asplin's model contributes significantly to the level of ED crowding, and this research adapts these phases in Asplin's conceptual model in developing the ED overcrowding quantification tool. Many previous studies take into consideration three ED operational aspects (emergency care demand, ED workload, and discharge status) in developing quantitative instruments for crowding (Table 2-6). These same operational aspects are adapted into the framework developed in this study, as shown in Figure 4-3. By utilizing fuzzy logic, this study overcomes the limitations of previous studies, by quantifying the opinion of experts with different perspectives, to reduce the introduction of bias in the final assessment of crowding.

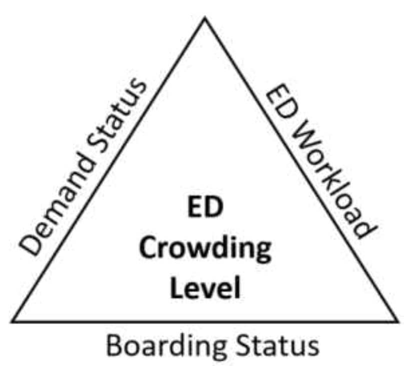

Figure 4-3: Determinants of ED crowding level

In addition to the three phases of Asplin's model, information from ED professionals and experts is integral to the framework used in this study. This research proposes a three-level hierarchical fuzzy logic system which is developed based on available information and knowledge from experts. The purpose of this proposed fuzzy system is to accurately determine the level of ED crowding. Like the fuzzy system as shown in Figure 4-2, the proposed fuzzy logic system includes seven inputs, four fuzzy inference systems (fuzzy subsystems), and one output. The seven inputs of the proposed fuzzy logic system are developed corresponding to four subsystems, related to Asplin's three interdependent phases, and are defined as follows:

Input 1: Patient Demand; Ratio of Waiting Patients to ED Capacity

Input 2: Patient Complexity (Waiting Area)

Input 3: ED Physician Staffing

Input 4: ED Nurse Staffing

Input 5: ED Occupancy Rate

Input 6: Patient Complexity (Emergency Room)

Input 7: Boarding Status; Ratio of Boarded Patients to ED Capacity

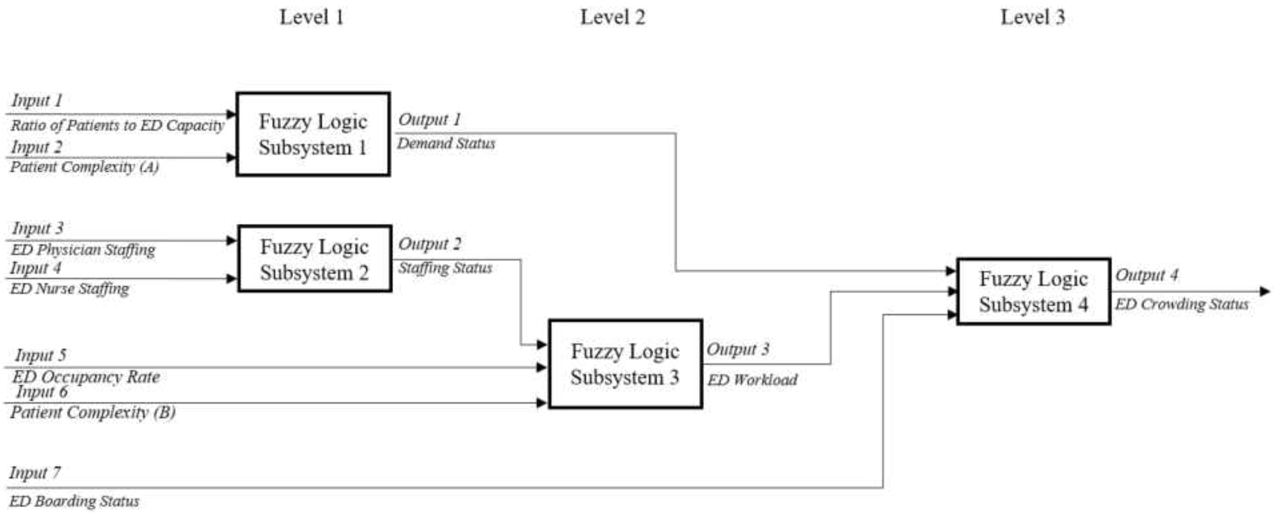

Figure 4-4: Three-level hierarchical fuzzy expert system

Figure 4-4 further illustrates the relation of these inputs to the proposed fuzzy logic system. Level one of the hierarchical fuzzy expert system contains two fuzzy subsystems.

The first fuzzy subsystem aims to assess the ED demand status by evaluating the ratio of patients in an ED waiting area to that emergency room’s capacity, and the average patient complexity. Figure 4-5 illustrates the components of fuzzy subsystem I. the first input to the fuzzy subsystem I is the ratio of waiting patients to ED capacity which is characterized by four fuzzy membership functions; “Low”, “Medium”, “High”, and “Very High”. To assess this input variable, trapezoidal functions are utilized to evaluate the membership degree on an interval [0, 2]. The patient complexity, the second input to the fuzzy subsystem I, is represented by three membership functions; “Low”, “Medium”, and “High”. Similarly, a trapezoidal function is used for this input, evaluating the membership degree on the interval [1, 5], which is adapted from the five levels of the emergency severity index (Appendix G). Given these fuzzy classes, the total number of fuzzy rules from this subsystem will be 12 fuzzy rules (4×3). The output of fuzzy subsystem I is ED demand status, which is represented by five membership functions; "Very Low", "Low", "Medium", "High", and "Very High". This output is evaluated with a triangular function for the interval [0, 100]. The demand status is an intermediate variable rather than a final indicator, which feeds the fourth and final fuzzy subsystem with a crisp value, to contribute to the final assessment of the ED crowding level.

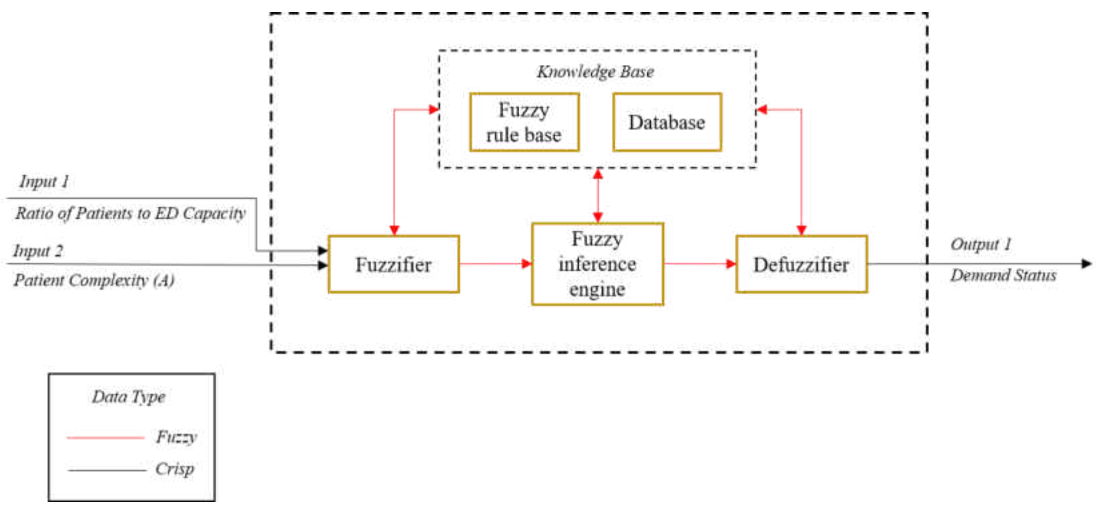

Figure 4-5: Fuzzy logic subsystem I

The second fuzzy logic subsystem, with two inputs and one output, is designed to determine the level of ED staffing. Figure 4-6 presents the components of fuzzy subsystem II. ED staffing status is subjective in nature and the membership functions that represent this aspect of crowding reflect this subjectivity based on the knowledge from health care experts. The two inputs of this fuzzy subsystem are the level of ED physician staffing and ED nurse staffing. Both inputs are represented by three membership functions; “Inadequate”, “Partially adequate”, and “Adequate”, which are assessed on the intervals [0, 0.32], and [0, 50], respectively, with trapezoidal functions. With these membership functions, the total number of fuzzy rules in this subsystem will be 9 rules (3^2). The output of the fuzzy subsystem two is ED staffing status. The output is represented by the same three membership functions; “Inadequate”, “Partially adequate”, and “Adequate”, and is evaluated on a trapezoidal function with the interval [0, 100]. The ED staffing status is an intermediate variable that feeds the third fuzzy subsystem with a crisp value, which will serve as another variable for the assessment of the ED workload. Finally, the ED workload will feed into the fourth fuzzy subsystem.

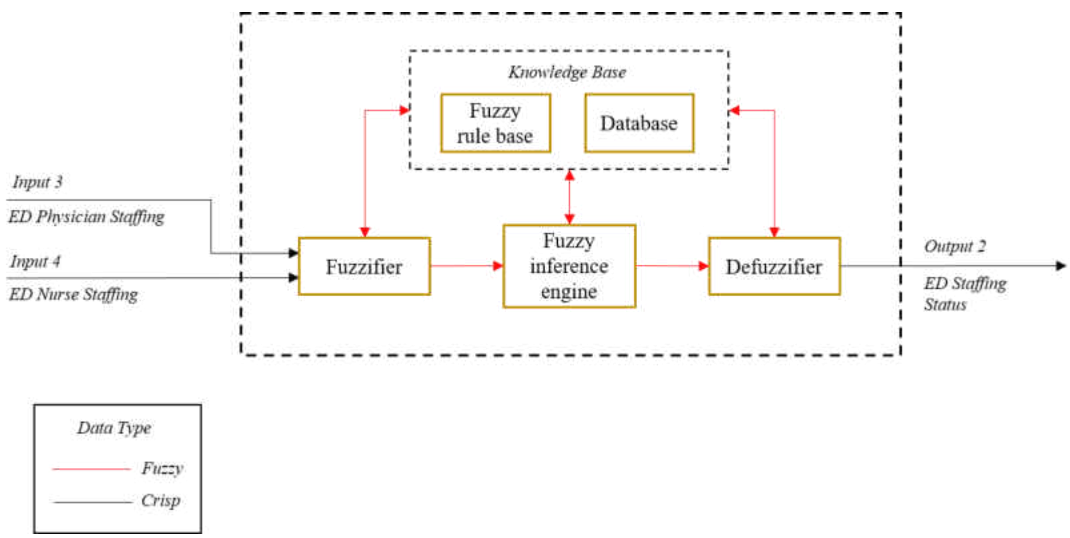

Figure 4-6: Fuzzy logic subsystem II

The third fuzzy logic subsystem evaluates the ED workload. The three inputs of this fuzzy subsystem are ED staffing level, ER occupancy rate, and average complexity of patients who are being treated in the emergency room. It should be noted that the third input shares the same characteristics of the second input of subsystem one, with the difference being that the populations of these similar inputs are separate. Figure 4-7 illustrates the components of fuzzy subsystem III. The ED staffing status, input one, is the output from subsystem II, and is represented by three membership functions; "Inadequate", "Partially adequate", and "Adequate". Using the same membership function, this input is evaluated with a trapezoidal function on the interval [0, 100]. The ER occupancy rate, which is an independent input, is characterized by four membership functions; "Low", "Medium", "High", and "Very High". The occupancy rate is evaluated with a trapezoidal function in the interval [0, 100]. The third input, patient complexity shares characteristics from the second input to the fuzzy subsystem I, as previously mentioned. Therefore, this third input is represented by three membership functions; "Low", "Medium", and "High", and is evaluated with a trapezoidal function in the interval [1, 5]. With the three sets of membership indicators in this subsystem, the number of fuzzy rules will now reach 36 rules ($3^2 \times 4$). The single output of the third fuzzy logic subsystem is the ED workload. It is represented by four membership functions; "Low", "Medium", "High", and "Very High". As other outputs are evaluated in this interval of [0,100], this output is evaluated in the same interval, and its membership value is assessed with a triangular function. The ED workload is an intermediate variable that feeds the fourth fuzzy subsystem, and represents a major determinate of crowding by containing four of the seven inputs alone. Combined with the output of subsystem I and the final input, the output of subsystem III will contribute to subsystem IV's assessment of emergency department crowding.

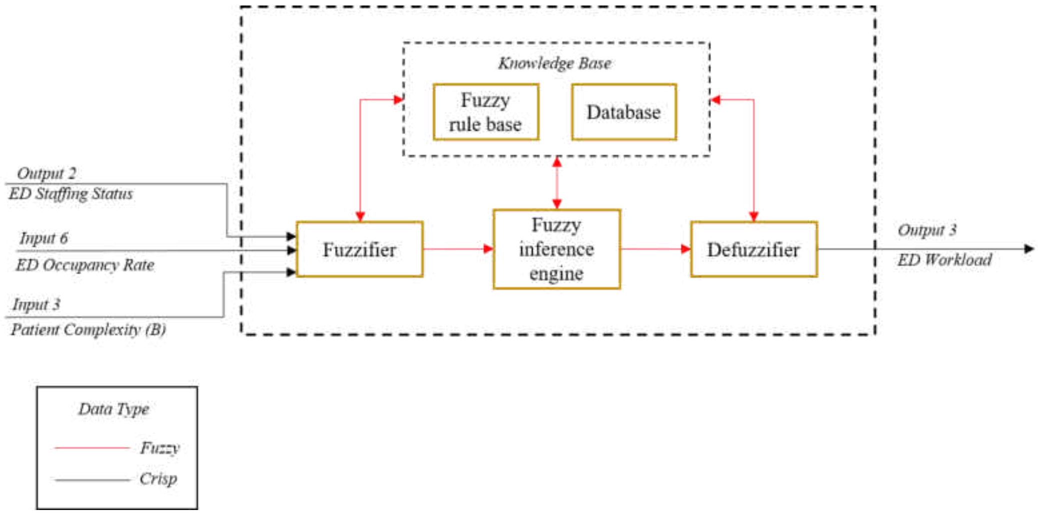

Figure 4-7: Fuzzy logic subsystem III

In review, the first level of the hierarchical fuzzy expert system was composed of two fuzzy logic subsystems, with the second level containing one subsystem, which is also detailed in figure 4-4. Level three of the hierarchical fuzzy expert system contains the fourth and final fuzzy logic subsystem, which receives inputs in some manner from every previous subsystem.

This fourth fuzzy logic subsystem is the main component of this hierarchical fuzzy expert system which aims to assess the ED crowding level. The three inputs of this fuzzy subsystem include the two previously mentioned indicators ED demand status and ED workload, and the third, new input, which is the seventh independent input of the entire hierarchical system, is ED boarding status. The components of fuzzy subsystem IV are illustrated in Figure 4-8. The first input to this subsystem, the ED demand status, as previously described, is represented by five triangular membership functions; “Very Low”, “Low”, “Medium”, “High”, and “Very High”, with an interval of [0, 100]. The second input, the ED workload is represented by four triangular membership functions; “Low”, “Medium”, “High”, and “Very High”. Its interval of the crisp value is [0,100]. The third input, ED boarding status, is an independent variable, which is derived from the ratio of boarded patients to the capacity of the emergency room. This input has four fuzzy classes as the second input, but is evaluated with a trapezoidal membership function on an interval of [0, 0.4]. With the three sets of membership indicators in this subsystem, the number of fuzzy rules is 80 ($4^2 \times 5$). The output of the fourth fuzzy logic subsystem is the ED crowding level, and is the final output for the entire hierarchical system. It is represented by five membership functions; "Insignificant", "Low", "Medium", "High", and "Extreme", which are used to indicate the degree of crowding in emergency departments. Like other outputs, the interval of the crisp value for the final output is [0,100], and is evaluated with a triangular function.

Utilizing the hierarchical fuzzy system appears to be the most appropriate approach for this study, rather than the standard fuzzy system. This approach creates different indicators, such as demand status, workload, and staffing indicators, while reducing the total number of fuzzy rules from 5184 (under the standard fuzzy system) to just 137 rules. This difference represents a great reduction in calculation and simplifies the process of acquiring knowledge from experts, and potentially reduces the threshold for academic access to meaningful results.

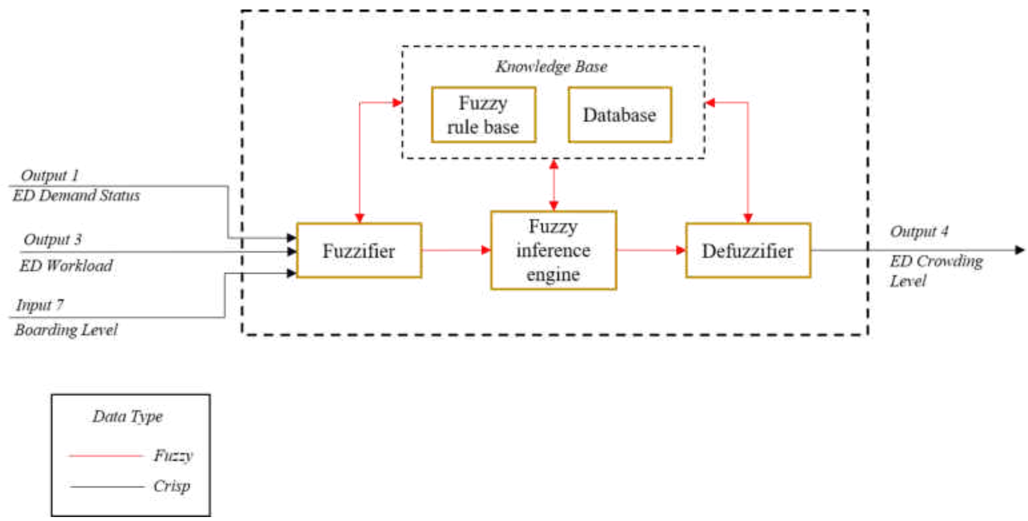

Figure 4-8: Fuzzy logic subsystem IV

4.4 Fuzzy Logic System Development

This section describes the technical process of developing the proposed fuzzy expert system, which would equip the designed framework with a knowledge base, a fuzzy inference engine, fuzzifier and defuzzifier. The knowledge base consists of a fuzzy database and a fuzzy rule base, in order to fuel the fuzzifier, defuzzifier, and inference engine portions of the fuzzy subsystems.

First, the elicitation of expert knowledge for building the fuzzy database is described. Secondly, this section also describes the process of developing fuzzy rules. Finally, the fuzzification and the defuzzification processes are conceptually and mathematically represented.

4.4.1 Knowledge Base

The knowledge base is an indispensable component of any fuzzy logic system, as it contains both the fuzzy rules base and the database. The development of the knowledge base is keystone for the fuzzy system, and is the most challenging aspect of designing the proposed model. The importance of this knowledge base stems from the dependency of the other component of the system on it, including the fuizzifier, defuzzifier, and fuzzy inference engine. Effectively, the knowledge base is the brain of the fuzzy system, simulating reasoning from a human perspective. The creation of the knowledge base involves systematic collection of qualitative and quantitative data from subject matter experts. These experts have to meet the following criteria in order to be eligible to participate in the membership intervals determination and fuzzy rules evaluation:

- The expert works or has recently worked in Saudi Arabia healthcare institutions for at least five years, or has conducted research in the field of Saudi healthcare.
- The expert has deep experience in the daily operations of emergency care centers.
- The expert has solid knowledge in staffing, performance management, healthcare administration, patient flow analysis, and bed management.

To create a robust knowledge base for the proposed fuzzy system, a minimum of ten experts are required who meet these qualifications. While discussing these experts here for the purposes of analyzing their data, and elsewhere in this study, an assigned code “HCE-k” will be issued for each participated expert, where HCE stands for Healthcare Expert, and k stands for the expert number.

4.4.1.1 Database

The database is one of two components of the knowledge base, which contains the fuzzy sets and their membership functions of all fuzzy variables of the system. This information feeds the fuzzifier and defuzzifier, stating the degree of membership and the type of the membership function of the crisp input and output values.

In order to develop the database and construct the membership functions, different approaches for eliciting expert knowledge were considered. Each considered approach is based on different assumptions for assigning membership degree of an element to a fuzzy set, and these approaches vary in terms of question length, and response length and confidence. Five elicitation methods are identified (Mendel & Wu, 2010). The methods include, point estimation (or polling) (Hersh & Caramazza, 1976), direct rating, interval estimation, reverse rating, and transition interval estimation.

Point estimation allows experts to indicate whether a specific crisp value belongs to a certain fuzzy class in their responses. For example, an expert may be asked: “Do you consider a 30% ED occupancy ratio be classified as medium?” Although this method of elicitation does not require membership function knowledge, and poses relatively simple questions, the number of questions required to obtain an interval of data would be prohibitively large.

Direct rating requires either multiple experts providing numerical values for a membership function in a single instance, or a single expert providing the values for the function multiple times. A question associated with this approach could be written as “To what degree of high occupancy would you attribute a 30% ED occupancy rate?" This elicitation method would require experts to have knowledge of both fuzzy logic and membership functions prior to the study, and there would be many questions required to construct the function, as one question would be required for each crisp value. Moreover, there will be increased difficulty in providing precise answers as the number of questions increase, introducing uncertainty.

In the approach of interval estimation, multiple experts identify crisp intervals with a range of associated linguistic terms. When the intervals are analyzed, membership degrees are assigned to construct membership functions. A question utilizing this approach could ask responders "What range of occupancy rates characterize low occupancy in an emergency room?" This elicitation method does not require any prior knowledge on fuzzy logic and membership functions, because the questions do not directly ask for membership degree. Another advantage of interval estimation is that there is only one question assigned per fuzzy class.

Reverse rating asks experts to determine a single crisp value that is associated with a fuzzy class at a given membership degree. A question created with this method may ask "What is an occupancy rate that is considered 'high' at a degree of 0.4?" This elicitation method requires responding experts to have knowledge on membership functions and fuzzy logic, utilizing a large number of questions, and the questions could be challenging to accurately answer.

For the transition interval rating method, the expert provides interval values in a given membership class at a given membership degree. Utilizing this approach, a question could be written as "What is a range of ED occupancy rates which are 'very high' to a degree of 0.7?" This method is the most difficult one to implement, as it requires deep knowledge of both fuzzy logic and membership functions, and the number of questions required to obtain expert knowledge would be large.

This study adapts the indirect interval estimation elicitation method. Such a method carries advantages such as allowing responses from multiple subject matter experts, while not requiring knowledge of membership functions. Additionally, under this approach, fewer questions may be used, and given questions may be easier to answer than those in other approaches.

To elicit the degrees of membership for a fuzzy class, let $[x_{ji}, y_{ji}]$ represent the interval values of the fuzzy class j that is determined by expert i. The steps to elicit and analyze expert knowledge are described as follows:

- Determine all interval values for each j obtained from experts.
- Perform an intersection for j subset intervals to obtain expert consensus.
- Find ambiguous areas among determined intervals.

The obtained intervals and the ambiguous areas among them will be utilized in constructing the membership functions. The elicitation method involves a survey (Appendix J) including five questions for subject matter experts, which are derived from scenarios in emergency departments, citing specific numbers to characterize the capacity and patient flow in a given question. The objective of the survey is to elicit the opinion of subject matter experts, by obtaining each numerical interval for a given linguistic fuzzy class from their responses. For each given scenario in each questions, 50 beds will be the given standard for capacity. From the responses which are based on 50 bed scenarios, such as in questions one, two, three and five, more calculation will be necessary to make the results applicable to any ED setting. Specifically, the ratio of given responses to the capacity will be obtained for these questions.

Questions one, two, three, and five, which will require further calculation, each contribute to the inputs of the different fuzzy subsystems described previously by providing data for the membership functions. Ratios calculated from the responses to question one will provide the membership function for the input to subsystem I, patient demand. Questions two and three will provide the membership functions for the two inputs of subsystem II, nurse staffing and physician staffing. Responses from question four will determine the membership function for occupancy rate, which is the input for subsystem III. Question five will provide the membership function for patient boarding, one of the inputs to the major subsystem, subsystem IV.

The results from this survey will become the main source of data for constructing the membership functions. There are five commonly used types of membership functions including triangular, trapezoidal, bell curves, Gaussian, and Sigmoidal, some of which require large amounts of data to construct. Due to the limitations of available data, trapezoidal membership functions (Figure 4-9) and triangular membership functions (Figure 4-10) are the most appropriate for this study. These membership function features are defined by three characteristics, namely; core, support, and boundary. The membership degrees are assigned a value between 0 and 1. The core region in the function is the universe space where an element has full membership in a fuzzy set (i.e. $\mu(x) = 1$). The support region is the universe space where an element has nonzero membership in a fuzzy set (i.e. $\mu(x) > 0$). The boundary region defines the universe space at which an element takes a nonzero membership degree but not a full membership degree in a fuzzy set (i.e. $0 < \mu(x) < 1$) (Sivanandam, Sumathi, & Deepa, 2007). The trapezoidal membership function is defined with the following formula:

$$\mu(x;a,b,c,d) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{b-c}, & c \leq x \leq d \\ 0, & d \leq x \end{cases} \tag{8}$$

Where parameters b and c define the core area of the trapezoid MF and parameters a and d define the support area of the trapezoid MF. Figure 4-9 illustrates the shape and parameters of the trapezoidal membership function.

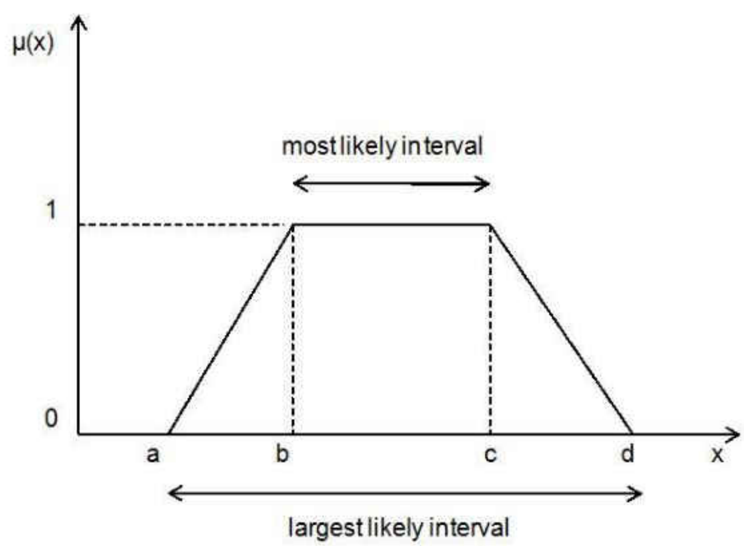

Figure 4-9: Trapezoidal membership function.

Adapted from (Abdallah, 2013)

The triangular membership function is defined with the following formula:

$$f(x;a,b,c) = \begin{Bmatrix} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{Bmatrix} \tag{9}$$

Where the parameter b define the core area of the triangular MF and parameters a and c define the support area of the triangular MF. Figure 4-10 illustrates the shape and parameters of the triangular membership function.

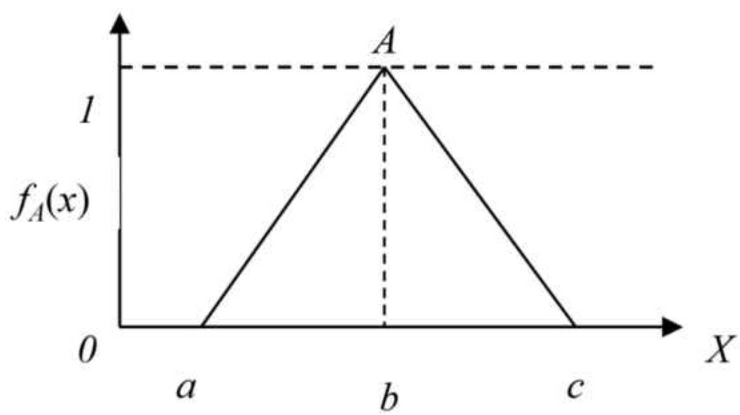

Figure 4-10: Triangular membership function.

Adapted from (Sivanandam et al., 2007)

4.4.1.2 Fuzzy Rule Base

The fuzzy rule base is the other key part to the knowledge base, including the database. It stores all derived fuzzy rules, which is intended to provide the fuzzy inference engine with decision support information within each subsystem.

To robustly create fuzzy rules for each fuzzy logic subsystem, experts are given a form to assess the consequences of each condition statement, developed from the permutation of each fuzzy class for a given fuzzy subsystem. Appendix J shows the components of the assessment form. As mentioned earlier, a total of 10 healthcare experts will participate in the fuzzy rules assessment process. The total number of fuzzy rules to be evaluated by subject matter experts for the fuzzy logic subsystems I, II, III, and IV are 12 (3×4), $9(3^2)$, $36(4 \times 3^2)$, and $80(5 \times 4^2)$, respectively. Therefore, the proposed three-level hierarchical fuzzy expert system includes a total of 137 fuzzy rules, meaning that there will be a total of 1370 fuzzy rule assessments from the ten experts. The process of developing the fuzzy rules is detailed in the following steps:

- List all possible permutations of "AND" rules for each fuzzy logic subsystem.
- Code each rule with "FLSm-n" where FLS stands for Fuzzy Logic Subsystem, m stands for the number of subsystem, and n stands for the rule number within the m subsystem.
- Code "HCE-k" for each participating expert, where HCE stands for Healthcare Expert, and k stands for the expert number.
- The Expert HCE-k determines the consequence of the fuzzy conditional statement FLSm-n based on their expertise.

- The fuzzy conditional statement FLSm-n must meet a 50% consensus rate among experts, and must be the only consequence to receive a 50% consensus rate, to be accepted as a valid fuzzy rule.
- If the consensus rate does not meet the determined criteria, further iterations should be conducted with a new expert until the consensus rate achieves the criteria in the previous step.

The process for developing fuzzy rules is illustrated in figure 4-11, where the consensus feedback is elaborated upon in more detail.

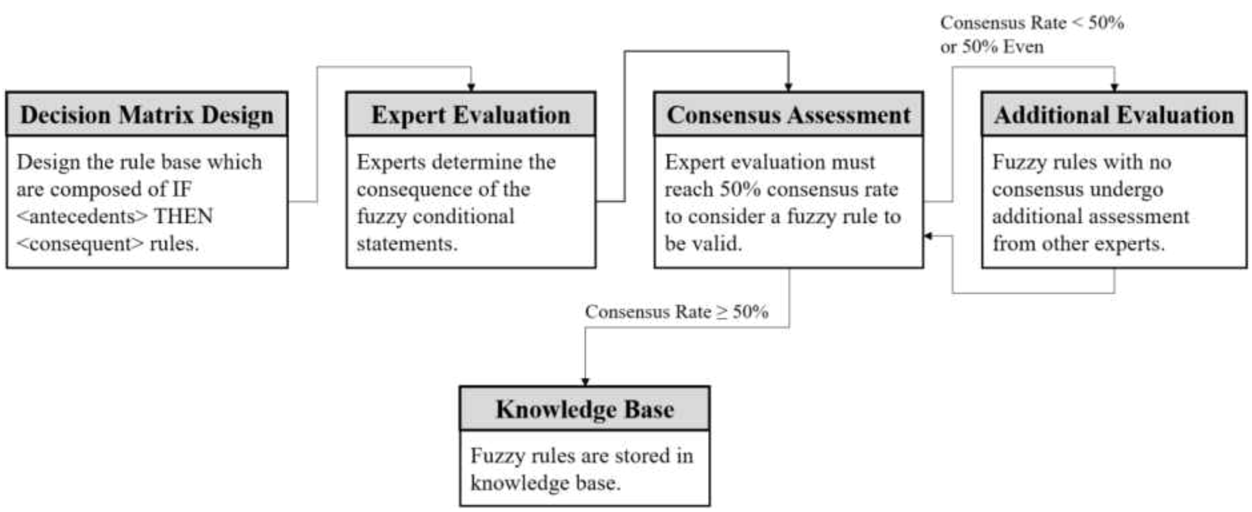

Figure 4-11: Process for Developing Fuzzy Rules

4.4.2 Fuzzification Process

Fuzzification is the first step in the fuzzy system, as it obtains both the membership function type and the degree of membership from the database. This database is built from the surveyed expert determination of membership function intervals. In the fuzzification process, crisp values which are within the universe of discourse of the input variable are translated into fuzzy values, and the fuzzifier determines the degree to which they belong to a membership function. The fuzzifier for this designed fuzzy system adapts the Minimum approach. Whereas the input is crisp, the output is a degree of membership in a qualitative set. The fuzzified outputs allow the system to determine the degree to which each fuzzy condition satisfies each rule.

4.4.3 Defuzzification Process

After the fuzzifier converts numerical inputs into fuzzy values, and the fuzzy inference engine is fed by the knowledge base to logically link the inputs to the output, last step remaining in the fuzzy system occurs in the defuzzifier. Defuzzification is the process where the fuzzy values are converted into crisp values. The defuzzifier is fed by the database, and its importance lies in the fact that its crisp output is the desired product of the entire system. Seven defuzzification methods are identified (Sivanandam et al., 2007): centroid method, max-membership method, mean-max membership, weighted average method, center of sums, first of maxima or last of maxima, and center of largest area. This research adapts the centroid method for the defuzzification process, and its formula is defined as following:

$$z^* = \int \frac{\mu_C(z)\, zdz}{\mu_C(z)\, dz} \tag{10}$$

4.5 Summary

In summary, this chapter details the development process for creating the proposed fuzzy system for quantifying emergency department overcrowding, and its components. Hierarchical and standard fuzzy logic systems were compared, and the hierarchical system was chose for its ability to reduce the number of fuzzy rules necessary to construct the knowledge base, in addition to its ability to emulate the different operational aspects of crowding. The structure of this hierarchical system was described as consisting of four subsystems, fed with a total of seven inputs. The four subsystems were defined as demand status, staffing status, workload status, and crowding level. The inputs and outputs of these subsystems were related to subsystem IV, which is the most important part of the system. The knowledge base, consisting of both the database and fuzzy rule base was described, where this knowledge feeds the inference engine and fuzzifier and defizzifier to obtain outputs for the system. The knowledge base is the most crucial part of the subsystem architecture, as it is constructed from the assessments of ten experts. Next chapter shows the computation of the model based on the data collected from experts.

CHAPTER 5 IMPLEMENTATION AND RESULTS

5.1 Introduction

This chapter details the process of implementing the designed framework by constructing the knowledge base and analyzing the produced results. First, the preparation of the fuzzy system knowledge base is discussed, encompassing the results from expert knowledge elicitation and the construction of membership functions. A deeper statistical analysis is provided for the expert evaluations of membership intervals and consensus rates for assessments of fuzzy rules. Next, the fuzzy system results are analyzed for each subsystem, and the different surface plots representing the relation of subsystem inputs and outputs are presented. Implementation and validation of the model is also discussed, where results from implementation are compared against subjective expert assessment. Finally, concluding remarks are made to reflect on the insights developed from analysis of the data collected from the knowledge base construction and validation steps.

5.2 Fuzzy System Preparedness

In chapter four, the protocol was provided for eliciting expert knowledge on to obtain membership intervals, rule assessments and consensus rates, along with other data. With this step complete, a preparatory step must be taken to obtain results for the proposed model. In this step, data will be prepared before it is added to the knowledge base, interval values will be used to construct membership functions, and data from expert rule assessments will contribute to the rule base.

Expert knowledge was sought from ten experts, designated with HCE expert codes. The occupation and qualifications of these experts are described as follows:

- **HCE-01:** An experienced healthcare administrator in the Saudi public healthcare sector
- **HCE-02:** A physician, professor, and consultant of emergency medicine in several healthcare organizations in Saudi Arabia
- **HCE-03:** An academic researcher specializing in operations management
- **HCE-04:** An emergency room physician working in a Saudi private healthcare sector
- **HCE-05:** An experienced emergency room nurse
- **HCE-06:** An academic researcher with experience in healthcare studies
- **HCE-07:** A researcher with vast experience in emergency room operations management
- **HCE-08:** A physician from the ICU department who oversees emergency department transfers to the ICU
- **HCE-09:** An emergency room physician
- **HCE-10:** A general physician

The backgrounds of these experts will be made more relevant in the discussion section when results from the developed model are discussed.

5.2.1 Results of Expert Knowledge Acquisition

In this section, results from subject matter experts are detailed across five tables. For each table, the results from ten experts answering five questions are listed, providing a total of 220 intervals which are used to construct membership functions. Chapter five will detail the calculation of the fuzzy numbers, based on the results provided by the subject matter experts. Table 5-1 contains answers from question one of the survey, in which experts were posed with a scenario of an emergency room capacity of 50 beds. The answers from the expert evaluation are divided by 50 to obtain the ratio of waiting patients to ED capacity, which can be applicable to any ED. This question in the survey specified the minimum and maximum values for the patient demand as 0 and 100, respectively, in order to introduce boundaries for the membership functions. After converting these values into ratios, the minimum and maximum values became 0 and 2, respectively. Experts determined the patient demand on four levels; “low”, “medium”, “high”, and “very high”. The total number of obtained intervals from question one was 40.

Table 5-1: Interval assignment for patient demand based on ratio of no. of waiting patients to ED capacity

Expert	**Interval Value**							
	Low		**Medium**		**High**		**Very High**	
	Lower value	Upper value	Lower value	Upper value	Lower value	Upper value	Lower value	Upper value
HCE-01	0	0.4	0.42	0.6	0.62	1.2	1.22	2
HCE-02	0	0.3	0.32	0.7	0.72	1.1	1.12	2
HCE-03	0	0.2	0.22	0.6	0.62	1	1.02	2
HCE-04	0	0.3	0.32	0.8	0.82	1.2	1.22	2
HCE-05	0	0.5	0.52	0.8	0.82	1.1	1.12	2
HCE-06	0	0.2	0.22	0.7	0.72	1	1.02	2
HCE-07	0	0.3	0.32	0.7	0.72	1.2	1.22	2
HCE-08	0	0.4	0.42	0.8	0.82	1.2	1.22	2
HCE-09	0	0.5	0.52	0.7	0.72	1.1	1.12	2
HCE-10	0	0.4	0.42	0.6	0.72	0.9	0.92	2

Using the data from table 5-1, figure 5-1 was constructed to compare the responses between each expert at each level in question one. Expert responses are similar between upper and lower values of adjacent levels, as they are the boundaries for fuzzy classes. Variation can be observed in different levels between expert responses. For the upper bound of the low level, experts HCE-03 and HCE-06 share the lowest values. Experts HCE-05 and HCE-09 report the highest values of the upper bound of the low level, and experts HCE-02, HCE-04, and HCE-07 each have average values assigned for the upper bound of the low level. At the upper bound of the medium level, it can be noticed that there was minimal variation between expert responses. In the upper value of the high level, HCE-01, HCE-04, HCE-07, and HCE-08 responded with higher values, while HCE-03, HCE-06, and HCE-10 responded with low values, and the remaining experts responded with average values. It can be also noted that the evaluations provided by experts HCE-03 and HCE-06 were lower than average values of other experts.

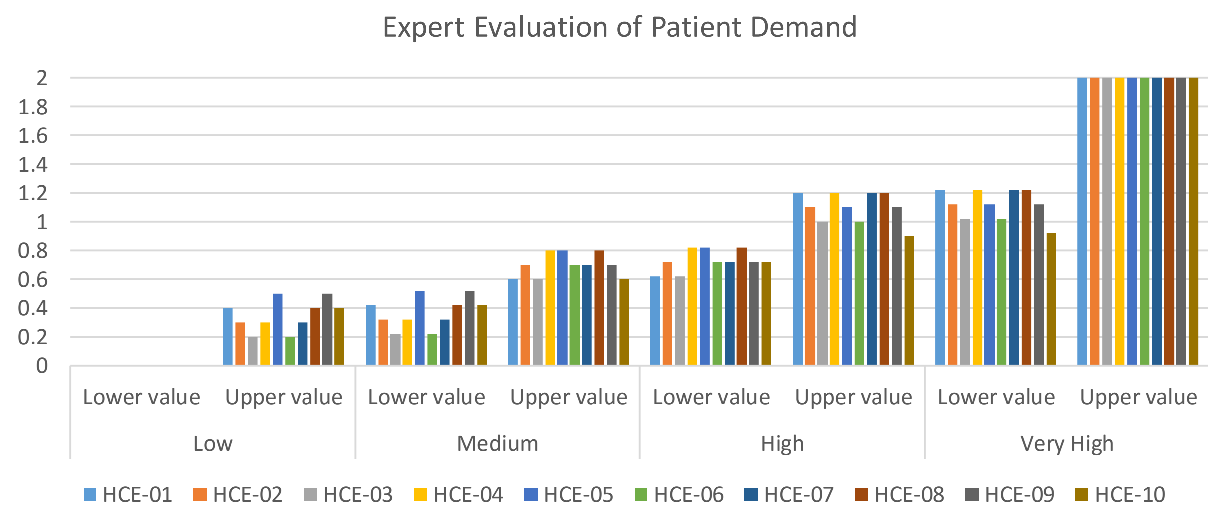

Figure 5-1: Expert evaluation of patient demand

Table 5-2 contains answers from question two of the survey, which is related to a scenario with an emergency room capacity of 50 beds. The ratios were obtained from the answers from subject matter experts. This question in the survey did not specify the maximum value for the patient demand, meaning that the membership function did not have an imposed boundary. After converting these values into ratios, the minimum and maximum values became 0 and 0.32, respectively. Experts determined the patient demand on three levels; “inadequate”, “partially adequate”, and “adequate”. The total number of obtained intervals from question two was 30.

Table 5-2: Interval assignment for physician staffing

Expert	Interval Value					
	Inadequate		Partially Adequate		Adequate	
	Lower value	Upper value	Lower value	Upper value	Lower value	Upper value
HCE-01	0.02	0.06	0.08	0.18	0.16	0.24
HCE-02	0.02	0.1	0.12	0.16	0.18	0.2
HCE-03	0.04	0.1	0.12	0.18	0.2	0.3
HCE-04	0.04	0.08	0.1	0.18	0.2	0.28
HCE-05	0	0.12	0.14	0.24	0.26	0.3
HCE-06	0	0.08	0.1	0.16	0.18	0.3
HCE-07	0	0.08	0.1	0.18	0.2	0.3
HCE-08	0.02	0.08	0.1	0.18	0.2	0.24
HCE-09	0.02	0.06	0.08	0.16	0.22	0.2
HCE-10	0.02	0.1	0.12	0.2	0.22	0.32

Figure 5-2 compares the differences between the experts' responses. It can be observed that in inadequate and partially adequate levels, HCE-05 responded with a higher ratio than average, while HCE-09 provided the lowest ratio. The remaining experts for inadequate and partially adequate appear to provide consistent evaluations compared to experts HCE-05 and HCE-09. Additionally, there is large variation in the upper bound of the adequate class, which may be due to the lack of a specified upper bound on the level of physician staffing.

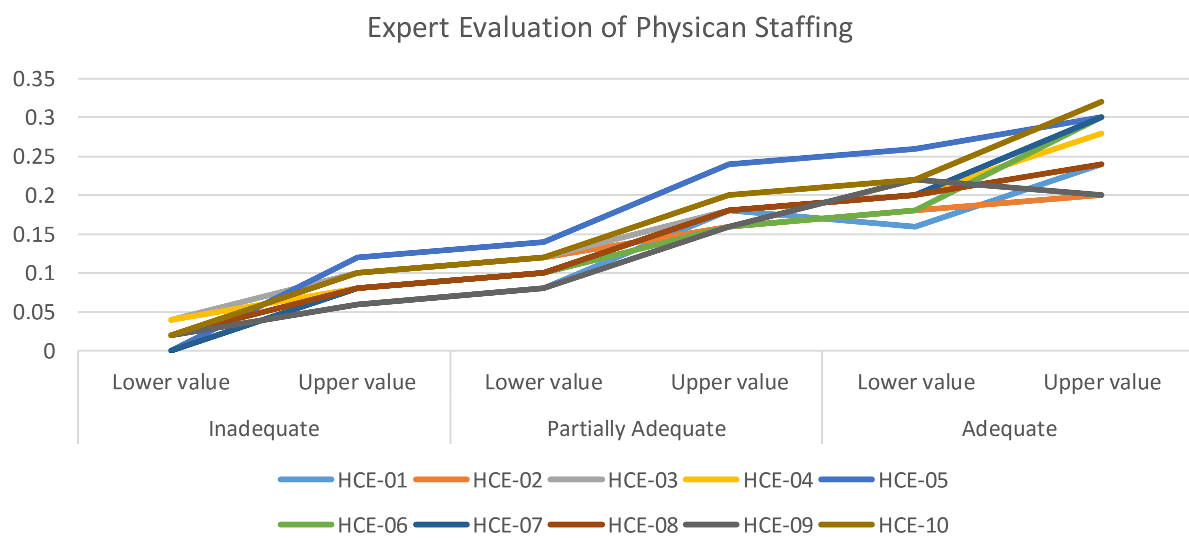

Figure 5-2: Expert evaluation of physician staffing

Table 5-3 contains answers from question three of the survey, which is related to a scenario with an emergency room capacity of 50 beds. Similarly in this table, there is no imposed upper bound for nurse staffing, which also impacts the upper bound of the last fuzzy class. The maximum value for nurse staffing was 0.5, or 25 out of 50 beds, and experts provided their evaluations on three fuzzy classes; “inadequate”, “partially adequate”, and “adequate”. 30 total intervals were obtained from question three.

Table 5-3: Interval assignment for nurse staffing

Expert	Interval Value					
	Inadequate		Partially Adequate		Adequate	
	Lower value	Upper value	Lower value	Upper value	Lower value	Upper value
HCE-01	0.06	0.14	0.16	0.3	0.32	0.5
HCE-02	0.02	0.08	0.1	0.26	0.22	0.34
HCE-03	0.04	0.1	0.12	0.32	0.34	0.5
HCE-04	0.08	0.12	0.14	0.24	0.26	0.4
HCE-05	0.08	0.12	0.14	0.24	0.26	0.4
HCE-06	0	0.14	0.16	0.28	0.3	0.36
HCE-07	0	0.1	0.12	0.24	0.26	0.4
HCE-08	0.08	0.16	0.18	0.32	0.34	0.5
HCE-09	0.02	0.18	0.2	0.28	0.3	0.4
HCE-10	0.02	0.16	0.18	0.3	0.32	0.46

In figure 5-3, the experts responded consistently, and it can be observed that the upper values of the inadequate class may allow values in the upper value of the partially adequate class to be anticipated, if they were followed linearly. The greatest variation can be observed in the upper value of the adequate class, which may also be influenced by the absence of a defined upper bound value. Experts HCE-02 and HCE-07 provided the lowest values in their responses, while expert HCE-08 provided the highest average response.

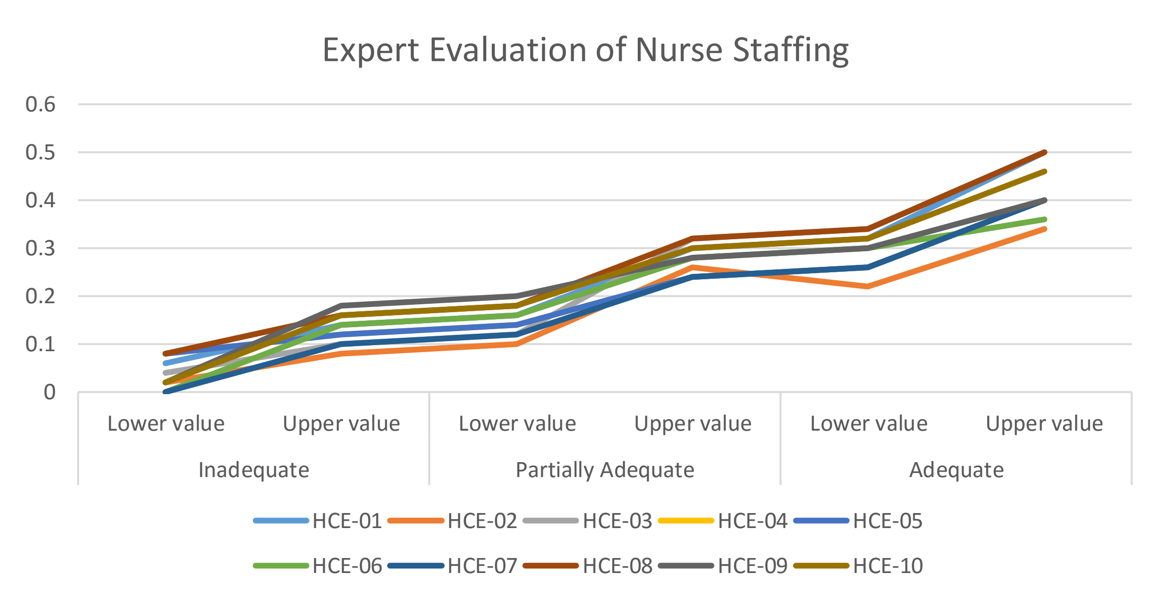

Figure 5-3: Expert evaluation of nurse staffing

Table 5-4 contains answers from question four of the survey, regarding ER occupancy rate, where the maximum occupancy rate was assumed to be 100 percent. Ten experts provided intervals from their perspective on an appropriate lower and upper value for each of the four fuzzy classes, "low", "medium", "high", and "very high". In total, 40 evaluated intervals were obtained to construct the membership functions.

Table 5-4: Interval assignment for ER occupancy rate

Expert	Interval Value							
	Low		Medium		High		Very High	
	Lower value	Upper value	Lower value	Upper value	Lower value	Upper value	Lower value	Upper value
HCE-01	0	25	26	45	46	75	76	100
HCE-02	0	20	21	50	51	74	75	100
HCE-03	0	35	36	55	56	80	81	100
HCE-04	0	25	26	60	61	70	71	100
HCE-05	0	25	26	50	51	70	71	100
HCE-06	0	20	21	65	66	84	85	100
HCE-07	0	30	31	48	49	74	75	100
HCE-08	0	35	36	55	56	85	86	100
HCE-09	0	33	34	60	61	90	91	100
HCE-10	0	20	21	50	51	80	81	100

In figure 5-4, expert responses are compared. In the upper value of the low fuzzy class, the experts with the highest recorded values are HCE-03, HCE-07, HCE-08, and HCE-09, while those with the lowest values are HCE-02, HCE-06, and HCE-10. The remaining experts in this class responded with average values. In the upper value of the medium class, experts HCE-04, HCE-06, and HCE-09 have the highest recorded values, and experts HCE-01 and HCE-07 have the lowest recorded values. Overall in the upper value of the medium class, the variation in responses is high. The upper value of the high class features the highest values among experts HCE-06, HCE-08, and

HCE-09, while the lowest values belong to HCE-04 and HCE-05. Similarly, variation of responses is high in this class.

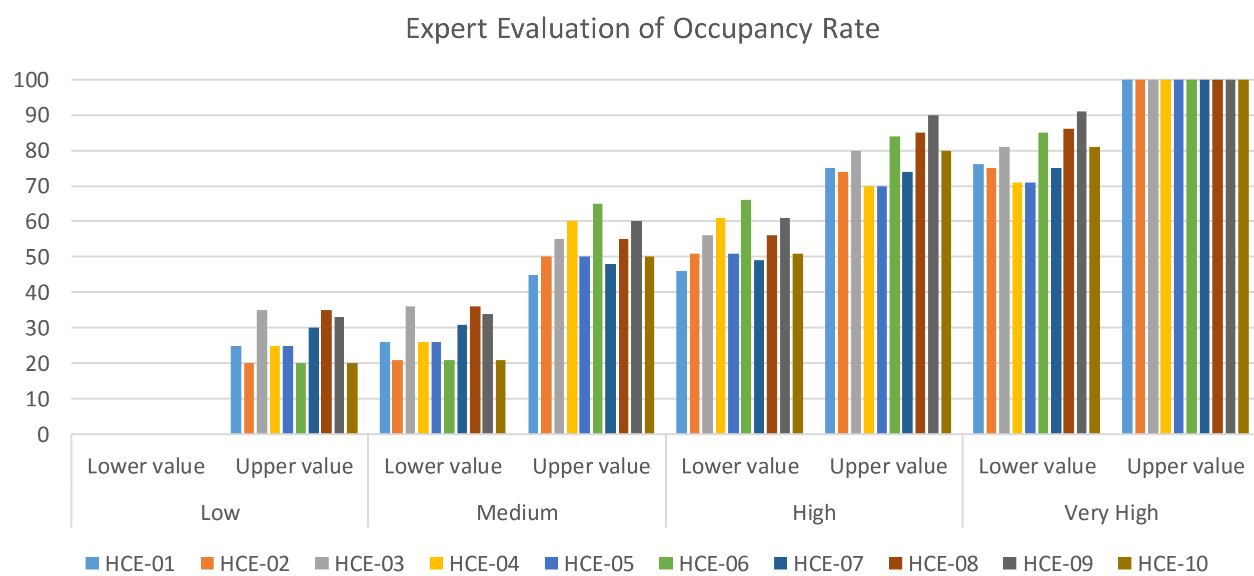

Figure 5-4: Expert evaluation of occupancy rate

Table 4-5 contains answers from the survey's fifth question, and is concerned with patient boarding. Similarly to questions one, two, and three, this question was based on a scenario with 50 beds, which was later converted to a ratio of boarded patients to the ER capacity. The minimum and maximum intervals were specific at 0 and 20 patients, respectively, which translated to ratios of 0 and 0.4. From the ten experts' responses across the four fuzzy classes, 40 evaluated intervals were obtained.

Table 5-5: Interval assignment for patient boarding

Expert	Interval Value							
	Low		Medium		High		Very High	
	Lower value	Upper value	Lower value	Upper value	Lower value	Upper value	Lower value	Upper value
HCE-01	0	0.08	0.1	0.22	0.24	0.32	0.34	0.4
HCE-02	0	0.1	0.12	0.2	0.22	0.3	0.32	0.4
HCE-03	0	0.08	0.1	0.2	0.22	0.3	0.32	0.4
HCE-04	0	0.06	0.08	0.16	0.18	0.26	0.28	0.4
HCE-05	0	0.12	0.14	0.22	0.24	0.3	0.32	0.4
HCE-06	0	0.12	0.14	0.22	0.24	0.3	0.32	0.4
HCE-07	0	0.04	0.06	0.16	0.18	0.26	0.28	0.4
HCE-08	0	0.12	0.14	0.2	0.22	0.3	0.32	0.4
HCE-09	0	0.06	0.08	0.2	0.22	0.3	0.32	0.4
HCE-10	0	0.08	0.1	0.24	0.26	0.32	0.34	0.4

Figure 5-5 displays the variation in responses from the subject matter experts. From the upper value of the low class, expert HCE-07 has the lowest recorded average value, and experts HCE-05, HCE-06, and HCE-08 accounted for the highest recorded average values. In the upper value of the medium class, there was not much variation, with exception of experts HCE-04 and HCE-07 who provided lower values. This case is similar in the upper value of the high class, there is minimal variation, aside from experts HCE-04 and HCE-07 who provide lower average values.

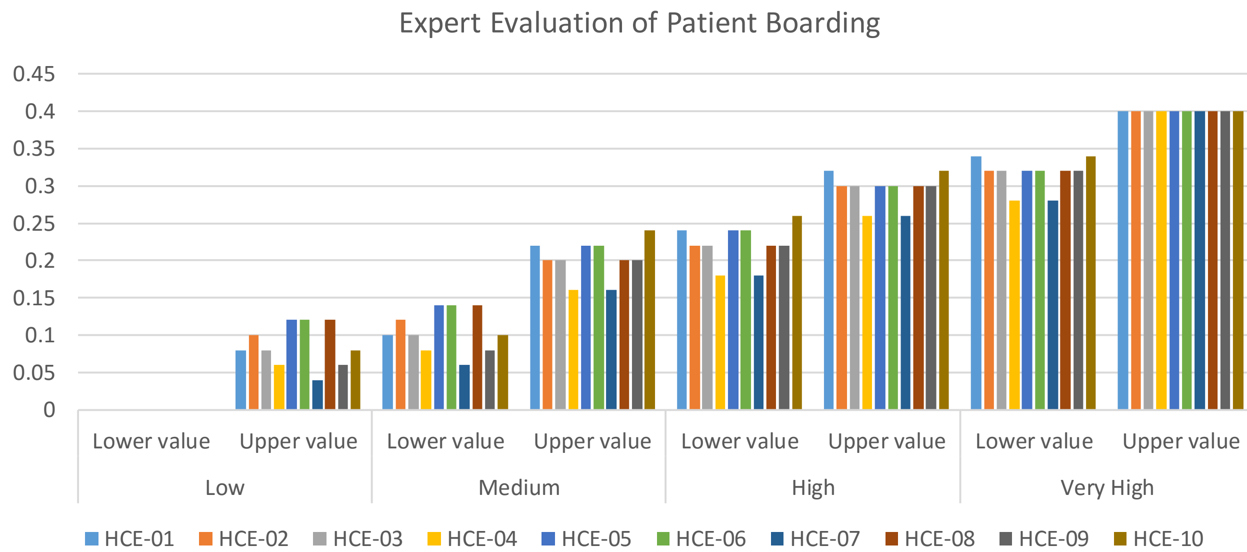

Figure 5-5: Expert evaluation of patient boarding

These results identify underlying differences between the evaluations of subject matter experts, which may lead to the introduction of bias when relying on only one perspective to implement a solution. The expert panel members who responded to each survey question each have different backgrounds and experience rooted in different areas of emergency departments. These experts view the ER from their different perspective, as internal and external stakeholders. Relying on only one perspective can lead to overestimated or underestimated interval values, as seen in some cases such the one discussed in question two, represented in figure 5-2. The variation in the experts' responses create foggy areas in the collected data, which can be modeled by fuzzy logic. Without considering these variations, data from experts can lead to biased conclusions.

5.2.1.1 Membership Functions

The database for subsystem I consists of membership functions for both inputs and the output, and are structured according to the data from table 5-6. Variable one, or the demand status, consists of four trapezoidal membership functions, while variable two, patient complexity, consists of three trapezoidal membership functions, and variable three, the ED demand, is the output of the subsystem and has five triangular membership functions.

Table 5-6: Parameters of fuzzy subsystem I's membership functions

Variable	**Fuzzy Linguistic Class**	**Fuzzy Number [a, b, c, d]**
Ratio of No. of Waiting Patients to ED Capacity	Low	[0, 0, 0.20, 0.50]
	Medium	[0.20, 0.50, 0.60, 0.80]
	High	[0.60, 0.80, 0.90, 1.20]
	Very high	[0.90, 1.20, 2.00, 2.00]
Patient Complexity	Low	[1, 1, 2, 2.5]
	Medium	[2, 2.5, 3.5, 4]
	High	[3.5, 4, 5, 5]
ED Demand	Very low	[0, 0, 25]
	Low	[0, 25, 50]
	Medium	[25, 50, 75]
	High	[50, 75, 100]
	Very high	[75, 100, 100]

The membership function representing patient demand in figure 5-6 is constructed using the fuzzy number intervals and linguistic classes provided in table 5-6. For the "low" linguistic class interval, the minimum value in the upper bound of the low class (as observed in table 5-1) is 0.2, meaning that there is 100% agreement among experts between the values of 0 and 0.2 for "low". The maximum value in the upper bound of the low class is 0.5, yet the minimum value of the lower bound in the medium class is 0.2, meaning that some experts varied in assigning the term "low" and "medium" between the interval [0.2, 0.5]. In figure 5-6, this accounts for the structure of the low class, where the core exists between 0 and 0.2, and the support exists between 0.2 and 0.5, overlapping the support of the medium class. The boundary for the medium class began at 0.2 and ended at 0.8, while the boundary for the high class was between 0.6 and 1.2, and the boundary for the very-high class was between 0.92 and 2. The core structures of the medium and high class are small, compared to the low and very-high classes.

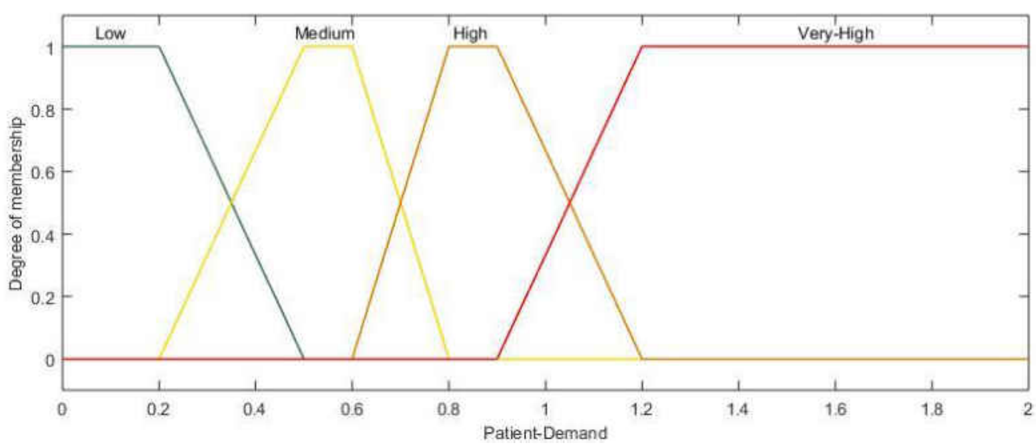

Figure 5-6: Membership function of patient demand

The membership function for patient complexity in figure 5-7 was constructed from the data provided by one expert using reverse interval estimation method. This was done due to the need for an expert possessing medical expertise in the triage process and familiarity with the emergency severity index. This expert directly constructed the membership function, providing data for the three linguistic classes. Patients rated with a value of 2 or 1 were considered "low" average complexity, and supports of this membership function consist of patients rated between 2 and 2.5, meaning the boundary for the low class was between 1 and 2.5. Similarly for "medium" average complexity, patients rated between 2.5 and 3.5 make up the core structure, and with the supports assigned values between 2 and 2.5, and between 3.5 and 4, the entire class boundary lies between 2 and 4. For "high" average complexity, the expert assigned values between 4 and 5 for the core area, with values between 3.5 and 4 for the support, making the boundary for the high class between 3.5 and 5. The core areas of each class are consistent in size, due to the data being taken from one expert instead of ten.

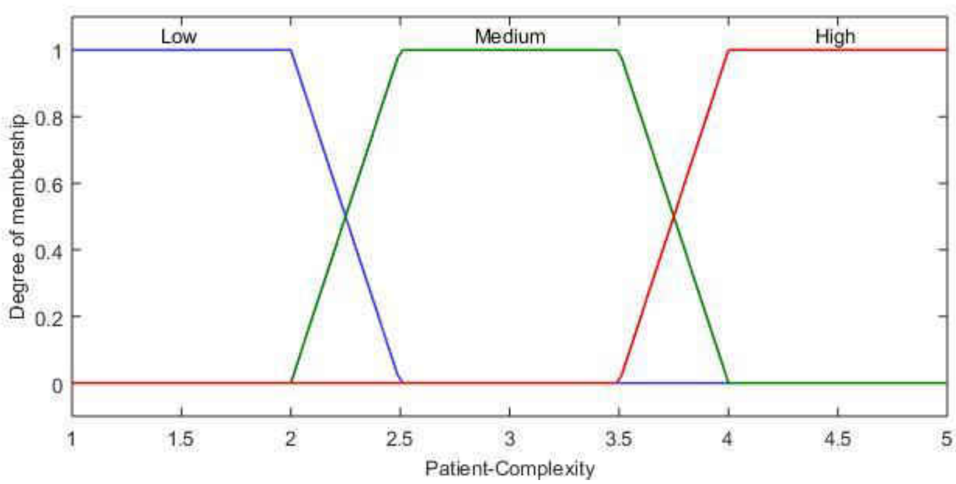

Figure 5-7: Membership function of patient complexity

The membership function for ED demand in figure 5-8 represents the output for subsystem one, which is considered the standard membership function for outputs. The function is triangular, with membership degree values peaking at 1, and the boundaries for different classes overlap the peaks of adjacent classes perfectly, demonstrating that the membership function always obtains membership from two classes. This also means that at any given point, the membership degree from two overlapping classes always equals 1, but there are only five points where classes obtain membership completely. These points occur at 0, 25, 50, 75, and 100 for “very-low”, “low”, “medium”, “high”, and “very-high”, respectively.

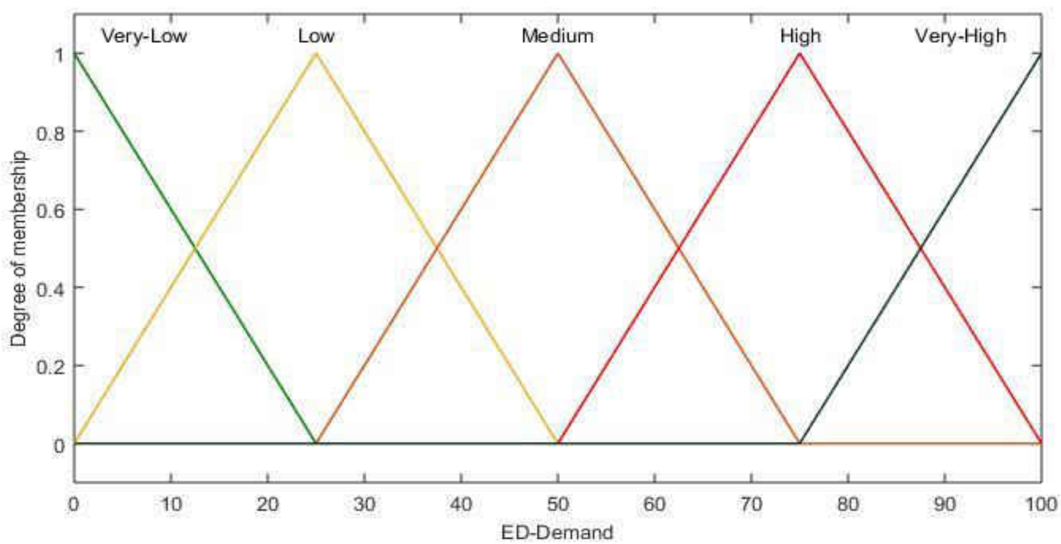

Figure 5-8: Membership function of ED demand

In subsystem II, the membership functions for the physician staffing and nurse staffing inputs are constructed with trapezoids for three classes. The output, ED staffing, is also represented with a trapezoidal membership function, which features equally spaced boundaries across three classes. Table 5-7 details the linguistic classes and fuzzy numbers for subsystem II and its membership functions.

Table 5-7: Parameters of fuzzy subsystem II's membership functions

Variable	Fuzzy Linguistic Class	Fuzzy Number [a, b, c, d]
Physician staffing	Inadequate	[0, 0, 0.06, 0.12]
	Partially adequate	[0.06, 0.12, 0.16, 0.24]
	Adequate	[0.16, 0.24, 0.32, 0.32]
Nurse staffing	Inadequate	[0, 0, 0.08, 0.18]
	Partially adequate	[0.08, 0.18, 0.24, 0.32]
	Adequate	[0.24, 0.32, 0.50, 0.50]
ED staffing	Inadequate	[0, 0, 25, 35]
	Partially adequate	[25, 35, 65, 75]
	Adequate	[65, 75, 100, 100]

Physician staffing is represented in the membership functions in figure 5-9. The three classes overlap as seen in subsystem I, representing the regions where linguistic terms did not reach full degrees of membership. For instance, the inadequate class core boundary begins at 0 and ends at 0.06, representing full membership for the linguistic term "inadequate". The upper bound for the inadequate class is 0.12, where the linguistic term "inadequate" achieves partial membership, and the lower bound for the partially adequate class is 0.06, where its term also achieves partial membership. The boundaries for the three classes are between 0 and 0.12 for the inadequate class, between .06 and 0.24 for the partially adequate class, and between 0.16 and 0.32 for the adequate class. The partially adequate class has the smallest core area, and the supports for all classes are similar in size relative to each other.

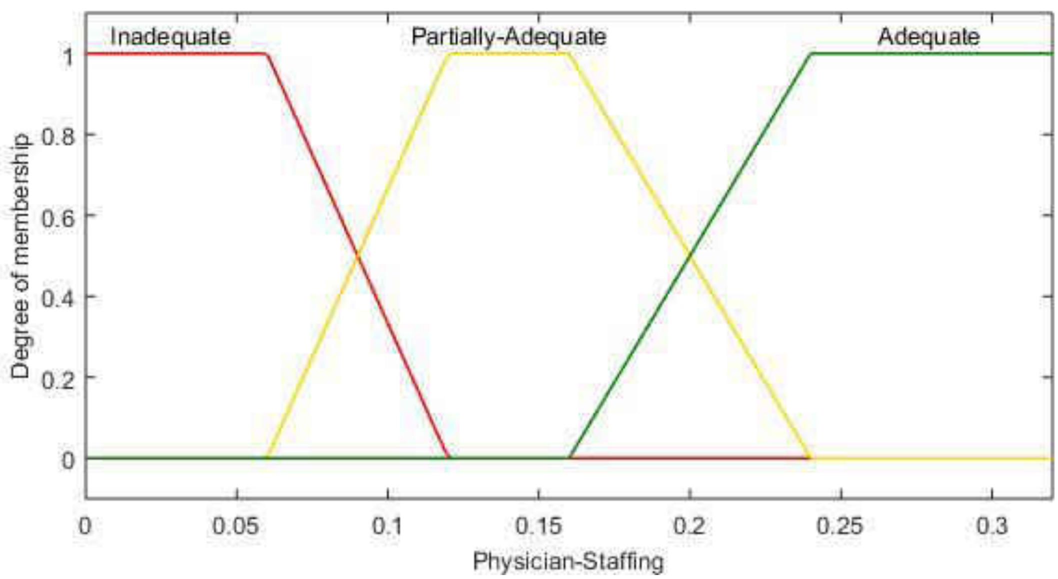

Figure 5-9: Membership function of physician staffing

The second input in subsystem II, nurse staffing, is represented by the membership functions in figure 5.10. The inadequate class boundaries are at 0 and 0.18, with the core structure representing full membership existing between 0 and 0.8. The partially adequate class lies between boundaries of 0.8 and 0.32, while the core area exists between 0.18 and 0.24. For the adequate class, the boundaries lie at 0.24 and 0.5, with the core structure existing between 0.32 and 0.5. It is apparent that the adequate class has the largest core area, meaning that the adequate linguistic term was given the widest variety of interval values for full membership, while values that defined the partially adequate class were more restrictive.

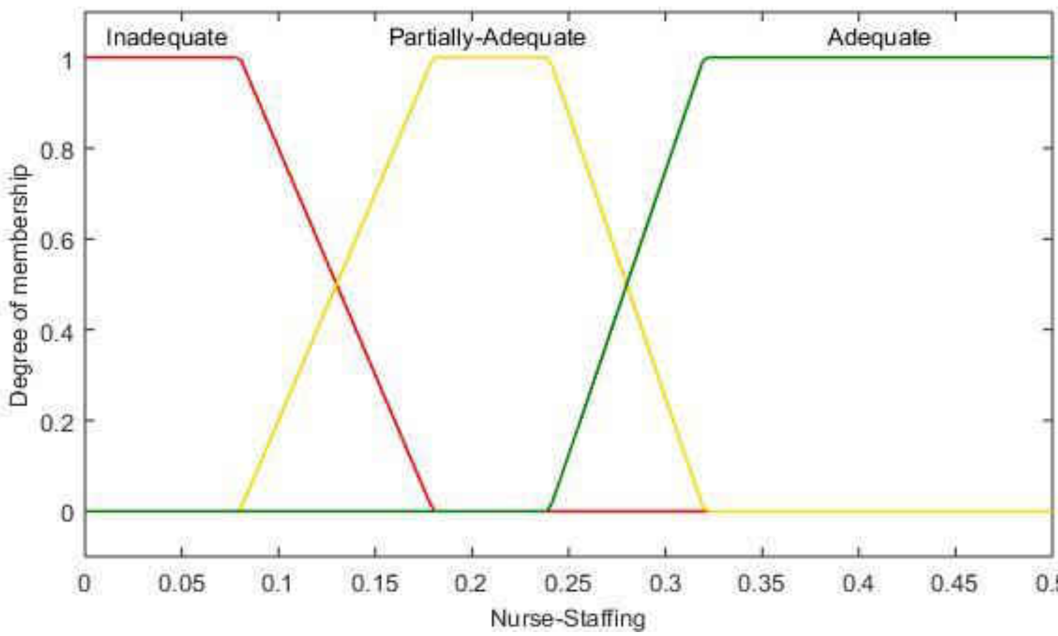

Figure 5-10: Membership function of nurse staffing

Figure 5-11 contains the membership functions for the output of the subsystem, ED staffing. The membership functions are trapezoidal, but the intervals are assigned to create similarly sized membership classes. In this figure, the boundaries for the inadequate class lie between 0 and 35, with the core existing between 0 and 25, representing a full degree of membership. The boundaries for the partially adequate class are 25 and 75, with the core existing between 35 and 65. For the adequate class, the boundaries are 65 and 100, with the core area defined between 75 and 100. It can be noted that the midpoint between the boundaries for the partially adequate class lies at 50, which is the halfway point on the ED staffing axis, further demonstrating the uniformity in the membership functions.

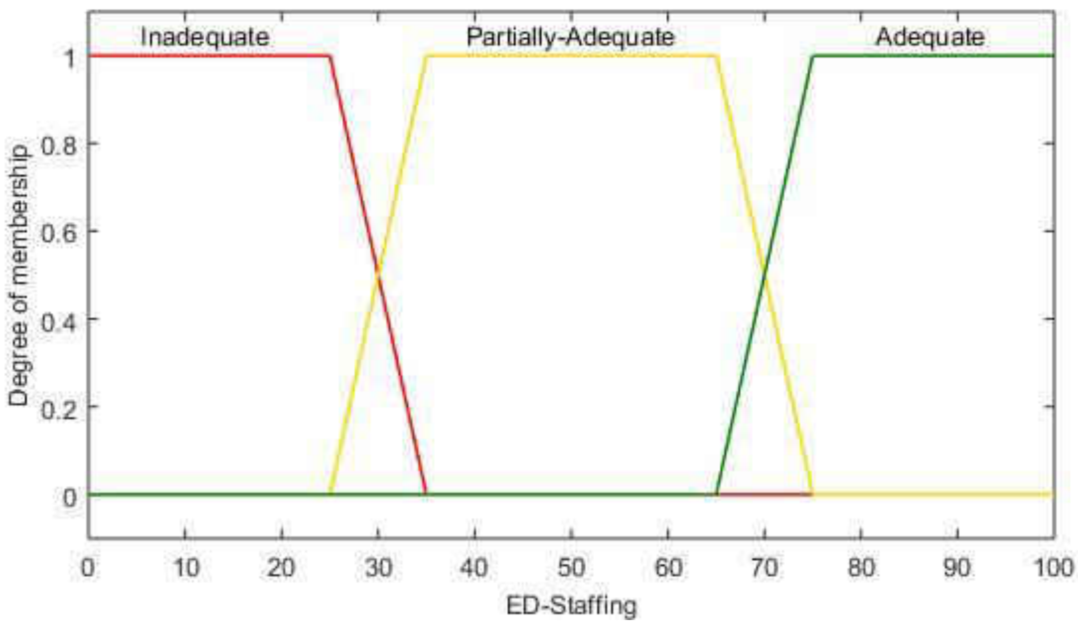

Figure 5-11: Membership function of ED staffing

Table 5-8 details the data used in the membership functions of subsystem III, where both trapezoidal and triangular membership functions are used across the three inputs and one output. It should be noted again that the output of subsystem II, ED staffing, is an input in subsystem III, dictating the use of a trapezoidal membership function for this subsystem's associated input. As this input shares the same membership function characteristics as previously described, it will be omitted in the description of this subsystem's membership functions. While the populations for patient complexity input are separate between this subsystem and subsystem I, the membership functions share the same characteristics, and thus the membership functions for patient complexity will not be discussed in this subsystem as well.

Table 5-8: Parameters of fuzzy subsystem III's membership functions

Variable	Fuzzy Linguistic Class	Fuzzy Number [a, b, c, d]
ED Staffing	Inadequate	[0, 0, 25, 35]
	Partially adequate	[25, 35, 65, 75]
	Adequate	[65, 75, 100, 100]
ER Occupancy Rate	Low	[0, 0, 20, 35]
	Medium	[20, 35, 45, 65]
	High	[45, 65, 70, 90]
	Very high	[70, 90, 100, 100]
Patient Complexity	Low	[1, 1, 2, 2.5]
	Medium	[2, 2.5, 3.5, 4]
	High	[3.5, 4, 5, 5]
ED Workload	low	[0, 0, 33.34]
	Medium	[0, 33.34, 66.67]
	High	[33.34, 66.67, 100]
	Very high	[66.67, 100, 100]

Figure 5-12 provides the trapezoidal membership functions for ER occupancy rate, which is the second variable in table 5-8, and is characterized by four linguistic terms. The low class is bounded between the values 0 and 35, while the medium, high, and very high classes lie between values of 20 and 65, 45 and 90, and 70 and 100, respectively. The low class has the largest core structure, which is bounded between the values of 0 and 20, and represents the largest interval of assigned values for full class membership. The medium and very high classes appear to have similarly sized core areas, bound between the values of 35 and 45 for "medium", and 90 and 100 for "very high". The core area for "high" is the smallest, bound between the values of 65 and 70, and represents the smallest interval of assigned values for full class membership.

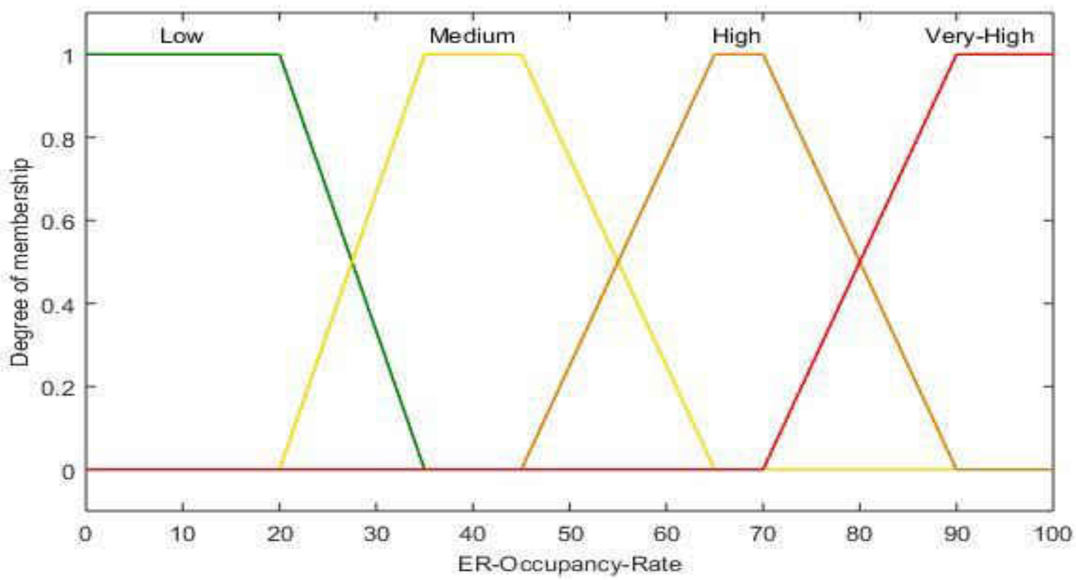

Figure 5-12: Membership function of ER occupancy rate

Figure 5-13 provides the membership functions for the output of subsystem III, ED workload, and triangular membership functions are assigned to four classes. Similarly to the membership functions from the output of subsystem I, the membership classes exist on overlapping intervals such that at any point, the degree of membership for two classes add up to a value of one, and there are only four points at which classes reach full degrees of membership. These points occur at 0, 33.34, 66.67, and 100, for the low, medium, high, and very-high classes, respectively.

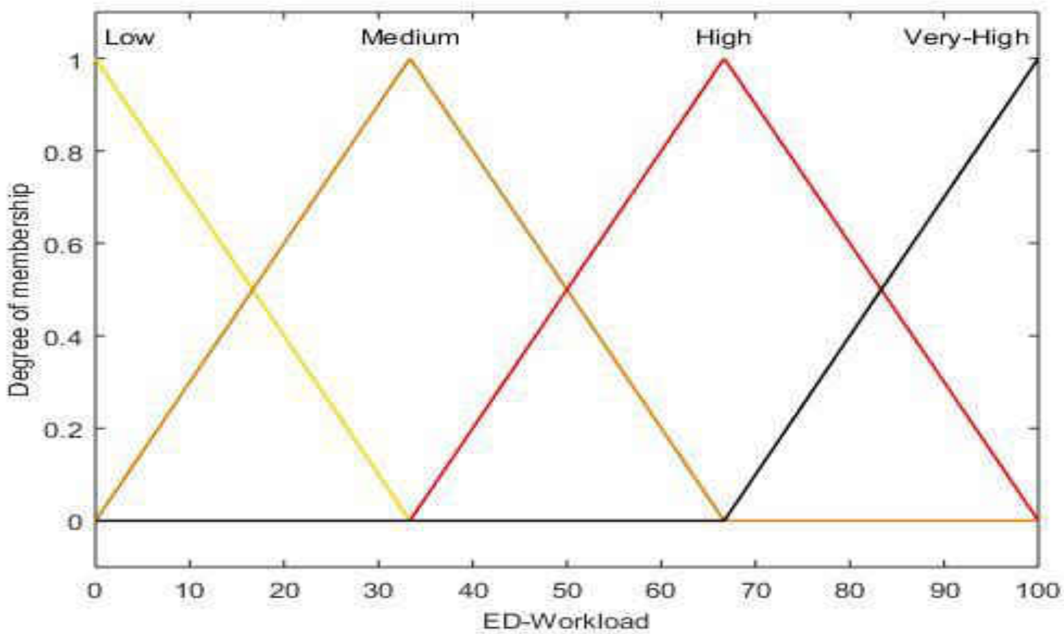

Figure 5-13: Membership function of workload

In table 5-9, information is provided for the membership functions of the final subsystem, subsystem IV. Among the three inputs, ED demand and ED workload have been previously discussed in subsystems II and III, and they will be omitted in the description of this subsystem's membership functions.

Table 5-9: Parameters of fuzzy subsystem IV's membership functions

Variable	Fuzzy Linguistic Class	Fuzzy Number [a, b, c, d]
ED Demand	Very low	[0, 0, 15, 25]
	Low	[15, 25, 35, 45]
	Medium	[35, 45, 55, 65]
	High	[55, 65, 75, 85]
	Very high	[75, 85, 100, 100]
ED Workload	low	[0, 0, 20, 30]
	Medium	[20, 30, 50, 60]
	High	[50, 60, 80, 90]
	Very high	[80, 90, 100, 100]
Patient Boarding	Low	[0, 0, 0.04, 0.12]
	Medium	[0.04, 0.12, 0.16, 0.24]
	High	[0.16, 0.24, 0.26, 0.32]
	Very high	[0.26, 0.32, 0.40, 0.40]
ED Crowding	Insignificant	[0, 0, 15, 25]
	Low	[15, 25, 35, 45]
	Medium	[35, 45, 55, 65]
	High	[55, 65, 75, 85]
	Extreme	[75, 85, 100, 100]

The trapezoidal membership functions in figure 5-14 represent the four classes used for the boarding input in subsystem IV. Boarding was considered to be "very high" between values of 0.26 and 0.4, making its core structure the largest while indicating the largest interval of values where a class was assigned full membership. Between the values of 0.16 and 0.32, boarding was considered "high", which is associated with the smallest membership function core structure belonging to the high class. The low and medium classes existed between the intervals of [0, 0.12], and [0.04, 0.24], respectively.

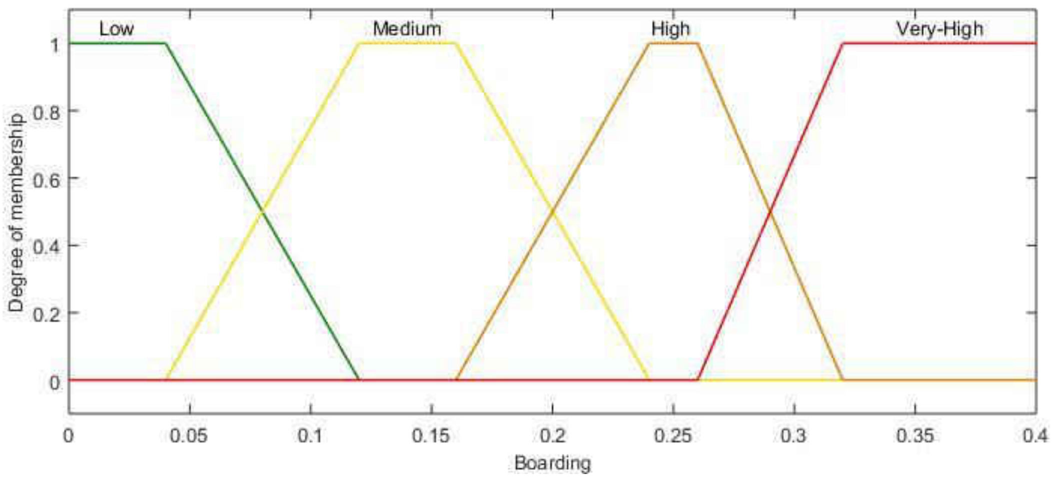

Figure 5-14: Membership function of patient boarding

Crowding, the final output of the system, is represented by the triangular membership functions in figure 5-15. The linguistic terms “insignificant”, “low”, “medium”, “high”, and “extreme” were associated with the five classes. The membership functions were assigned boundaries to create evenly distributed classes on the crowding axis, and similarly to subsystem III and I, the degree of membership is equivalent to 1 among the two classes existing at any given point. Only at the points 0, 25, 50, 75, and 100, do the five respective classes individually obtain full degrees of membership.

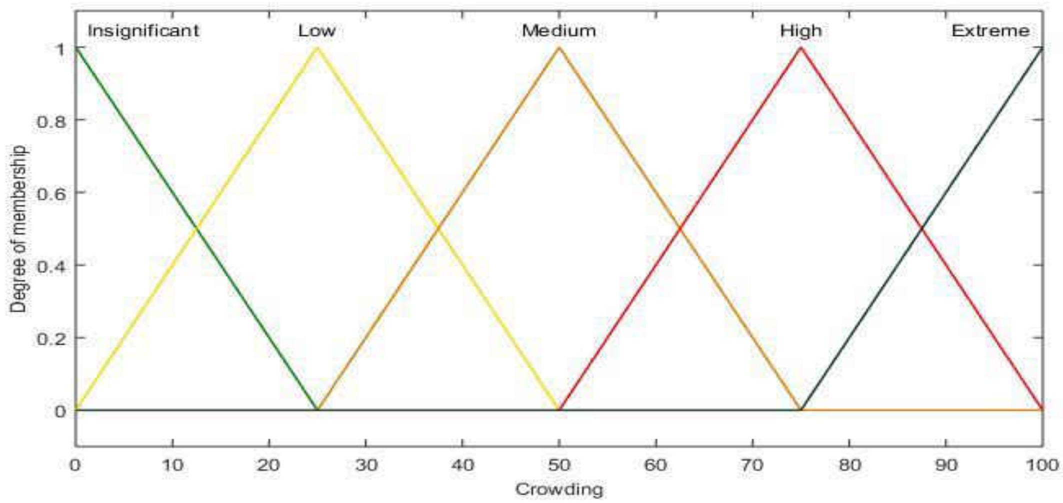

Figure 5-15: Membership function of crowding

5.2.2 Results of Expert Evaluation

This section presents the results of the fuzzy rule base development and analyzes the level of agreement among experts, the reliability of their evaluations, and the consensus rate. The fuzzy rule base assessments are divided by subsystem, with subsystem I producing 120 rules assessments, and subsystem II, III, and IV producing 90, 360, and 800 rule assessments, respectively, for a total of 1370 assessments obtained. After reaching consensus, the final version of the fuzzy rules are listed in this section.

Table 5-10 details the results from the expert assessment of the fuzzy rules from subsystem I. This table consists of 12 columns, beginning with the rule code, followed by ten expert evaluations, and ending with consensus status. Below the table is a legend comprising five linguistic classes which are color-coded. In this subsystem, two fuzzy rules reached full consensus

(100%); FLS1-11, and FLS1-12. Two rules achieved 90% consensus: FLS1-05, and FLS1-06; four reached 80%: FLS1-01, FLS1-04, FLS1-07, and FLS1-08; one rule reached 70% consensus: FLS1-03, and three reached 60% consensus: FLS1-02, FLS1-09, and FLS1-10. The average consensus rate for this subsystem's rule assessments is 79%. Seven of the twelve evaluated rules received assessments across only two linguistic classes, while two were assessed across three linguistic classes, and only one received assessments exceeding more than three types of linguistic assessment. The majority of the data in this subsystem is centralized around two linguistic classes. Regarding the frequency of linguistic class use, "medium" was most frequently used to assess rules, with 42 uses, while "high", "low", "very high", and "very low" were used 30, 21, 15, and 12 times, respectively.

Table 5-10: Results of expert evaluation for subsystem I's fuzzy rules

	Health Care Expert										
Rule Code	HCE-01	HCE-02	HCE-03	HCE-04	HCE-05	HCE-06	HCE-07	HCE-08	HCE-09	HCE-10	**consensus**
FLS1-01	Very Low	Very Low	Very Low	Low	Very Low	Very Low	Very Low	Low	Very Low	Very Low	Very Low
FLS1-02	Low	Very Low	Low	Medium	Very Low	Very Low	Low	Low	Low	Low	Low
FLS1-03	Medium	Very Low	Medium	High	Medium	Medium	Low	Medium	Medium	Medium	Medium
FLS1-04	Low	Low	Low	Medium	Low	Low	Low	Medium	Low	Low	Low
FLS1-05	Medium	Medium	Medium	Medium	Low	Medium	Medium	Medium	Medium	Medium	Medium
FLS1-06	High	High	High	High	Medium	High	High	High	High	High	High
FLS1-07	Very High	Low	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
FLS1-08	High	High	High	Medium	High	High	High	Medium	High	Medium	High
FLS1-09	Very High	Very High	Very High	High	High	Very High	Very High	High	Very High	High	Very High
FLS1-10	Medium	Medium	High	Medium	High	High	High	Medium	Medium	Medium	Medium
FLS1-11	High	High	High	High	High	High	High	High	High	High	High
FLS1-12	Very High	Very High	Very High	Very High	Very High	Very High	Very High	Very High	Very High	Very High	Very High

Very Low | Low | Medium | High | Very High

Further analysis of the data in table 5-10 reveals the level of agreement between experts by using inter-item correlation (Appendix K). Excluding one outlier, the range of averages of absolute agreement between nine experts was between 0.870 and 0.980. The excluded outlier has an average correlation coefficient of 0.634. Additionally, the highest correlation between the experts' responses was between experts HCE-06 and HCE-03, with a correlation coefficient of 0.980, and the lowest correlation occurred between HCE-07 and HCE-04, with a correlation coefficient of 0.358. The intra-class correlation for this subsystem is 0.806, with a 95% confidence interval of [0.656, 0.926].

In table 5-11, all of the fuzzy rule statements for subsystem I, after consensus, are listed according to their rule number. This final version of the rules will be stored in the fuzzy rule base of the knowledge base to fuel the fuzzy inference engine.

Table 5-11: Fuzzy rule statements for subsystem I

Rule No.	Fuzzy Rule Statement
FLS1-01	If the ratio of patients to ED capacity is low and patient complexity is low then ED demand status is very low.
FLS1-02	If the ratio of patients to ED capacity is low and patient complexity is medium then ED demand status is low.
FLS1-03	If the ratio of patients to ED capacity is low and patient complexity is high then ED demand status is medium.
FLS1-04	If the ratio of patients to ED capacity is medium and patient complexity is medium then ED demand status is low.
FLS1-05	If the ratio of patients to ED capacity is medium and patient complexity is high then ED demand status is medium.
FLS1-06	If the ratio of patients to ED capacity is medium and patient complexity is low then ED demand status is high.
FLS1-07	If the ratio of patients to ED capacity is high and patient complexity is low then ED demand status is medium.
FLS1-08	If the ratio of patients to ED capacity is high and patient complexity is medium then ED demand status is high.
FLS1-09	If the ratio of patients to ED capacity is high and patient complexity is high then ED demand status is very high.
FLS1-10	If the ratio of patients to ED capacity is very high and patient complexity is low then ED demand status is medium.
FLS1-11	If the ratio of patients to ED capacity is very high and patient complexity is medium then ED demand status is high.
FLS1-12	If the ratio of patients to ED capacity is very high and patient complexity is high then ED demand status is very high.

Table 5-12 is comprised of results from the assessments of the fuzzy rules from subsystem II. This table shares similar features from table 5-10, consisting of the same number of columns and expert evaluations. Below the table is a legend comprising three linguistic classes which are color-coded.

Within subsystem II, five of the nine rules received 90% consensus or greater, consisting of FLS2-01, FLS2-04, FLS2-05, FLS2-06, and FSL2-09. Three of these rules received 80% consensus, which were FLS2-02, FSL2-07, and FSL2-08. FSL2-03 received 50% consensus. The average consensus rate for the whole subsystem was 84%, which is higher than the previous subsystem, which featured more fuzzy rules and linguistic classes. Seven of the evaluated fuzzy rules were assessed with only two linguistic terms or less, and two rules were assessed with three terms. The frequency of linguistic classes used in assessing rules was the highest in "inadequate" with 41 uses, followed by "partially adequate", and "adequate", with 34 and 15 uses, respectively.

Table 5-12: Results of expert evaluation for subsystem II's fuzzy rules

	Health Care Expert										
Rule Code	HCE-01	HCE-02	HCE-03	HCE-04	HCE-05	HCE-06	HCE-07	HCE-08	HCE-09	HCE-10	**consensus**
FLS2-01	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate
FLS2-02	Inadequate	Inadequate	Partially Adequate	Partially Adequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate
FLS2-03	Inadequate	Inadequate	Partially Adequate	Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Inadequate	Inadequate	Inadequate	Inadequate
FLS2-04	Inadequate	Inadequate	Partially Adequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate
FLS2-05	Partially Adequate	Partially Adequate	Partially Adequate	Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate
FLS2-06	Partially Adequate	Partially Adequate	Partially Adequate	Adequate	Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate
FLS2-07	Inadequate	Inadequate	Partially Adequate	Inadequate	Inadequate	Partially Adequate	Inadequate	Inadequate	Inadequate	Inadequate	Inadequate
FLS2-08	Inadequate	Partially Adequate	Partially Adequate	Partially Adequate	Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate	Partially Adequate
FLS2-09	Adequate	Adequate	Adequate	Adequate	Adequate	Adequate	Adequate	Adequate	Adequate	Adequate	Adequate

Inadequate	Partially Adequate	Adequate

Statistical analysis of data from table 5-12 shows that range of the averages of the correlation among the experts was between 0.715 and 0.959 in this subsystem. Interestingly, the correlation between HCE-02 and HCE-08, HCE-09, and HCE-10, and between HCE-09 and HCE-08, and between HCE-08 and HCE-10, and between HCE-09 and HCE-10 were 1.00. The lowest correlation was 0.539, between HCE-03 and HCE-04. Finally, the intra-class correlation for this assessment is 0.729 with a 95% confidence interval of [0.516, 0.912].

Table 5-13 lists the final fuzzy rule statements for subsystem II after consensus, according to their rule number. These final nine rules are stored in the fuzzy rule base of subsystem II to feed the decision engine of the fuzzy system.

Table 5-13: Fuzzy rule statements for subsystem II

Rule No.	Fuzzy Rule Statement
FLS2-01	If ED physician staffing is inadequate and ED nurse staffing is inadequate then ED staffing status is inadequate.
FLS2-02	If ED physician staffing is inadequate and ED nurse staffing is partially adequate then ED staffing status is inadequate.
FLS2-03	If ED physician staffing is inadequate and ED nurse staffing is adequate then ED staffing status is inadequate.
FLS2-04	If ED physician staffing is partially adequate and ED nurse staffing is inadequate then ED staffing status is inadequate.
FLS2-05	If ED physician staffing is partially adequate and ED nurse staffing is partially adequate then ED staffing status is partially adequate.
FLS2-06	If ED physician staffing is partially adequate and ED nurse staffing is adequate then ED staffing status is partially adequate.
FLS2-07	If ED physician staffing is adequate and ED nurse staffing is inadequate then ED staffing status is inadequate.
FLS2-08	If ED physician staffing is adequate and ED nurse staffing is partially adequate then ED staffing status is partially adequate.
FLS2-09	If ED physician staffing is adequate and ED nurse staffing is adequate then ED staffing status is adequate.

Table 5-14 contains data from the expert assessments of the fuzzy rules of subsystem III. It is structured in the same manner as the previous fuzzy rule evaluation tables in terms of the number of columns and what they represent, however there are four color-coded linguistic terms that are associated with the fuzzy classes. There are a total of 360 rule assessments in this table, which represents the assessment of 36 rules by ten experts. It is apparent that 31 of the 36 evaluated rules were evaluated using two or fewer linguistic terms, and the remaining rules were evaluated with no more than three terms. Five assessed rules reached full consensus, with an agreement rate of 100%; FLS3-09, FLS3-20, FLS3-24, FLS3-26, and FLS3-31. It is also observed that twelve assessed rules received a consensus rate between 80% and 90%, while eighteen rules reached the range of 60% to 70%. Finally, one rule, FLS3-02, achieved a minimum consensus rate of 50%. The average consensus rate for this subsystem is 76%, which when compared to the average rate of 79% for subsystem I, is relatively close, even though subsystem III featured more inputs. When compared to subsystem II's average consensus rate of 84%, 76% is still satisfactory, although subsystem III contained more assessment classes. The frequency of linguistic class use in assessing rules was the highest in the "high" class with 124 uses, followed by "medium" with 105 uses, while the least used classes were "low" and "very high", with 66 and 65 uses, respectively.

Table 5-14: Results of expert evaluation for subsystem III's fuzzy rules

Rule Code	Health Care Expert HCE-01	HCE-02	HCE-03	HCE-04	HCE-05	HCE-06	HCE-07	HCE-08	HCE-09	HCE-10	consensus
FLS3-01	Medium	Low	Low	Medium	Low	Low	Low	Low	Low	Low	Low
FLS3-02	High	Low	Medium	Medium	Low	Medium	Low	Low	Medium	Low	Low
FLS3-03	High	High	High	High	High	Medium	Low	High	High	Low	High
FLS3-04	High	Medium	Medium	High	Medium	Medium	Low	Medium	Medium	Medium	Medium
FLS3-05	Medium	High	High	High	Medium	Medium	Medium	High	High	High	High
FLS3-06	High	Very high	High	Very high	High	High	High	High	High	High	High
FLS3-07	High	High	Medium	High	High	High	Medium	High	High	High	High
FLS3-08	High	High	High	Medium	Medium	Very high	High	High	Very high	High	High
FLS3-09	Very high	Very high	Very high	Very high	Very high	Very high	Very high	Very high	Very high	Very high	Very high
FLS3-10	High	Very high	High	Very high	High	Very high	High	High	High	High	High
FLS3-11	High	Very high	Very high	Very high	High	Very high	High	High	High	High	High
FLS3-12	Very high	Very high	Very high	Very high	High	Very high	Very high	Very high	Very high	Very high	Very high
FLS3-13	Medium	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
FLS3-14	Medium	Low	Medium	Medium	Low	Medium	Low	Low	Low	Low	Low
FLS3-15	High	Medium	Medium	Medium	Medium	Medium	Low	Medium	High	Medium	Medium
FLS3-16	Medium	Medium	Low	Medium	Low	Low	Low	Medium	Medium	Medium	Medium
FLS3-17	Medium	Medium	Medium	High	Medium	Medium	Medium	High	High	Medium	Medium
FLS3-18	High	High	High	Medium	Medium	High	Medium	High	High	High	High
FLS3-19	High	Medium	Medium	High	Medium	Medium	Medium	Medium	Medium	Medium	Medium
FLS3-20	High	High	High	High	High	High	High	High	High	High	High
FLS3-21	Very high	Very high	Very high	High	High	Very high	High	Very high	Very high	Very high	Very high
FLS3-22	High	Medium	Medium	High	Medium	High	Medium	High	High	High	High
FLS3-23	High	High	High	Very high	High	Very high	High	High	High	High	High
FLS3-24	Very high	Very high	Very high	Very high	Very high	Very high	Very high	Very high	Very high	Very high	Very high
FLS3-25	Low	Low	Low	Low	Low	Low	Low	Very high	Low	Low	Low
FLS3-26	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
FLS3-27	Medium	Medium	Medium	Medium	Medium	Low	Low	Low	Medium	Medium	Medium
FLS3-28	Low	Low	Low	Medium	Low	Low	Medium	Low	Low	Low	Low
FLS3-29	Medium	Medium	Medium	High	Medium	Medium	Medium	Medium	Medium	Medium	Medium
FLS3-30	High	High	Medium	High	Medium	Medium	Medium	Medium	High	Medium	Medium
FLS3-31	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
FLS3-32	High	High	High	High	High	High	Medium	Medium	High	High	High
FLS3-33	High	Very high	High	Very high	High	High	High	High	Very high	High	High
FLS3-34	High	Medium	High	Medium	Medium	High	Medium	Medium	Medium	Medium	Medium
FLS3-35	Very high	High	High	Very high	High	Very high	High	High	High	High	High
FLS3-36	Very high	Very high	Very high	Very high	Very high	Very high	Very high	High	Very high	Very high	Very high

Low | Medium | High | Very high

Statistical analysis of the absolute agreement among the experts shows that the average correlation between evaluations ranged between 0.759 and 0.936. The lowest correlation occurred between experts HCE-01 and HCE-08 at 0.577, and the highest correlation was between experts HCE-02 and HCE-08.The intra-class correlation for the evaluation of subsystem III is 0.770, with a 95% confidence interval of [0.673, 0.856].

The final list of fuzzy rules for subsystem III is provided in table 5-15, which will be stored in the fuzzy rule base to build the fuzzy knowledge base.

Table 5-15: Fuzzy rule statements for subsystem III

Rule No.	Fuzzy Rule Statement
FLS3-01	If the ED staffing status is inadequate and ED occupancy rate is low and patient complexity is low then ED workload is low.
FLS3-02	If the ED staffing status is inadequate and ED occupancy rate is low and patient complexity is medium then ED workload is low.
FLS3-03	If the ED staffing status is inadequate and ED occupancy rate is low and patient complexity is high then ED workload is high.
FLS3-04	If the ED staffing status is inadequate and ED occupancy rate is medium and patient complexity is low then ED workload is medium.
FLS3-05	If the ED staffing status is inadequate and ED occupancy rate is medium and patient complexity is medium then ED workload is high.
FLS3-06	If the ED staffing status is inadequate and ED occupancy rate is medium and patient complexity is high then ED workload is high.
FLS3-07	If the ED staffing status is inadequate and ED occupancy rate is high and patient complexity is low then ED workload is high.
FLS3-08	If the ED staffing status is inadequate and ED occupancy rate is high and patient complexity is medium then ED workload is high.

Rule No.	Fuzzy Rule Statement
FLS3-09	If the ED staffing status is inadequate and ED occupancy rate is high and patient complexity is high then ED workload is very high.
FLS3-10	If the ED staffing status is inadequate and ED occupancy rate is very high and patient complexity is low then ED workload is high.
FLS3-11	If the ED staffing status is inadequate and ED occupancy rate is very high and patient complexity is medium then ED workload is high.
FLS3-12	If the ED staffing status is inadequate and ED occupancy rate is very high and patient complexity is high then ED workload is very high.
FLS3-13	If the ED staffing status is partially adequate and ED occupancy rate is low and patient complexity is low then ED workload is low.
FLS3-14	If the ED staffing status is partially adequate and ED occupancy rate is low and patient complexity is medium then ED workload is low.
FLS3-15	If the ED staffing status is partially adequate and ED occupancy rate is low and patient complexity is high then ED workload is medium.
FLS1-16	If the ED staffing status is partially adequate and ED occupancy rate is medium and patient complexity is low then ED workload is medium.
FLS3-17	If the ED staffing status is partially adequate and ED occupancy rate is medium and patient complexity is medium then ED workload is medium.
FLS3-18	If the ED staffing status is partially adequate and ED occupancy rate is medium and patient complexity is high then ED workload is high.
FLS3-19	If the ED staffing status is partially adequate and ED occupancy rate is high and patient complexity is low then ED workload is medium.
FLS3-20	If the ED staffing status is partially adequate and ED occupancy rate is high and patient complexity is medium then ED workload is high.
FLS3-21	If the ED staffing status is partially adequate and ED occupancy rate is high and patient complexity is high then ED workload is very high.
FLS3-22	If the ED staffing status is partially adequate and ED occupancy rate is very high and patient complexity is low then ED workload is high.
FLS3-23	If the ED staffing status is partially adequate and ED occupancy rate is very high and patient complexity is medium then ED workload is high.

Rule No.	Fuzzy Rule Statement
FLS3-24	If the ED staffing status is partially adequate and ED occupancy rate is very high and patient complexity is high then ED workload is very high.
FLS3-25	If the ED staffing status is adequate and ED occupancy rate is low and patient complexity is low then ED workload is low.
FLS3-26	If the ED staffing status is adequate and ED occupancy rate is low and patient complexity is medium then ED workload is low.
FLS3-27	If the ED staffing status is adequate and ED occupancy rate is low and patient complexity is high then ED workload is medium.
FLS3-28	If the ED staffing status is adequate and ED occupancy rate is medium and patient complexity is low then ED workload is low.
FLS3-29	If the ED staffing status is adequate and ED occupancy rate is medium and patient complexity is medium then ED workload is medium.
FLS3-30	If the ED staffing status is adequate and ED occupancy rate is medium and patient complexity is high then ED workload is medium.
FLS3-31	If the ED staffing status is adequate and ED occupancy rate is high and patient complexity is low then ED workload is medium.
FLS3-32	If the ED staffing status is adequate and ED occupancy rate is high and patient complexity is medium then ED workload is high.
FLS3-33	If the ED staffing status is adequate and ED occupancy rate is high and patient complexity is high then ED workload is high.
FLS3-34	If the ED staffing status is adequate and ED occupancy rate is very high and patient complexity is low then ED workload is medium.
FLS3-35	If the ED staffing status is adequate and ED occupancy rate is very high and patient complexity is medium then ED workload is high.
FLS3-36	If the ED staffing status is adequate and ED occupancy rate is very high and patient complexity is high then ED workload is very high.

The results for subsystem IV's rule assessments are provided in table 5-16, which is the most significant subsystem in the fuzzy system. In this subsystem, ten experts evaluated 80 rules against five assessment levels, with each rule consisting of a combination of three AND conditions. As each rule is designed with three combinations for the antecedent, to be assessed at five levels, this subsystem presents the highest complexity for expert assessment.

The results show that this subsystem is the only one in the entire designed fuzzy system that contained some rules which did not initially meet the given consensus criteria. These rules were FLS4-16, FLS4-22, FLS4-49, FLS4-52, FLS4-57, FLS4-72, and FLS4-78, and required an additional round of evaluation with new expert assessors. All seven rules in question achieved the minimum criteria upon the first additional round of evaluation, as it was likely to cause the consensus rate to cross beyond the threshold of 50%. The consensus rates of re-evaluated rules were all 54.5%, meeting the requirements. With these additional evaluations, the total number of rule assessments was brought to 807.

Upon analyzing the data, it can be found that seven of the assessed rules reached a consensus rate of 100%, which were FLS4-01, FLS4-03, FLS4-07, FLS4-64, FLS4-66, FLS4-76, and FLS4-80. Among the remaining rules, twenty-six reached consensus rates between 80% and 90%, while thirty-five reached rates between 60% and 70%, and five rules had a consensus rate of 50%, passing minimum consensus requirements. The average consensus rate of this subsystem is 72%, compared to 76%, 84%, and 79% in subsystems III, II, and I, respectively. Among the different linguistic terms used by experts, fifty-three rules were evaluated using two or fewer of the five assessment classes. The remaining rules received assessments using exactly three terms. For all 80 rules, the variation in expert assessment is small, as in cases where experts did not all unanimously agree using only one linguistic term, they reached consensus using either two linguistic terms in adjacent classes (such as “low”-“medium”, or “medium”-“high”), or three terms describing adjacent classes (such as “insignificant”-“low”-“medium”). After the final round of assessments, experts most frequently used “medium” to assess rules, with 277 uses, followed closely by “high” with 269 uses, while “extreme”, “low”, and “insignificant” were selected 126, 102, and 33 times, respectively.

Table 5-16: Results of expert evaluation for subsystem IV’s fuzzy rules

	Health Care Expert										
Rule Code	HCE-01	HCE-02	HCE-03	HCE-04	HCE-05	HCE-06	HCE-07	HCE-08	HCE-09	HCE-10	**consensus**
FLS4-01											
FLS4-02											
FLS4-03											
FLS4-04											
FLS4-05											
FLS4-06											
FLS4-07											
FLS4-08											
FLS4-09											
FLS4-10											
FLS4-11											
FLS4-12											
FLS4-13											
FLS4-14											
FLS4-15											
FLS4-16											
FLS4-17											
FLS4-18											
FLS4-19											
FLS4-20											
FLS4-21											
FLS4-22											
FLS4-23											
FLS4-24											

	Health Care Expert										consensus
Rule Code	HCE-01	HCE-02	HCE-03	HCE-04	HCE-05	HCE-06	HCE-07	HCE-08	HCE-09	HCE-10	
FLS4-25											
FLS4-26											
FLS4-27											
FLS4-28											
FLS4-29											
FLS4-30											
FLS4-31											
FLS4-32											
FLS4-33											
FLS4-34											
FLS4-35											
FLS4-36											
FLS4-37											
FLS4-38											
FLS4-39											
FLS4-40											
FLS4-41											
FLS4-42											
FLS4-43											
FLS4-44											
FLS4-45											
FLS4-46											
FLS4-47											
FLS4-48											
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FLS4-59											
FLS4-60											
FLS4-61											
FLS4-62											
FLS4-63											
FLS4-64											

	Health Care Expert										
Rule Code	HCE-01	HCE-02	HCE-03	HCE-04	HCE-05	HCE-06	HCE-07	HCE-08	HCE-09	HCE-10	**consensus**
FLS4-65	Low	medium	Low	medium	medium	medium	medium	medium	medium	medium	medium
FLS4-66	medium	medium	medium	medium	medium	medium	medium	medium	medium	medium	medium
FLS4-67	medium	medium	medium	medium	High	High	medium	medium	medium	medium	medium
FLS4-68	medium	medium	medium	Extreme	Extreme	High	medium	medium	medium	medium	medium
FLS4-69	medium	High	High	medium	medium	medium	medium	medium	medium	medium	medium
FLS4-70	High	Extreme	High	medium	High	High	High	High	High	High	High
FLS4-71	High	Extreme	High	medium	Extreme	High	High	High	High	High	High
FLS4-72	High	Extreme	High	Extreme	Extreme	Extreme	High	High	Extreme	High	High
FLS4-73	medium	Extreme	High	High	High	High	High	High	Extreme	High	High
FLS4-74	medium	Extreme	Extreme	Extreme	Extreme	High	High	High	Extreme	High	Extreme
FLS4-75	High	Extreme	Extreme	Extreme	Extreme	High	Extreme	Extreme	Extreme	Extreme	Extreme
FLS4-76	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme
FLS4-77	medium	High	High	Extreme	High	High	High	High	High	High	High
FLS4-78	High	Extreme	Extreme	Extreme	Extreme	High	High	High	Extreme	High	Extreme
FLS4-79	High	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme
FLS4-80	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme	Extreme

Insignificant	Low	medium	High	Extreme

From the data for subsystem IV, the range of the average correlation between experts was between 0.796 and 0.925, with the lowest correlation occurring between experts HCE-03 and HCE-04, and highest correlation was between experts HCE-07 and HCE-09. The intra-class correlation for the entire evaluation was 0.769, with a 95% confidence interval of [0.706, 0.828].

Statistical analysis of data from table 5-16 shows that range of the averages of the correlation among the experts was between 0.715 and 0.959 in this subsystem. Interestingly, the correlation between HCE-02 and HCE-08, HCE-09, and HCE-10, and between HCE-09 and HCE-08, and between HCE-08 and HCE-10, and between HCE-09 and HCE-10 were 1.00. The lowest correlation was 0.539, between HCE-03 and HCE-04. Finally, the intra-class correlation for this assessment is 0.729 with a 95% confidence interval of [0.516, 0.912].

The final fuzzy rules for subsystem IV are provided in table 5-17. These rules will become an essential part of the knowledge base for subsystem IV.

Table 5-17: Fuzzy rule statements for subsystem IV

Rule No.	Fuzzy Rule Statement
FLS4-01	If ED demand status is very low and ED workload is low and boarding status is low then ED crowding level is insignificant.
FLS4-02	If ED demand status is very low and ED workload is low and boarding status is medium then ED crowding level is insignificant.
FLS4-03	If ED demand status is very low and ED workload is low and boarding status is high then ED crowding level is low.
FLS4-04	If ED demand status is very low and ED workload is low and boarding status is very high then ED crowding level is medium.
FLS4-05	If ED demand status is very low and ED workload is medium and boarding status is low then ED crowding level is low.
FLS4-06	If ED demand status is very low and ED workload is medium and boarding status is medium then ED crowding level is low.
FLS4-07	If ED demand status is very low and ED workload is medium and boarding status is high then ED crowding level is medium.
FLS4-08	If ED demand status is very low and ED workload is medium and boarding status is very high then ED crowding level is medium.
FLS4-09	If ED demand status is very low and ED workload is high and boarding status is low then ED crowding level is medium.
FLS4-10	If ED demand status is very low and ED workload is high and boarding status is medium then ED crowding level is medium.
FLS4-11	If ED demand status is very low and ED workload is high and boarding status is high then ED crowding level is high.

Rule No.	Fuzzy Rule Statement
FLS4-12	If ED demand status is very low and ED workload is high and boarding status is very high then ED crowding level is high.
FLS4-13	If ED demand status is very low and ED workload is very high and boarding status is low then ED crowding level is medium.
FLS4-14	If ED demand status is very low and ED workload is very high and boarding status is medium then ED crowding level is high.
FLS4-15	If ED demand status is very low and ED workload is very high and boarding status is high then ED crowding level is high.
FLS4-16	If ED demand status is very low and ED workload is very high and boarding status is very high then ED crowding level is high.
FLS4-17	If ED demand status is low and ED workload is low and boarding status is low then ED crowding level is insignificant.
FLS4-18	If ED demand status is low and ED workload is low and boarding status is medium then ED crowding level is low.
FLS4-19	If ED demand status is low and ED workload is low and boarding status is high then ED crowding level is low.
FLS4-20	If ED demand status is low and ED workload is low and boarding status is very high then ED crowding level is medium.
FLS4-21	If ED demand status is low and ED workload is medium and boarding status is low then ED crowding level is low.
FLS4-22	If ED demand status is low and ED workload is medium and boarding status is medium then ED crowding level is low.
FLS4-23	If ED demand status is low and ED workload is medium and boarding status is high then ED crowding level is medium.
FLS4-24	If ED demand status is low and ED workload is medium and boarding status is very high then ED crowding level is medium.
FLS4-25	If ED demand status is low and ED workload is high and boarding status is low then ED crowding level is medium.
FLS4-26	If ED demand status is low and ED workload is high and boarding status is medium then ED crowding level is medium.

Rule No.	Fuzzy Rule Statement
FLS4-27	If ED demand status is low and ED workload is high and boarding status is high then ED crowding level is high.
FLS4-28	If ED demand status is low and ED workload is high and boarding status is very high then ED crowding level is high.
FLS4-29	If ED demand status is low and ED workload is very high and boarding status is low then ED crowding level is medium.
FLS4-30	If ED demand status is low and ED workload is very high and boarding status is medium then ED crowding level is medium.
FLS4-31	If ED demand status is low and ED workload is very high and boarding status is high then ED crowding level is high.
FLS4-32	If ED demand status is low and ED workload is very high and boarding status is very high then ED crowding level is high.
FLS4-33	If ED demand status is medium and ED workload is low and boarding status is low then ED crowding level is low.
FLS4-34	If ED demand status is medium and ED workload is low and boarding status is medium then ED crowding level is low.
FLS4-35	If ED demand status is medium and ED workload is low and boarding status is high then ED crowding level is medium.
FLS4-36	If ED demand status medium and ED workload is low and boarding status is very high then ED crowding level is medium.
FLS4-37	If ED demand status is medium and ED workload is medium and boarding status is low then ED crowding level is medium.
FLS4-38	If ED demand status is medium and ED workload is medium and boarding status is medium then ED crowding level is medium.
FLS4-39	If ED demand status is medium and ED workload is medium and boarding status is high then ED crowding level is medium.
FLS4-40	If ED demand status is medium and ED workload is medium and boarding status is very high then ED crowding level is high.
FLS4-41	If ED demand status is medium and ED workload is high and boarding status is low then ED crowding level is medium.

Rule No.	Fuzzy Rule Statement
FLS4-42	If ED demand status is medium and ED workload is high and boarding status is medium then ED crowding level is high.
FLS4-43	If ED demand status is medium and ED workload is high and boarding status is high then ED crowding level is high.
FLS4-44	If ED demand status is medium and ED workload is high and boarding status is very high then ED crowding level is high.
FLS4-45	If ED demand status is medium and ED workload is very high and boarding status is low then ED crowding level is high.
FLS4-46	If ED demand status is medium and ED workload is very high and boarding status is medium then ED crowding level is medium.
FLS4-47	If ED demand status is medium and ED workload is very high and boarding status is high then ED crowding level is high.
FLS4-48	If ED demand status is medium and ED workload is very high and boarding status is very high then ED crowding level is high.
FLS4-49	If ED demand status is high and ED workload is low and boarding status is low then ED crowding level is low.
FLS4-50	If ED demand status is high and ED workload is low and boarding status is medium then ED crowding level is medium.
FLS4-51	If ED demand status is high and ED workload is low and boarding status is high then ED crowding level is medium.
FLS4-52	If ED demand status high and ED workload is low and boarding status is very high then ED crowding level is high.
FLS4-53	If ED demand status is high and ED workload is medium and boarding status is low then ED crowding level is medium.
FLS4-54	If ED demand status is high and ED workload is medium and boarding status is medium then ED crowding level is medium.
FLS4-55	If ED demand status is high and ED workload is medium and boarding status is high then ED crowding level is high.
FLS4-56	If ED demand status is high and ED workload is medium and boarding status is very high then ED crowding level is high.

Rule No.	Fuzzy Rule Statement
FLS4-57	If ED demand status is high and ED workload is high and boarding status is low then ED crowding level is medium.
FLS4-58	If ED demand status is high and ED workload is high and boarding status is medium then ED crowding level is high.
FLS4-59	If ED demand status is high and ED workload is high and boarding status is high then ED crowding level is high.
FLS4-60	If ED demand status is high and ED workload is high and boarding status is very high then ED crowding level is extreme.
FLS4-61	If ED demand status is high and ED workload is very high and boarding status is low then ED crowding level is high.
FLS4-62	If ED demand status is high and ED workload is very high and boarding status is medium then ED crowding level is high.
FLS4-63	If ED demand status is high and ED workload is very high and boarding status is high then ED crowding level is extreme.
FLS4-64	If ED demand status is high and ED workload is very high and boarding status is very high then ED crowding level is extreme.
FLS4-65	If ED demand status is very high and ED workload is low and boarding status is low then ED crowding level is medium.
FLS4-66	If ED demand status is very high and ED workload is low and boarding status is medium then ED crowding level is medium.
FLS4-67	If ED demand status is very high and ED workload is low and boarding status is high then ED crowding level is medium.
FLS4-68	If ED demand status very high and ED workload is low and boarding status is very high then ED crowding level is medium.
FLS4-69	If ED demand status is very high and ED workload is medium and boarding status is low then ED crowding level is medium.
FLS4-70	If ED demand status is very high and ED workload is medium and boarding status is medium then ED crowding level is high.
FLS4-71	If ED demand status is very high and ED workload is medium and boarding status is high then ED crowding level is high.

Rule No.	Fuzzy Rule Statement
FLS4-72	If ED demand status is very high and ED workload is medium and boarding status is very high then ED crowding level is high.
FLS4-73	If ED demand status is very high and ED workload is high and boarding status is low then ED crowding level is high.
FLS4-74	If ED demand status is very high and ED workload is high and boarding status is medium then ED crowding level is extreme.
FLS4-75	If ED demand status is very high and ED workload is high and boarding status is high then ED crowding level is extreme.
FLS4-76	If ED demand status is very high and ED workload is high and boarding status is very high then ED crowding level is extreme.
FLS4-77	If ED demand status is very high and ED workload is very high and boarding status is low then ED crowding level is high.
FLS4-78	If ED demand status is very high and ED workload is very high and boarding status is medium then ED crowding level is extreme.
FLS4-79	If ED demand status is very high and ED workload is very high and boarding status is high then ED crowding level is extreme.
FLS4-80	If ED demand status is very high and ED workload is very high and boarding status is very high then ED crowding level is extreme.

The results presented in this section are a critical component of this research, as they provide validation for the design intent of the framework, and show that the consensus rates for rule assessments are good, necessitating only seven re-evaluations among the initial 137 rules. The average consensus rate was 72% or better between each of the four subsystems, which further highlights the consistency of results. It was observed that the average consensus rate decreased noticeably in subsystems where there were either an increase in assessment classes, more rules, or more complex rules with more conditions for experts to evaluate. These factors contributed to each subsystem's complexity, contributing to the overall decrease in average consensus rate. The reliability analysis showed that in general, the correlation between expert assessments was strong, but some weak correlations were noticed. These variations could be attributed to the differences between the experts' backgrounds, areas of expertise, years of experience, and possibly cultural values. In general, the consistency in evaluations was acceptable, as most expert evaluated rules using adjacent assessment classes. All of these assessed fuzzy rules will build upon the designed fuzzy system by feeding the four different fuzzy engines from subsystems I-IV with supporting information to link the inputs to the outputs.

5.3 Fuzzy System Results

The fuzzy logic toolbox of Matlab R2015b (Version 2.2.22) was used to construct and simulate each fuzzy subsystem individually, with data gathered from experts. Appendix L provides the written computer code to build the designed fuzzy systems. A series of 3-D surface plots were generated relating the inputs of each subsystem to their respective outputs. This was accomplished through the products of the proposed architecture, including the development of membership functions from quantitative data collected from experts, and the expert subjective assessment of rules. These generated surface plots allow for a clearer view of how the different fuzzy subsystems function, and it makes the relation between inputs more visually accessible. Additionally, the surface plots allow for determining the outputs of the subsystems in a straightforward manner by only using inputs, bypassing lengthy calculations. This section provides the results from the fuzzy logic subsystems and presents the surface plots for the output of the subsystems.

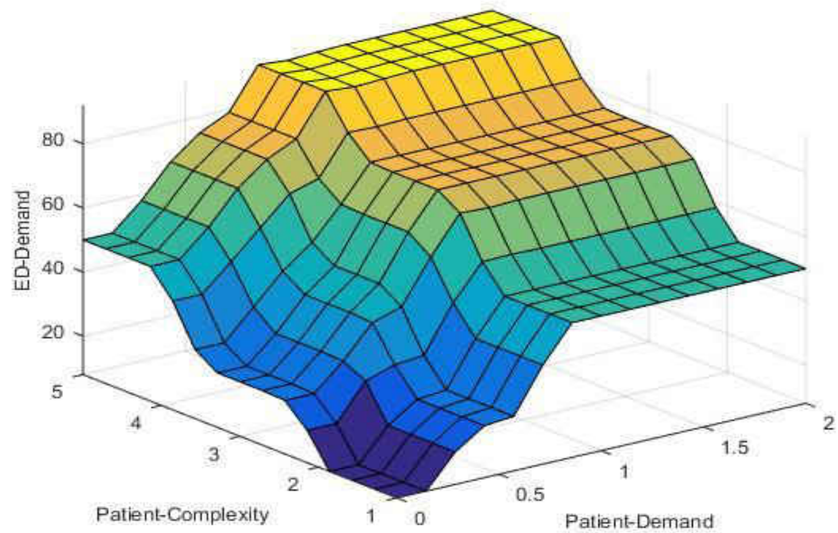


Figure 5-16: Surface of the fuzzy logic subsystem I

Figure 5-16 illustrates the surface of subsystem I, defined by two input axes, patient complexity and patient demand, and one output axis, ED demand. The values for ED demand on the surface plot range from 8 to 92, resulting from the centroid method used for defuzzification. Generally speaking, it can be observed on the surface that ED demand will increase with patient complexity if patient demand is held constant, and similarly ED demand will increase with patient demand if patient complexity is held constant. Interestingly, when patient demand is approaches a value of 1, the ED demand plateaus when patient demand is between 1 and 2, unless patient complexity increases. The step-like structure occurring for patient demand higher than 1 resembles another local step structure for patient complexity higher than 4, where ED demand cycles between plateaus and increases until it plateaus near its maximum value. For patient demand less than 1 and patient complexity less than 4, the surface appears to linearly increase in a more predictable manner than the two step-like structures near its extremes.

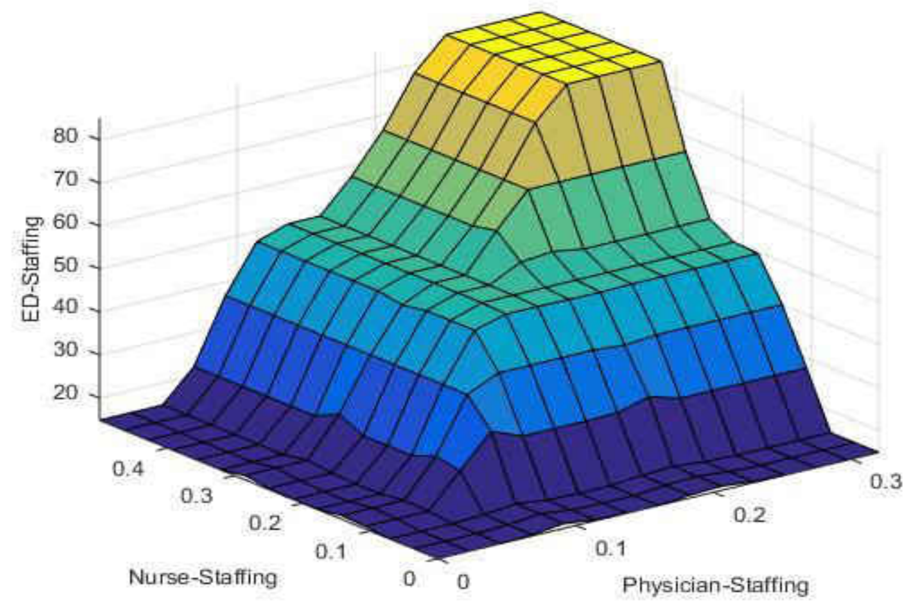


Figure 5-17: Surface of the fuzzy logic subsystem II

Figure 5-17 demonstrates the relation between the inputs (nurse staffing and physician staffing) and output (ED staffing) of subsystem II, where ED staffing ranges between scores of 14.9 and 89.1. ED staffing appears to increase in a similar manner with either nurse staffing or physician staffing when the other input is held constant, although the increase is not as high as when both inputs are proportionally increased. In other words, there are several plateau planes on the surface where ED staffing will only increase when both inputs are proportionally increased. When physician staffing is held constant, around 0.1 for instance, ED staffing will not increase after nurse staffing increases beyond 1.5, demonstrating the logical relation between the ED staffing and the ratio between nurses and physicians. If the ratio of physicians to nurses is low, ED staffing will be considered low, and an ED's staffing size and thus ability to see to patients would not likely increase if the nursing staff was increased in size. This illustrates that a proportional number of physicians and nurses would be required for an ED to effectively maintain a high staffing level. It may also be noted that the slope of the surface from 50 to 89 ED staffing score is steeper for increasing nursing staff than when physician staffing is increased, which may be due to the different scales of the input axes.

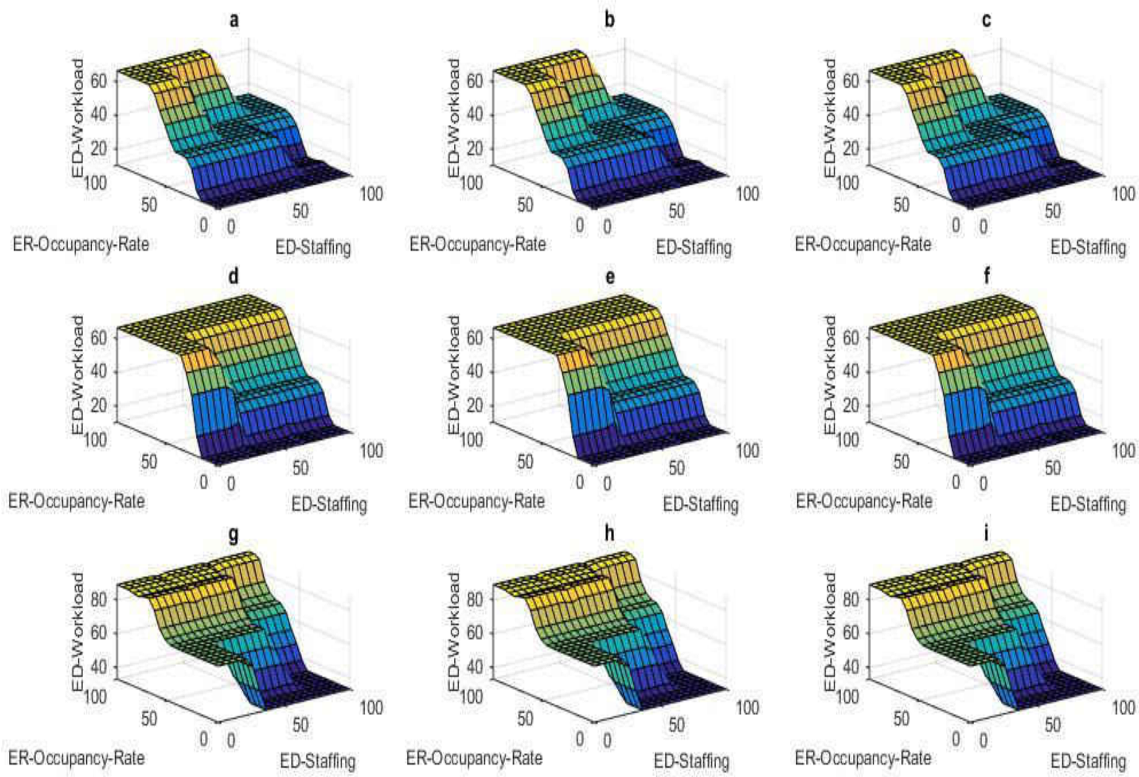


Figure 5-18: Parameter sensitivity analysis - Subsystem III (a)

Figure 5-18 features nine surface plots that represent part of subsystem III, showing how ED workload is affected by ER occupancy rate and ED staffing, when average patient complexity is held at nine different constants, which are 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, and 5 for surfaces a through i, respectively. For surfaces a, b, and c, when patient complexity is low, between 1 and 2, ED workload increases when ED staffing is low and ER occupancy is high, approaching a maximum scale value of 60. When ED staffing is increased in these cases, ED workload decreases. Only when ED staffing is high and occupancy is low does ED workload scale reach its minimum value of 10.8. When average patient complexity is held between 2.5 and 3.5, surfaces d, e, and f show a much steeper increase in workload when ER occupancy rate is increased, even when ED staffing is high. This demonstrates the impact that an increase in average patient complexity has on ED workload even when staffing may be considered adequate. With the maximum workload scale adjusted to 80 for surfaces g, h, and I, when average patient complexity is between 4 and 5, the effects of low ED staffing even at low occupancy rates show an impact on ED workload. For instance, even when both staffing and occupancy rates are close to 0 in these surfaces, the ED workload starts at non-zero values due to the increase in average patient complexity. Even under medium staffing and medium occupancy rates, the ED workload scale approaches high values.

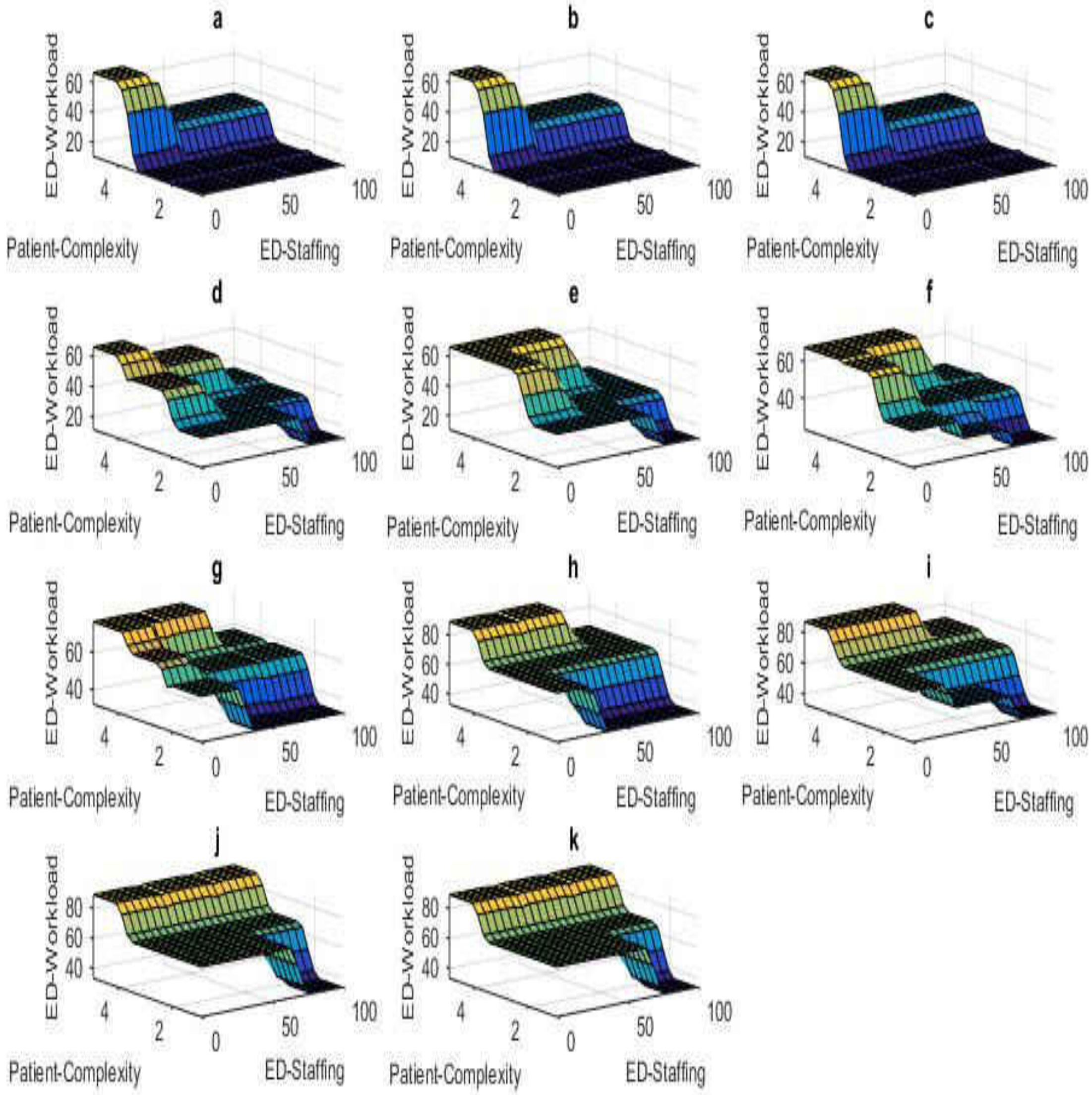


Figure 5-19: Parameter sensitivity analysis - Subsystem III (b)

Figure 5-19 consists of eleven surface plots, a through k, which show the impact of average patient complexity and ED staffing on ED workload, when occupancy rate is held at eleven different constants, starting near zero, 10, 20, and ending with 100. In surfaces a through c, when occupancy rates are held between zero and 20, ED staffing does not significantly impact ED workload until average patient complexity approaches 4. Around this value, ED workload sharply increases to a value of 60, and only an increase in ED staffing decreases ED workload beyond this complexity. Overall, ED staffing does not play a large role in ED workload under low occupancy until patients in severe condition increase patient complexity. Even a few serious cases can tie up resources in an ED and lead to an increase in workload when staffing may be considered adequate.

When occupancy rate is increased and maintain values between 30 and 60 in figure 5-19, surfaces d through g demonstrate the impact on workload. As occupancy rate increases in these surfaces, ED workload gradually reaches higher values when ED staffing is constantly low and average patient complexity is constantly high. It can also be observed that the possibilities for low ED workload slowly decrease with an increase in occupancy, even when staffing is high and average complexity is low.

In surfaces h through k in figure 5-19, when occupancy rate is between 70 and 100, the ED workload scale is adjusted to create new maximum values. In these surfaces, even when ED staffing is medium, and average patient complexity is low, ED workload is high. There is a steep increase in ED workload in surfaces j and k when average patient complexity exceeds a value of 4, even when ED staffing is high.

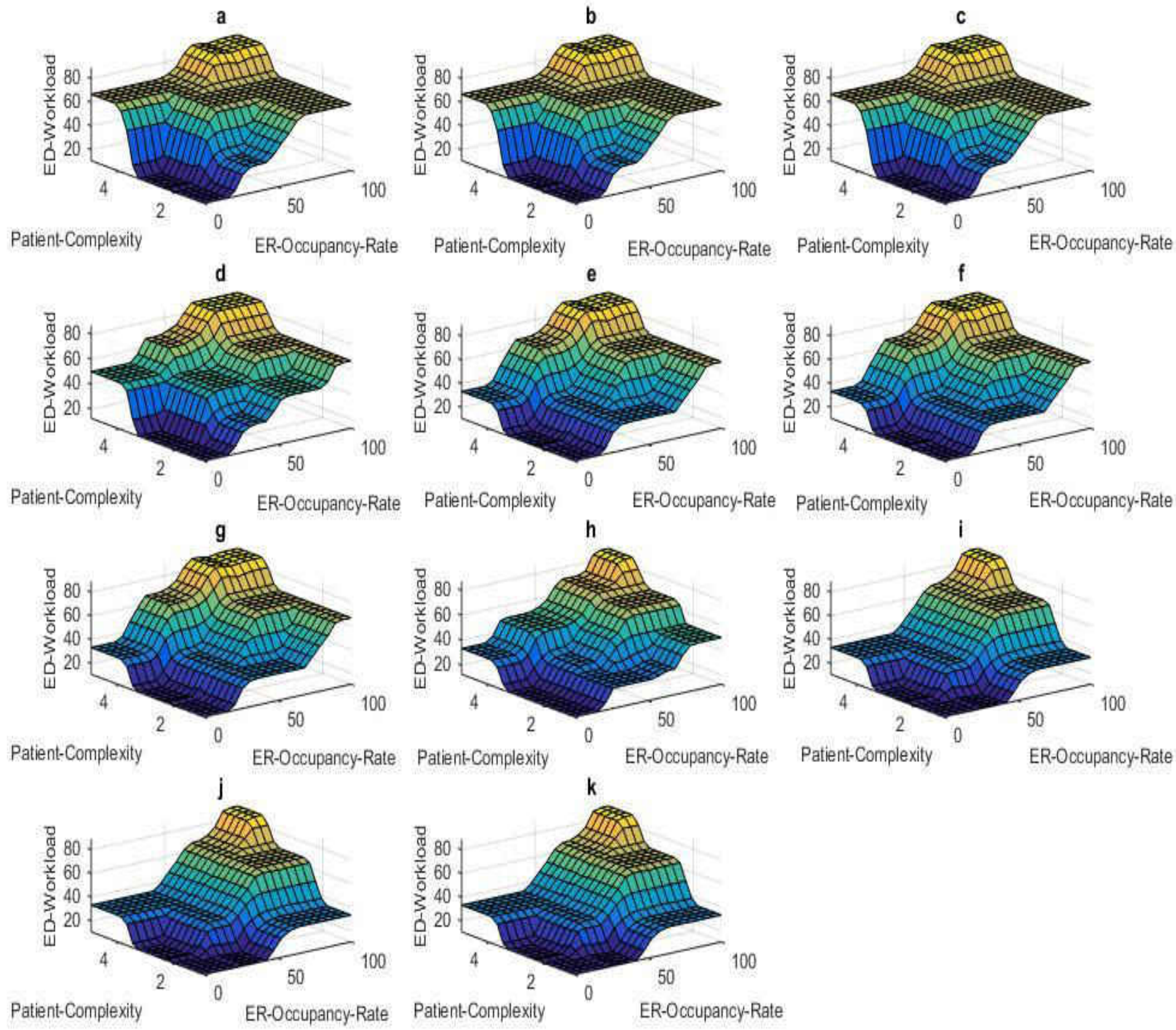


Figure 5-20: Parameter sensitivity analysis - Subsystem III (c)

In figure 5-20, surfaces a through k represent the relation between ED workload and its inputs, average patient complexity and ER occupancy rate when ED staffing is held at eleven different constants, ranging from near zero to 100 for each respective surface. For surfaces a, b, and c, when ED staffing is between near zero and 20, high ED workload reaches scores of 60 quickly with medium occupancy rates and average patient complexity. When average patient complexity achieves values higher than 4, and occupancy rates achieve values higher than 50, ED workload plateaus unless both average patient complexity and occupancy rates increase, leading to a peak area of the surface where ED workload reaches scores near 80. When ED staffing is between 30 and 60, for surfaces d through g, the impact of better staffing can be seen on ED workload. The increase of ED workload becomes more gradual with increasing average patient complexity and occupancy rates, and the size of the surface representing ED workload scores of 60 or higher decrease. In surfaces h through k, when ED staffing is between 70 and 100, the peak of the surface representing the highest scores for ED workload becomes smaller, and areas of the surface representing increases in ED workload become isolated in the plot, as higher values for average patient complexity and occupancy rate become necessary to achieve high values for ED workload. This represents the impact that increasing ED staffing to adequate levels has on ED workload, even when average patient complexity and occupancy rates are high. There are always areas of the surfaces where ED workload is high, however when ED staffing is increased, ED workload can be said to decrease even for moderate values of its other two inputs.

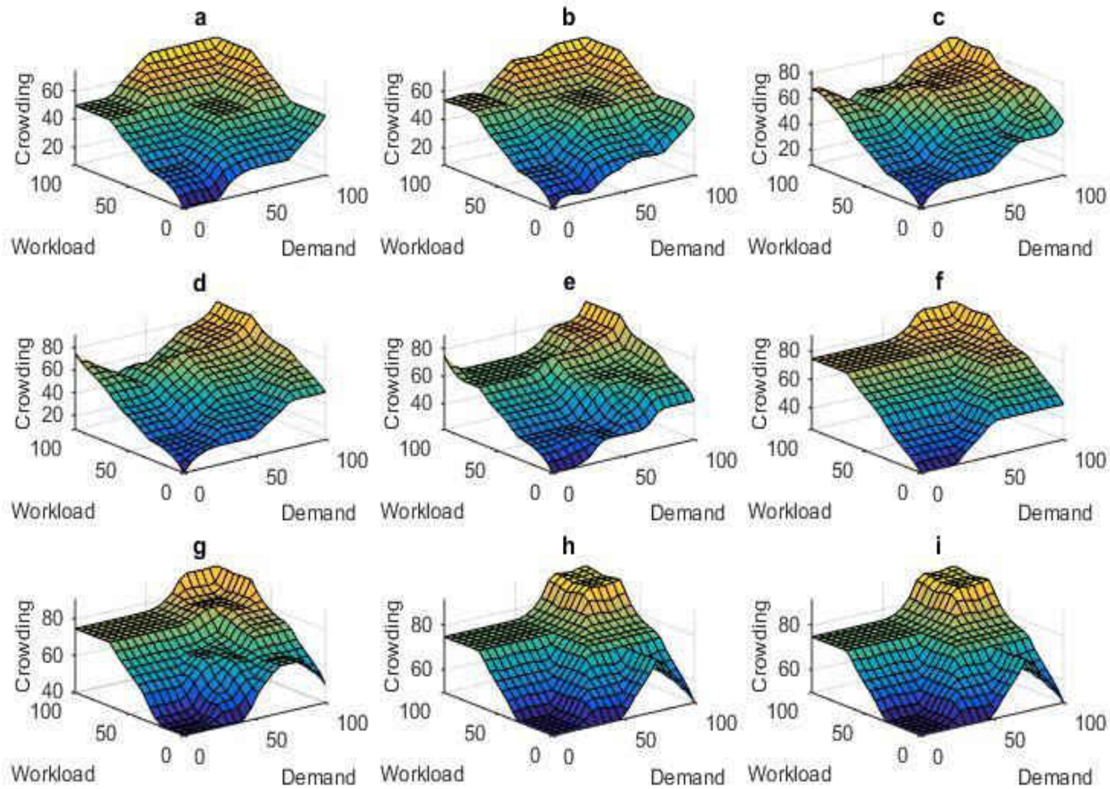


Figure 5-21: Parameter sensitivity analysis - Subsystem IV (a)

Figure 5-21 represents the surfaces of subsystem IV, which is the most important subsystem as it represents the final outcome for the entire system. In figure 5-21, surfaces a through i represent the relation between crowding and its inputs, workload and demand, when the variable boarding status is held at nine different constants, 0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, and 0.40. The variable boarding status represents the ratio of boarded patients to the emergency capacity. In surface a, when boarding status is held at 0, crowding increases gradually with workload and demand, with the highest levels of crowding occurring under high demand and workload. Surface b represents a similar effect from both inputs when boarding status is held at

0.05, however the surface appears to be smoother despite having a similar characteristics and shape. In surface c, when boarding status is increased to 0.10, the crowding level scale is adjusted to a maximum of 80, and an interesting saddle feature occurs when workload is high and demand is low. When demand is near zero in both surface c and d, crowding starts with high values near 60 on the surface when workload is at its maximum, but crowding appears to decrease when demand increases to values of 10 to 20, and then crowding increases again when demand further increases. This illogical feature could be due to the demand scale, which is between 8 and 92, meaning demand does not reach values near zero, and to simulate crowding at such a level could produce inaccuracy.

While surface d is smooth, a plateau begins to emerge in surface e, and is more apparent in surface f. For these surfaces, the minimum values for crowding begin to rise, isolating the low values of the surfaces. Crowding appears to increase faster with demand and workload than in previous surfaces. In surface g, when boarding status is held at 0.30, a peak begins to emerge on the surface, which is more pronounced in surfaces h and i when boarding status is near maximum values. In surfaces g through i, another illogical feature occurs when workload low and demand approaches maximum values. After approaching demand values of 60, crowding decreases after a steady increase, when workload is low. This could be caused a conflict in the knowledge base, where a conflict may exist in the rule base.

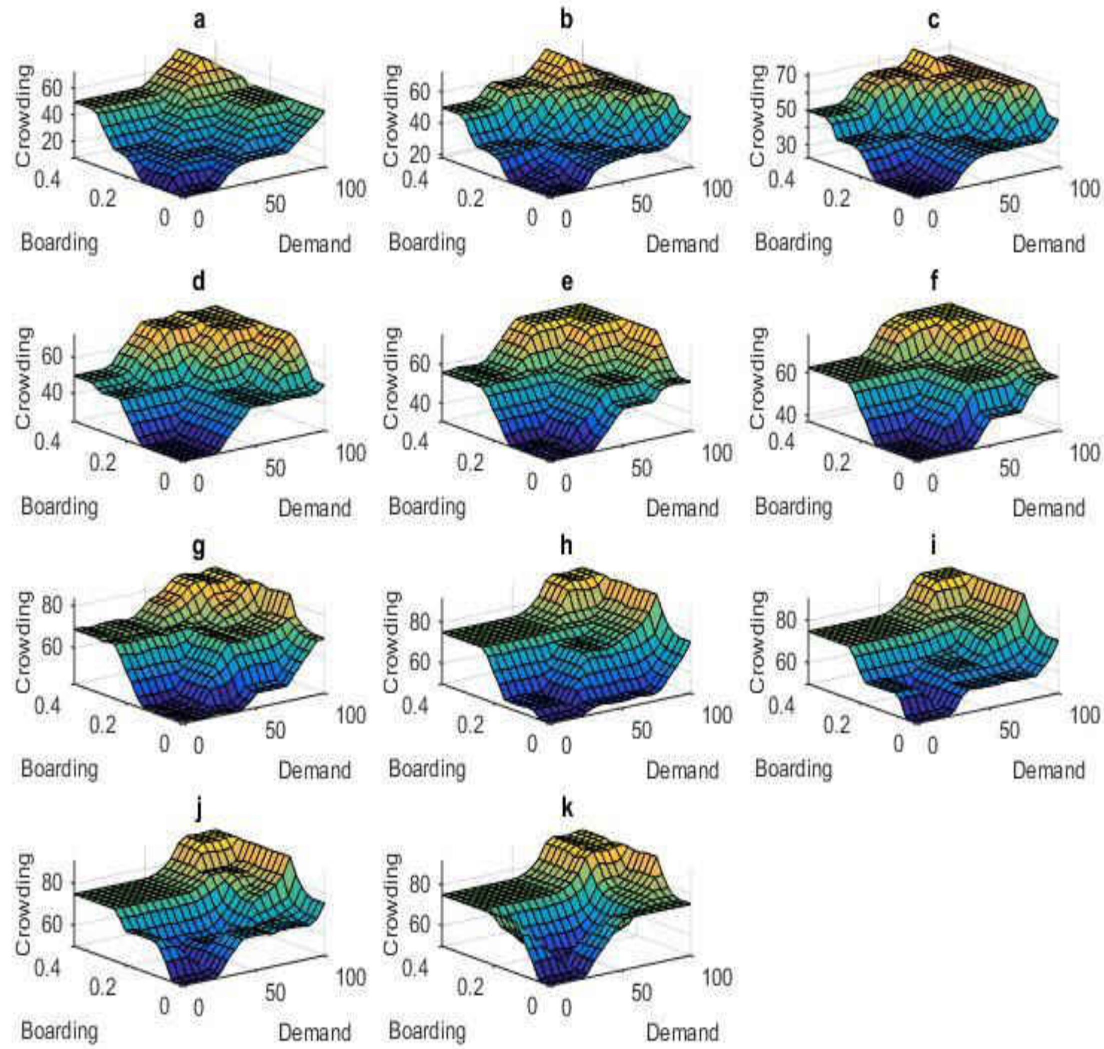


Figure 5-22: Parameter sensitivity analysis – Subsystem IV (b)

Figure 5-22 consists of surfaces a through k of subsystem IV, showing the impact that the inputs of boarding and demand have on the output of crowding, when the variable workload is held at eleven constants, 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 . In surfaces a through c, when workload is low, crowding generally increases with boarding and demand, however the peak values in surfaces b and c differ from surface a. The peak of the surface decreases in size and transitions into a plateau in surfaces b and c, indicating a wider range of input values that lead to the same high level of crowing.

In surfaces d through g when workload is between 30 and 60, the lower values of the surface become more isolated, and all points on the surfaces appear to rise, representing an overall increase in crowding for all values of boarding and demand. It can be observed that increasing the ED workload evenly increases crowding under any condition of boarding and demand.

As workload approaches values between 70 and 100, surfaces h through k show that crowding continues to generally increase for all boarding and demand values, and the surfaces peak at higher values. A plateau emerges in surface h, where crowding remains constant for boarding values which exceed 0.2, when demand is below 50. Beyond boarding values of 0.2, crowding will only increase when demand is increased beyond 50. This demonstrates that under high workload, there are consistent levels of crowding when boarding is high, but demand is low. Only when both boarding and demand are low does crowding achieve minimum values under high workload.

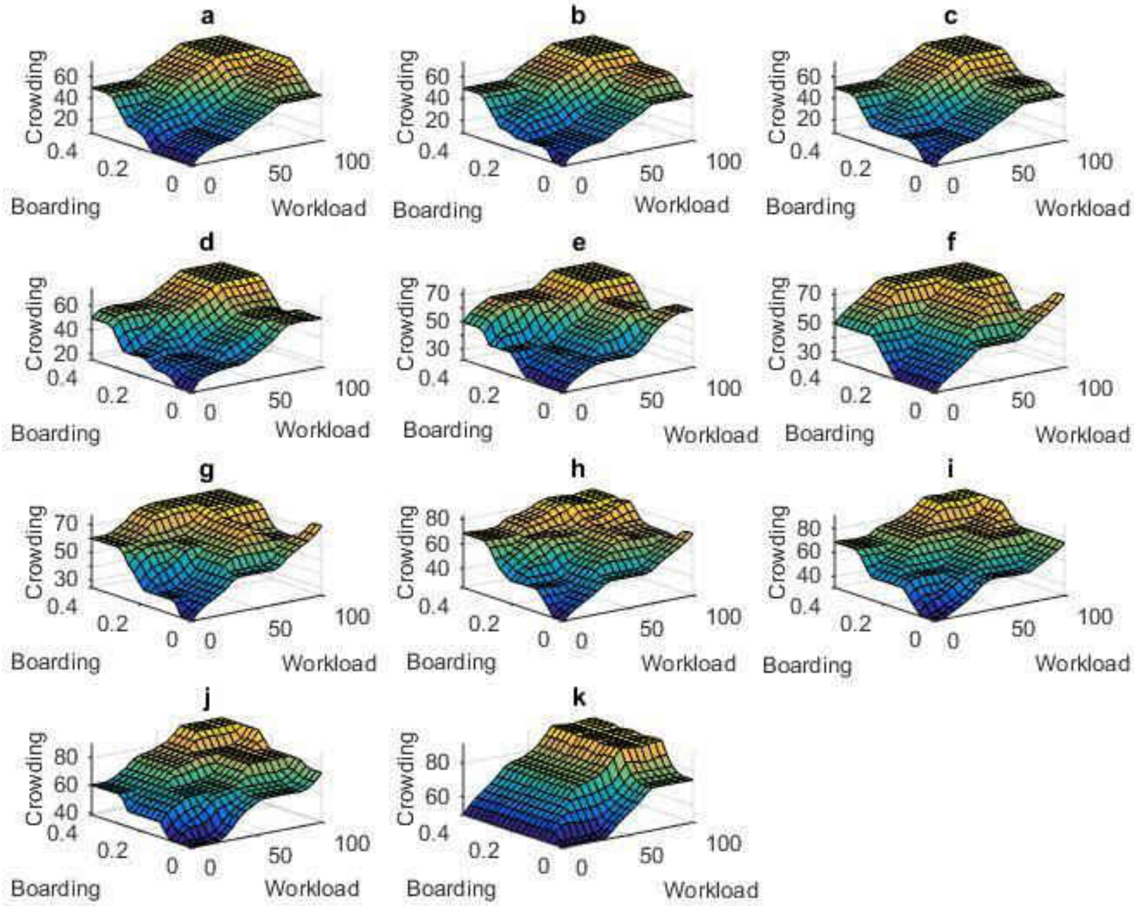


Figure 5-23: Parameter sensitivity analysis - Subsystem IV (c)

Figure 5-23 includes surfaces a through k, where crowding is related to boarding and workload when demand is held at eleven different constants, ranging from 0, 10, and 20, to 100. In surfaces a through d, when demand is between 0 and 30, crowding generally increases with an increase in boarding and workload, reaching maximum values when both inputs are high. Surfaces b and c appear to be smoother than surface a, when demand is the lowest.

Beginning with surface e, and continuing in surfaces f through h, when demand is between values of 40 and 70, an illogical feature emerges when workload is high and boarding is low. In surface f and g when this feature is most pronounced, crowding decreases when workload values increase beyond a value of 60, and in surface h this feature begins to disappear. This could result from a conflict that occurs in the knowledge base for medium values of demand. Otherwise, surfaces e through h show that crowding generally increases for all values of boarding and workload, and the crowding scale adjusts in surface e to a maximum of 70, and then it adjusts to a maximum of 80 in surface h.

In surfaces i through k, when demand is between 80 and 100, crowding can be said to generally increase with increasing boarding and workload as observed in surfaces a through c. In surface k, the surface becomes more uniform when workload increases beyond low values. It can be said that for boarding values higher than 0.1, crowding does not increase unless workload increases. This demonstrates that when demand is very high, boarding is not as significant, as it does not affect crowding beyond a certain point unless the ED workload is increased.

5.4 Framework Implementation and Validation

This section details the process for implementing and testing the accuracy of the proposed fuzzy model framework, which will be described as the Adaptable Index for Emergency Department Overcrowding, or AIEDOC. One of the main goals of the AIEDOC is to produce reliable results which can be reproducible in EDs of other healthcare systems. The design of the

GIEDOC accounts for this in the knowledge base, as ten healthcare experts from a nation in question may provide data to be fed into the knowledge base, allowing the fuzzy system to produce results. This is why the design of GIEDOC is unlike other developed indices, which when tested outside their countries of origin, do not show adequate reproducibility when implemented. In order to accurately assess the GIEDOC, it must be implemented in real ED environments to measure the level of crowding, and at the same time, an expert assessment of a native expert must be made of the same environment to compare the results from the GIEDOC.

For the purposes of measuring the accuracy of the GIEDOC, five classes within the GIEDOC were defined by five equal intervals on a scale from 0 to 100, so that the classes could be compared to the subjective assessment of experts. These five classes for assessing ED crowding on five subjective levels were: 1 for "insignificant", 2 for "low", 3 for "medium", 4 for "high", and 5 for "extreme". In other words, this was done to compare the agreement of the index to experts, by determining if this scale reflects the expert perspective for crowding. The GIEDOC was implemented for three days in a public Saudi Arabian hospital in Jeddah, which sees more than one hundred thousand patients in its emergency department on a yearly basis, possessing more than 400 inpatient beds and 42 emergency beds. During the validation, twenty four observations were made to collect data which focused on factors including the capacity of the emergency department, the number of patients in the waiting area, ER, and boarding areas, the number of present physicians and nurses, the average patient complexity in both the waiting area and the ER, and finally a healthcare expert's subjective assessment of crowding. These results are detailed in table 5-18, where the ED crowding level scale can be compared to class number assigned by experts

Kappa analysis (Equation 1) was used to test the agreement between the computed GIEDOC scores and the subjective assessment of the healthcare experts. These statistics allow for the comparison of the accuracy of the results from GIEDOC to those of other indices when assessing ED crowding.

Table 5-18: Crisp inputs and their computed crisp output using GIEDOC

Observation No.	Ratio of Patient to ED Capacity	Patient Complexity (A)	Demand Score	ED Physician Staffing	ED Nurse Staffing	Staffing Score	ED Occupancy Rate	Patient Complexity (B)	ED Workload Score	ED Boarding Score	ED Crowding Level	Expert Subjective Assessment
1	0.286	2	18.1	0.31	0.45	85.1	100%	3	66.7	0.070	62.5	4
2	0.095	2.5	25	0.35	0.47	85.1	100%	3.5	66.7	0.120	50	3
3	0.167	2.5	25	0.35	0.40	85.1	90%	3	66.7	0.140	50	3
4	0.240	1.5	8	0.31	0.40	85.1	100%	2	33.3	0.024	25	3
5	0.120	3	25	0.33	0.47	85.1	60%	3	57	0.119	41.9	3
6	0.167	1	8	0.29	0.50	85.1	86%	3.5	66.7	0.190	60	4
7	0	0	8	0.19	0.36	85.1	71%	2	33.3	0.143	25	2
8	0.190	1.5	8	0.33	0.43	85.1	100%	3.5	66.7	0.047	50	3
9	0.260	2	16	0.29	0.43	85.1	100%	4	89.2	0.024	50	3
10	0.047	4	50	0.35	0.40	85.1	43%	3	33.3	0.143	50	2
11	0.214	3	26.6	0.21	0.43	68.4	57%	2	31.3	0.166	27.6	3
12	0.262	3.5	31.2	0.33	0.47	85.1	100%	3	66.7	0.047	53.1	3
13	0.286	3	33.1	0.31	0.47	85.1	91%	4	89.2	0.190	60	4
14	0.071	2	8	0.31	0.47	85.1	100%	1.5	33.3	0.286	49.9	3
15	0.286	1.5	18.1	0.26	0.38	85.1	98%	2	33.3	0.047	25	2
16	0.643	3	56.4	0.31	0.45	85.1	83%	2	33.3	0.095	50	3
17	0.143	2	8	0.26	0.36	85.1	100	2.5	66.7	0	50	4
18	0.452	2	24.6	024	0.40	85.1	76%	3	66.7	0.214	66.1	4
19	0.500	2.5	50	0.26	0.29	68.4	100%	4	88.2	0.143	59.5	4
20	0.214	3.5	26.6	0.26	0.43	85.1	100%	4	89.2	0.143	52.4	4
21	0.333	4	61.4	0.21	0.38	68.4	100%	3	66.7	0.143	75	4
22	0.047	3	25	0.33	0.47	85.1	95%	3	66.7	0.119	50	3
23	0.309	1	19.7	0.16	0.50	50	81%	3	66.7	0.024	50	3
24	0.381	3	39.6	0.21	0.33	68.4	100%	3	66.7	0.047	53.5	3

Table 5-18 provides the data obtained from the twenty four observations conducted for validation of the GIEDOC, resulting in calculated scores for the major operational factors. The demand scores ranged from values of 8 to 61.4 according to the demand indicator of the GIEDOC, while staffing scores ranged from 50 to 85.1, and ED workload ranged from 33.33 to 89.2. It should be noted that the majority of staffing scores obtained their maximum values, indicating that over the three days of validation, the selected ED almost always maintained adequate staffing. There was higher variation in the range of demand and ED workload scores. ED crowding level scores achieved values between 25 and 75. To further study the variation in scores between observations, the scores were plotted in figure 5.24.

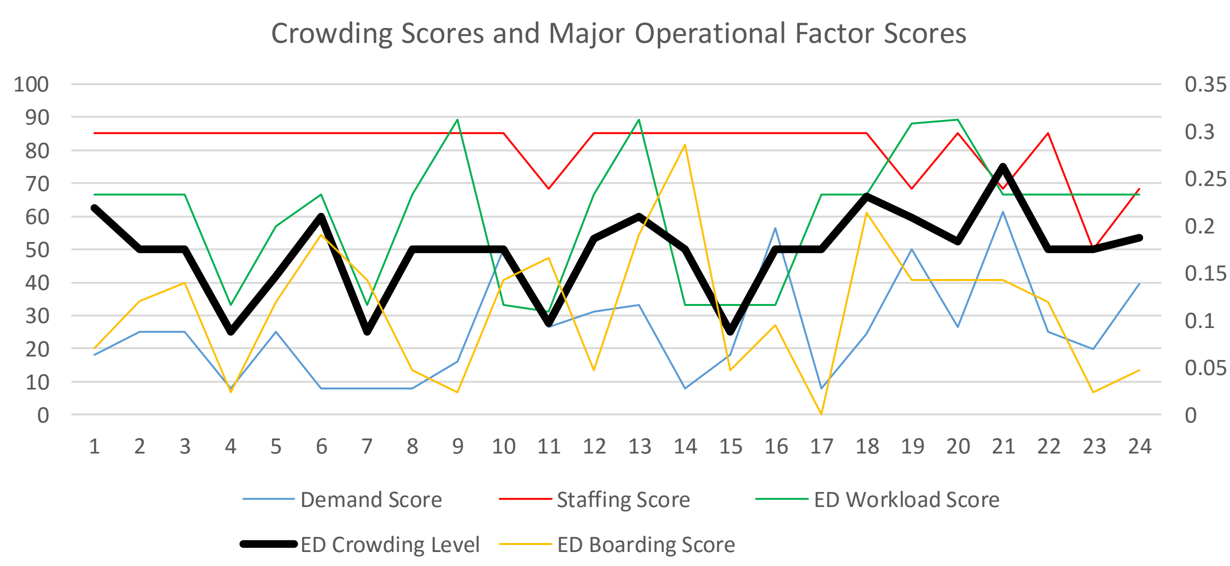


Figure 5-24: GIEDOC index scores

The plot in figure 5.24 further shows the consistency in the staffing score across the twenty four observations, varying slightly between observations 19 and 24. Generally speaking, when demand, boarding, and workload scores were decreasing or increasing between observations, such as in observation four, the crowding level decreased or increased accordingly. In other observations such as 8 and 9, when factor scores such as workload increased while another factor such as boarding decreased, the resulting crowding score exhibited no change. In observation 21 when other scores exhibited minimal change, a sharp increase in the demand score can be attributed to the sharp increase in crowding, demonstrating the significance of the role of demand in crowding.

The agreement between GIEDOC and expert assessment is analyzed in table 5.18, where assessments are documented according to the “low”, “medium”, and “high” classes (2, 3, and 4) from table 5-18. The GIEDOC issued 4 assessments for “low” scores, 15 for “medium”, and 5 for “high”, while the expert provided 3 “low” assessments, 13 “medium”, and 8 “high”. For the low class, the GIEDOC and the expert issued the same-assessment agreements twice, while they agreed eleven times for the medium class, and five times for the high class. When measured against the expert assessments, the GIEDOC overestimated once for the low class, (providing a score of “medium” where the expert provided a score of “low”), and underestimated the medium class twice (providing “low” while the expert provided “medium”), while underestimating the high class three times. It should be noted that the insignificant and extreme classes could not be predicted, as the ED during this study was neither empty nor extremely overcrowded according to both scores from the expert and the GIEDOC. Most activity regarding the major operation factors occurred in the third level or “medium” class according to their scores.

The Kappa value found for the system was 0.562, 95% CI [0.45, 0.66], which indicates moderate agreement between the objective and subjective scores of GIEDOC and the expert (Appendix N).

5.5 Concluding Remarks

This chapter presents several opportunities to discuss the accuracy of the proposed model and the implications it has on bias from expert assessment, and the influence that each of the factors for ED crowding carry in constructing an understanding of how an effective index should function. When the interval values were provided by experts to construct membership functions, some variation was observed in responses, and it can be speculated that these varying responses could be due to factors such as the expert's background and expertise in EDs, their years of experience, and possibly cultural values. For instance, it was found that the determined physician staffing and nurse staffing intervals varied greatly in figures 5-2 and 5-3, indicating some different perspectives. For instance, physicians were found to overestimate values for the classes of nurse staffing, and vice versa, demonstrating the problems of relying on only one perspective. It is important to minimize bias in this study by avoiding reliance upon one assessment or embracing only one perspective when implementing a solution to a problem which exists in several different healthcare systems. The variation in these class intervals created foggy data, which was modeled with membership functions for the proposed fuzzy logic system. The interval estimation method was a very effective elicitation method, as it produced the desired membership functions for each subsystem.

Several lessons can be learned from the evaluation of the 137 fuzzy rules, which produced the consensus rates between expert assessments. Among the different fuzzy rules with different permutations of conditional consequents (from tables 5-10, 5-12, 5-14, and 5-16), it is possible to detect different perspectives in the differing rule assessments provided by experts. Experts with similar backgrounds such as physicians appear to have consistent responses. With regard to rule consensus, only seven of the 137 assessed rules did not reach the minimum criteria in the first round, indicating that the fuzzy rule assessment structure was effective. With these consensus rates for each subsystem, deeper analysis could determine when and why bias happens in the evaluations. While this assessment provides more insight into patterns of bias, other studies which rely on one stakeholder to inform their results can produce indices which are skewed in the perspective of that stakeholder. The average consensus rate between the four subsystems was consistently better than 72%, with increasing complexity in the fuzzy rules accounting for the slight decreases in consensus rate between subsystems. The intra-class correlation for the whole system was 0.817, with a 95% confidence interval of [0.777, 0.854], which demonstrates good agreement.

The generated surfaces which related each of the subsystems' inputs to their output revealed patterns of influence between these input variables. The demand score in Subsystem I based on expert assessment behaved in a logical manner, and with more membership functions, more fuzzy rules, or more complex rules, the surfaces could be made smoother. In Subsystem II, the surface reflected the relationship between the ratio of nurses and physicians to ED staffing in a logical manner. When the ratio of physicians to nurses was high, and vice versa, ED staffing did not increase beyond a certain value, and only when both physician and nursing staffing increased did ED staffing also increase. This shows how an excess of either physicians or nurses will not contribute to a higher considered level of overall ED staffing, as both roles are critical within ED staffing. Subsystem III demonstrated the significant impact that occupancy rate and staffing had on workload, with patient complexity having the most distinct effect upon workload across the surfaces for the entire subsystem. Subsystem IV featured some interesting surfaces, which demonstrated the large impact that demand and workload had on crowding. Some aspects of the surfaces can be explained by the limits of the scale involved, or a possible conflict in the knowledge base. These surfaces are useful for determining crowding level output for the system by using one known factor.

The steps taken to validate the model produced good results for an initial validation, including a kappa value of 0.562, indicating moderate agreement. The validation did not capture the highest and lowest classes on the scale, as measurements could not be taken to validate these classes, given the conditions of the ED over the three days. With a longer validation period, more data could be collected, and it could then be possible to draw conclusions on the extreme classes. Moreover, a more robust validation process would include more experts' assessments when comparing the results of this model. The resulting kappa value for this initial validation represents the agreement of the model's results to the one expert assessment, meaning that if the model were developed with only that expert's perspective, the kappa value would be higher. However, this model benefits from the perspective of multiple experts, and thus the inclusion of more expert assessment would improve the validation process.

CHAPTER 6 CONCLUSION AND FUTURE RESEARCH

6.1 Conclusion

In the modern era, healthcare systems face many challenges both operationally and financially. As a growing industry, healthcare organizations take many measures to meet growing demand and standards for care, in addition to expanding access. Individually, hospitals face their own unique challenges which are defined by their size, location, and other factors. Within hospitals, the emergency departments also face increases in demand which is confounded by both the number of patients and their severity, as well as the readiness of emergency centers. ED demand continues to rise, and overcrowding has become a common issue for many hospitals which are dedicated to providing high standards in service.

The issue of overcrowding has many dimensions, impacting stakeholders such as patients and hospitals alike, where errors caused by the burdens of overcrowding may lead to further delays, tie up valuable resources, or lead to further risk of morbidity. Overcrowding is not universally defined by a clear set of criteria, and existing criteria varies according to different local and regional standards, different policies on measures taken to ameliorate it, and most importantly it is perceived differently by the different professionals who work in ED environments. These different views lead to different ideas of when EDs become overcrowded, how overcrowding can be prevented, and how it should be characterized.

One approach to mitigating the operational problems that overcrowding present is to quantify it to enable and inform decision making regarding staffing, ambulance diversion, boarding, and others. In addition to informing policy, quantifying and classifying overcrowding makes it easier for EDs to prepare for and reduce overcrowding in their environments. To achieve this, many studies have sought to develop indices to measure ED crowding. Many of these indices have proven to be ineffective in reproducing results for accurately identifying overcrowding in healthcare systems outside the ones these indices were defined in. In addition, many indices are founded upon the feedback from one stakeholder, introducing bias into the index. These difficulties in quantifying crowding in diverse environments have led experts to call upon the application of industrial engineering techniques to analyze and research this issue.

This study sought to assess the validity of two existing indices by applying them in a healthcare system of a new region in which they had not been applied previously. The application of the indices to the Saudi Arabian healthcare system provided the opportunity to perform such a validation in a representative region. The indices chosen are known as the NEDOCS and EDWIN indices, as they are the most compatible for the Saudi Arabian healthcare system, such that all of the proper inputs are both relevant and obtainable. This validation was carried out as a preliminary study to learn more about the performance of established indices, finding that they were not accurate in measuring overcrowding. This is due to the inaccuracies in reflecting physician and nursing perspectives of ED overcrowding, which the developed indices exclusively relied on. The results of the preliminary study confirm the inaccuracies of ED crowding indices when they are applied outside the regions in which they were initially developed.

This study proposed a framework for quantifying overcrowding within different healthcare contexts, seeking to overcome the shortcomings of previous indices by founding the framework upon the perspective of multiple experts and stakeholders. With a method for quantifying overcrowding in qualitative and quantitative terms provided by a variety of experts, and identifying and reducing bias, this study strives for reproducibility of results in other settings.

The framework of the proposed study takes into consideration operational factors such as patient demand, workload, boarding status, and others when defining the crowding level in an ED. The hierarchical fuzzy logic approach is used to accomplish the goals of this framework by combining a diverse pool of expert perspectives while addressing the complexity of the overcrowding issue. The designed fuzzy logic system acknowledges the interconnectedness of dimensions of overcrowding by organizing subsystems in a manner which reflects the three operational determinants of crowding, as discussed from figure 4-4.

The three-level hierarchical fuzzy logic system consists of four fuzzy inference engines, or subsystems, which each contain their own knowledge base containing a database and fuzzy rule base. The novel feature of this model is that it allows for the use of a combined pool of expert evaluation and knowledge from multiple stakeholders when the crowding level is determined. The architecture of the system integrates a total of seven inputs into the four fuzzy logic subsystems, allowing information from the knowledge base to state the degree of membership and assign a membership function to input and output values. Each subsystem is developed to assess an output which is a key contributing factor to the crowding level, which is assessed in the fourth subsystem. In level one, the first subsystem determined the ED demand status, and the second subsystem determined the level of ED staffing. The second level contained the third subsystem, which evaluated the ED workload, and finally the fourth subsystem quantified the crowding status in the third level.

The analysis from chapter five showed that the results from the construction of the knowledge base were logical, and the obtained visual relation between the operational determinants of crowding provided more insight into the dynamics of crowding. Analysis of the initial measures taken to validate the developed GIEDOC index demonstrated its accuracy when tested against subjective expert assessment. The results from this validation showed that the accuracy of the GIEDOC index was superior in comparison to the level of accuracy of the NIEDOCS and EDWIN indices in the same setting. Finally, the innovative and novel design features which allow this developed index to accurately assess ED crowding also contribute to its capability to produce accurate results in other healthcare systems.

The research accomplished in this study contributes to existing knowledge in the field of quality systems engineering by designing a robust and novel index for assessing ED crowding. The designed index overcomes shortcomings of previous indices by both reducing bias through the inclusion of perspective from different types of stakeholders, and identifying patterns of bias in the analysis of the results from the construction of the fuzzy logic system. The index developed in this research offers opportunities to both researchers and practitioners. For researchers, this index can empower the development of future improvements within ED settings, in addition to offering a new technique for quantifying subjective operational challenges. Practitioners can use this index to make better informed decisions while assessing ED crowding, contributing to the improvement of overall care, outcomes, quality of service, and patient safety.

6.2 Limitations and Future Research

The design of the proposed framework introduced several challenges which were overcome with decisions to reduce the number of calculations and simplify the system architecture. These decisions carry implications which can be used to identify limitations to this study, and identify opportunities for future researchers to improve the framework.

The design of the knowledge base for the fuzzy system focused on using conditional statements using only AND rules when eliciting expert assessment of fuzzy rules. While the benefit of this was the reduction in the number of rules, it imposed limitations on the assessments by restricting the possible range of responses. In addition, the hierarchical fuzzy system adapted contributing factors to ED from the Asplin's overcrowding model, which consists of only three main determinants. While seven inputs were chosen to represent these determinants, other ED settings may present other important contributing factors to overcrowding that could be additionally included in a refinement of the developed framework. When defining factors such as patient complexity, this research adapted the definition provided by the Emergency Severity Index, which may not be compatible with the emergency triage systems used in other healthcare settings. This research allowed experts to subjectively assess the impact of patient complexity on ED crowding, and more membership functions could be implemented to increase the number of fuzzy classes used to define patient complexity, and thus increase the precision of results.

When building the knowledge base, the rules to be assessed by experts were assumed to be of equivalent importance or weight, whereas a future design may allow experts to assign different values of importance to different rules as they contribute to overcrowding. When validating the developed index, the observation period was limited to three days, in which the conditions for insignificant and extreme crowding were not observed. A more rigorous validation may take advantage of a longer period to obtain a larger pool of data to assess the other classes of crowding provided by the model.

Conducting this research and constructing the proposed framework presents new opportunities for expanding the field of research on the issue of ED overcrowding. Based upon the observations made in previous chapters, several ways to further advance of the body of knowledge in this field can be identified. With regard to the design of the fuzzy system, future research could focus on either increasing the number of inputs to the system, or identifying more crowding determinants. Other design improvements could include an expansion of the hierarchical fuzzy system, in which more subsystems could be implemented in association with other identified inputs or determinants of crowding. These determinants could further vary according to the policy of different triage systems. Accordingly, efforts made to further test the index could seek to apply it in healthcare settings which use different triage systems, which may shed light on the influence that the chosen determinants have on the index results.

In designing the knowledge base, further research could attempt to integrate other quantitative tools into the fuzzy system to process some inputs independently, such as patient demand. Methods such as simple linear regression or multiple regression could be used to model the demand side of the problem in such a way to make the index more robust and accurate. The fuzzy rule base, which is one of the most important components of the model, could be optimized by incorporating a method to determine the weighting of each fuzzy rule. To accomplish this, different classification algorithms could be applied to a fuzzy rule base classification system to assign weights to each rule. This could increase the overall performance of the index, which utilizes 137 rules in this research, and the impact of weighting on an increased number of rules would be more pronounced. In addition to this, the rule base could be further enriched by including more complicated rules. Specifically, the rules could use OR statements in addition to the AND statements used in the conditional statements of this research. For instance, a new rule might ask an expert: “If the patient demand is low, or if the workload is low, and the boarding status is medium, then would ED crowding be considered low, or medium?”

Implementing the index in other settings is another important research opportunity. The developed index could be studied when applied in other EDs in the same studied healthcare system, or the index might be applied in other healthcare systems which have similar characteristics to that of the region in which the validation in this research was carried out. Both of these implementation strategies could be used to further compare the accuracy and applicability of the developed index across different healthcare settings. If the proposed model were to be implemented in a sufficiently different healthcare system, another worthwhile task for researchers would include the development of a knowledge base for such a setting.

Aside from altering the architecture of the index, other research efforts could focus on developing index integration strategies within EDs. Integrating the developed index with an ED decision support system could aid in analyzing major operational factors in EDs, including demand, patient flow, staffing levels, workload, congestion after treatment, and the overall crowding. The analysis of these factors could help in determining the root causes of overcrowding in the moment of observation. Furthermore, researchers could use this index to create an alarm system based on the hourly observations of ED crowding. An alarm system could specify both prevention policies to avoid crowding, as well as reaction policies designed to respond to overcrowding when it occurs, when specific conditions are met in the index.

A separate research effort could focus on developing a set of action protocols for EDs, to specify a course of action to both prevent and react to overcrowding when it occurs, as identified by the index. The index could be further adjusted to adapt to different settings by adjusting the interval of crowding for an individual hospital. This could be done by linking policies in a given healthcare system to the developed index in a way that modifies the fuzzy classes according to the local overcrowding policy and protocols.

Finally, a more rigorous validation study could simulate the index by integrating it with a discrete event simulation model to study its performance over a longer period of time. With such a simulation, the impact of the determinants on the overcrowding score could be more accurately observed. Patterns of simulated data used to more closely observe the impact of each factor on overcrowding could also be used to draw conclusions for the development of future ED policy.

APPENDIX A UCF IRB APPROVAL

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Exempt Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Abdulrahman Albar**

Date: **January 06, 2015**

Dear Researcher:

On 1/6/2015, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review:	Exempt Determination
Project Title:	Evaluating the Applicability and Validity of NEDOCS and EDWIN indices in Saudi Arabian Healthcare Organizations: Assessment of Crowding in Emergency Departments
Investigator:	Abdulrahman Albar
IRB Number:	SBE-14-10845
Funding Agency:	
Grant Title:	
Research ID:	N/A

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Patria Davis on 01/06/2015 02:53:11 PM EST

IRB Coordinator

APPENDIX B STUDY INFORMED CONCENT

EXPLANATION OF RESEARCH

Title of Project: Evaluating the Applicability and Validity of NEDOCS and EDWIN indices in Saudi Arabian Healthcare Organizations: Assessment of Crowding in Emergency Departments

Principal Investigator: Abdulrahman Albar

Faculty Supervisor: Ahmad Elshennawy

You are being invited to take part in a research study. Whether you take part is up to you.

The purpose of this research is to evaluate the applicability and validity of the National Emergency Department Overcrowding Scale (NEDOCS) and the Emergency Department Work Index (EDWIN) in your hospital. The collected data will be analyzed to quantitatively validate those emergency department crowding indices within Saudi Arabian healthcare settings.

This research includes two major parts. First part aims to examine whether the NEDOCS index is valid in Saudi Arabian emergency care settings or not. Part one includes two surveys, one targets ED physicians, and the other targets ED nurses. The participants will answer questions about the degree of overcrowding and the feeling of being in rush in a given time. It is expected to take the participant about one minute to finish the survey. Part one also includes a section for collecting information about the capacity of the ED, availability of beds, as well as the amount of patients in a given time. This section can be filled by a member from the ED registration office. It is expected to take 5 minutes to finish this section. The participant will be asked to fill the survey in a specific time. He or She can fill the survey at 1 am, 5 am, 9 am, 1 pm, 5 pm, or 9 pm. Part one will last for about three weeks.

Second part aims to examine whether the EDWIN index is valid in Saudi Arabian emergency care settings or not. This part includes two surveys, one targets ED physicians, and the other targets ED nurses. The participants will answer one questions about the level of ED busyness in a given time. It is expected to take the participant about one minute to finish the survey. Part one also includes a section for collecting information about the capacity of the ED, availability of beds, as well as the number of patients in each triage category in a given time. This section can be filled by a member from the ED registration office. It is expected to take 5 minutes to finish this section. The participant will be asked to fill the survey in a specific time. He or She can fill the survey at 1 am, 5 am, 9 am, 1 pm, 5 pm, or 9 pm. Part two will last for about five weeks.

Both parts of this study will take place at the same time.

You must be 18 years of age or older to take part in this research study.

Study contact for questions about the study or to report a problem: If you have questions, concerns, or complaints, please contact Abdulrahman Albar, Graduate Student, Department of Industrial Engineering and Management Systems at (407) 617-7446 or by email at aalbar@knights.ucf.edu or Dr. Ahmad Elshennawy, Faculty Supervisor, Department of Industrial Engineering and Management Systems at (407) 823-5742 or by email at Ahmad.Elshennawy@ucf.edu.

IRB contact about your rights in the study or to report a complaint: Research at the University of Central Florida involving human participants is carried out under the oversight of the Institutional Review Board (UCF IRB). This research has been reviewed and approved by the IRB. For information about the rights of people who take part in research, please contact: Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901.

APPENDIX C MINISTRY OF HEALTH IRB APPROVAL

Kingdom of Saudi Arabia
Ministry of Health
King Fahad Medical City
(162)

المملكة العربية السعودية
وزارة الصحة
مدينه الملك فهد الطبية
(١٦٢)

IRB Registration Number with KACST, KSA:	H-01-R-012
IRB Registration Number with OHRP/NIH, USA:	IRB00008644
Approval Number Federal Wide Assurance NIH, USA:	FWA00018774

February 2, 2015
IRB Log Number: 15-021E
Department: External
Category of Approval: EXEMPT

Dear Mr. Abdulrahman M. Albar,

I am pleased to inform you that your submission dated January 27, 2015 for the study titled **'Evaluating the Applicability and Validity of NEDOCS and EDWIN Indices in Saudi Arabian Healthcare Organizations: Assessment of Crowding in Emergency Departments'** was reviewed and was approved. Please note that this approval is from the research ethics perspective only. You will still need to get permission from the head of department or unit in KFMC or an external institution to commence data collection.

We wish you well as you proceed with the study and request you to keep the IRB informed of the progress on a regular basis, using the IRB log number shown above.

If you have any further questions feel free to contact me.

Sincerely yours,

Prof. Omar H. Kasule
Chairman Institutional Review Board--IRB.
King Fahd Medical City, Riyadh, KSA.
Tel: + 966 1 288 9999 Ext. 17540
E-mail: okasule@kfmc.med.sa

K F M C
Approved
02 FEB 2015
I R B

APPENDIX D LETTERS OF PERMISSION FOR DATA COLLECTION

المملكة العربية السعودية
وزارة الصحة
الإدارة العامة للبحوث والدراسات

الإدارة العامة للبحوث والدراسات
القيد: 1060043
التاريخ: 27-04-1436هـ 16-02-2015
مرفقات: 10

الموضوع: بحث الطالب/عبدالرحمن البار.

سعادة/ مديرالشؤون الصحية بمحافظة جدة **المحترم**

صورة لسعادة / مدير مستشفى الملك فهد بجدة **المحترم**

السلام عليكم ورحمة الله وبركاته، ، ،

إشارة إلى موضوع الطالب / عبدالرحمن بن محمد البار، المبتعث من جامعة جازان لدراسة درجة الدكتوراة في تخصص "الهندسة الصناعية" بكلية الهندسة جامعة سنترال فلوريدا بأمريكا، رقم الهوية الوطنية ([redacted]) والرقم الأكاديمي ([redacted]) وعنوان الرسالة:

" تقييم دقة و صلاحية موشرات قياس الإزدحام بأقسام الطوارئ في مستشفيات المملكة العربية السعودية "

نحيطكم علماً بأن الطالب قد إستوفى كافة المستندات المطلوبة وتمت مراجعتها من قبل اللجان المعنية بالإدارة العامة للبحوث والدراسات بوزارة الصحة ولجنة الأخلاقيات بمدينة الملك فهد الطبية (مرفق صورة)، وتمت الموافقة على تسهيل مهمة إجراء هذا البحث، وحيث أن المذكور عاليه سينفذ دراسته في مستشفى الملك فهد بجدة.

وعليه، نأمل من سعادتكم التفضل بالإطلاع والإيعاز لمن يلزم بتسهيل مهمته لجمع البيانات اللازمة بما يضمن أن لا يكون هناك أي تأثير على خدمة المراجعين خلال قيامه بمهام بحثه، مع العلم بأن وزارة الصحة لا تتحمل أية أعباء مالية في البحث والوزارة تضمن حقوقها في نتائج هذا البحث من خلال إتفاقية المشاركة في البيانات والتي تم توقيعها بين الباحث والإدارة العامة للبحوث والدراسات.

Dr. Aziz

وتفضلوا بقبول خالص تحياتـي ، ، ،

مرفق عليه ملخص للمقترح البحثي، ، ،

وكيل الوزارة المساعد لتخطيط وتطوير رأس المال البشري

د. عماد بن علي الحجيلي

الرمز البريدي: ١١١٧٦ ص.ب الرياض: ٢٧٧٥ فاكس: ٠١١٤٧٣٥٠٣٩ هاتف: ٠١١٤٧٣٥٠٣٨
e-mail: research@moh.gov.sa

المملكة العربية السعودية
Kingdom of Saudi Arabia
مديرية الشؤون الصحية بمحافظة جدة
Directorate of Health Affairs - Jeddah
(٢٠٢/٢٧٥)
إدارة البحوث والدراسات الطبية

وزارة الصحة
Ministry of Health

الموضوع: الموافقة على إجراء بحث

سعادة مدير مستشفى الملك فهد العام بمحافظة جدة.

السلام عليكم ورحمة الله وبركاته...

نفيدكم بأن الباحث اسمه أدناه سوف يقوم بإجراء البحث كالتالي:

اسم الباحث:	عبد الرحمن محمد البار
رقم البحث:	٠٠٥٧٨
رقم الموافقة:	A٠٠٢٤٤
عنوان البحث	تقييم دقة وصلاحيات مؤشرات قياس الإزدحام بأقسام الطوارئ في مستشفيات المملكة العربية السعودية.
مدة الموافقة:	سنة من تاريخه.

وبناء على موافقة الإدارة العامة للبحوث والدراسات بوزارة الصحة ولجنة الأخلاقيات بمدينة الملك فهد الطبية ، وجد أنه لا مانع من إجراء البحث.

أمل تسهيل مهمة الباحث في إجراء البحث **مع مراعاة الآتي:**

١. **اتباع قوانين اللجنة الوطنية للأخلاقيات الحيوية والطبية.**
٢. **في حال أي تغيير في خطة البحث يجب الحصول على موافقة إدارة الأبحاث.**
٣. **عدم تأثر الخدمة في المرافق المعنية.**
٤. **المحافظة على حقوق الأشخاص الخاضعين للبحث وخصوصياتهم.**
٥. **استخدام المعلومات لأغراض البحث العلمي فقط.**
٦. **تقديم تقرير عن سير الدراسة لإدارة البحوث كل ستة أشهر.**

شاكرين تعاونكم.

ولكم تحياتي،،

مدير إدارة البحوث والدراسات الطبية

د/ محمد عبد الرؤوف توفيق

٦/٥/١٤٣٦هـ

مساعد مدير الشؤون الصحية للتخطيط والتطوير
بمحافظة جدة

د/ محمود مدني العلي

٥/٩ /١٤٣٦هـ

APPENDIX E NEDOCS ASSESSMENT FORM

Section Code: NEDOCS-Physicians

Date: / / 2015

Please circle the time.						
Time:	1 AM	5 AM	9 AM	1 PM	5 PM	9 PM

Dear ER Physician,

You are invited to participate in this study by completing a brief anonymous survey. It is expected to take you less than one minute to finish the questions.

Thank you, and We appreciate your participation,

The Research Team

****

Please circle the opinion on ED 'Degree of Overcrowding'
1 = not busy 2 = busy 3 = extremely busy but not overcrowded 4 = overcrowded 5 = severely overcrowded 6 = dangerously overcrowded
Please circle the opinion on 'Feeling rushed' in ED, 1 = not rushed, 6 = rushed 1 2 3 4 5 6

Section Code: NEDOCS-Nurses

Date: / / 2015

Please circle the time.						
Time:	1 AM	5 AM	9 AM	1 PM	5 PM	9 PM

Dear ER Nurse,

You are invited to participate in this study by completing a brief anonymous survey. It is expected to take you less than one minute to finish the question.

Thank you, and We appreciate your participation,

The Research Team

****

Please circle the opinion on ED 'Degree of Overcrowding'

1 = not busy
2 = busy
3 = extremely busy but not overcrowded
4 = overcrowded
5 = severely overcrowded
6 = dangerously overcrowded

Section Code: NEDOCS-Quantitative

Date: / / 2015

Please circle the time.						
Time:	1 AM	5 AM	9 AM	1 PM	5 PM	9 PM

Dear ER Administrator,

You are invited to participate in this study by completing brief quantitative questions. It is expected to take you less than five minute to finish the questions.

Thank you, and We appreciate your participation,

The Research Team

****

number of ED treatment beds	
number of licensed hospital beds	

number of patients in ED beds and other treatment spaces such as hallways beds	
number of admitted patients	
waiting time for last patient placed in an ED bed	
longest time among boarding patients since registration	
number of occupied respirators	

APPENDIX F EDWIN ASSESSMENT FORM

Section Code: EDWIN-Physicians

Date: / / 2015

Please circle the time.						
Time:	1 AM	5 AM	9 AM	1 PM	5 PM	9 PM

Dear ER Physician,

You are invited to participate in this study by completing a brief anonymous survey. It is expected to take you less than one minute to finish the questions.

Thank you, and We appreciate your participation,

The Research Team

****

‘‘How busy would you say the ED is right now?
Please take into account your workload, the workload of all other doctors and nurses, the numbers of patients in the ED and waiting room, and numbers of holds (admitted patients waiting for beds)

1 not busy at all, not crowded
2 steady, easily keeping up
3 average: working hard, but keeping up
4 more crowded and busy than desirable
5 extremely busy, very crowded.’’

Section Code: EDWIN-Nurses

Date: / / 2015

Please circle the time.						
Time:	1 AM	5 AM	9 AM	1 PM	5 PM	9 PM

Dear ER Nurse,

You are invited to participate in this study by completing a brief anonymous survey. It is expected to take you less than one minute to finish the questions.

Thank you, and We appreciate your participation,

The Research Team

****

‘‘How busy would you say the ED is right now?
Please take into account your workload, the workload of all other doctors and nurses, the numbers of patients in the ED and waiting room, and numbers of holds (admitted patients waiting for beds)

1 not busy at all, not crowded
2 steady, easily keeping up
3 average: working hard, but keeping up
4 more crowded and busy than desirable
5 extremely busy, very crowded.’’

Section Code: EDWIN-Quantitative

Date: / / 2015

Please circle the time.
Time: 1 AM 5 AM 9 AM 1 PM 5 PM 9 PM

Dear ER Administrator,

You are invited to participate in this study by completing brief quantitative questions. It is expected to take you less than five minute to finish the questions.

Thank you, and We appreciate your participation,

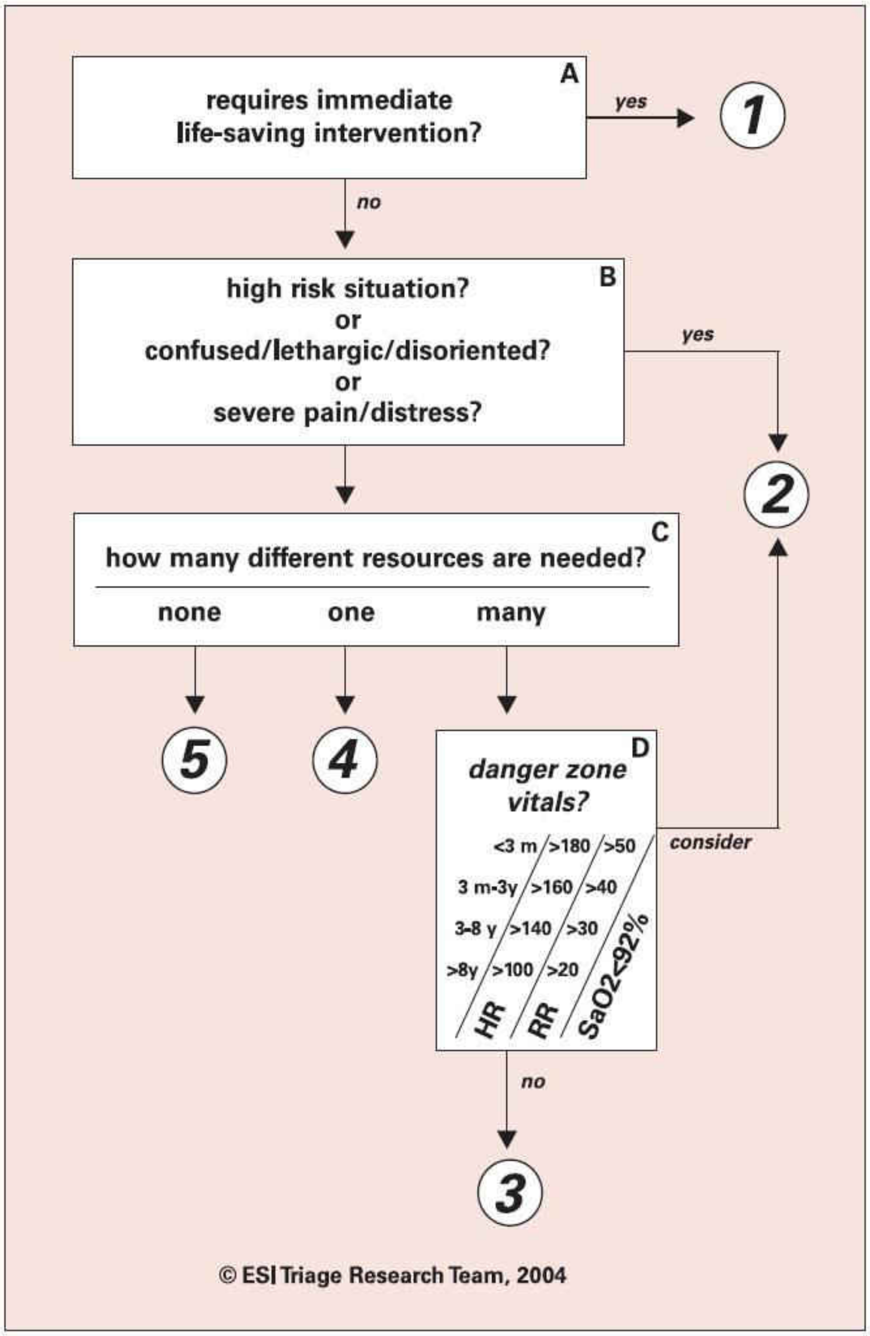
The Research Team

****

number of ED patients in triage category i	triage category				
	1	2	3	4	5

Number of available beds in the ED	
number of ED physicians	
number of admitted patients	

APPENDIX G ESI TRIAGE ALGORITHM



ESI Triage Algorithm. Adapted from (Gilboy, 2012)

APPENDIX H NEDOCS AND EDWIN RELIABILITY ANALYSIS

```
CROSSTABS
  /TABLES=P1A BY P2A
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
P1A * P2A	90	100.0%	0	0.0%	90	100.0%

P1A * P2A Crosstabulation

Count

		P2A						Total
		1	2	3	4	5	6	
P1A	1	0	2	1	0	0	0	3
	2	2	8	2	5	0	0	17
	3	2	3	6	6	0	0	17
	4	0	0	3	13	1	0	17
	5	0	5	3	7	9	0	24
	6	0	0	2	1	6	3	12
Total		4	18	17	32	16	3	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.297	.062	5.966	.000
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

```
CROSSTABS
  /TABLES=P1B BY P2B
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
P1B * P2B	90	100.0%	0	0.0%	90	100.0%

P1B * P2B Crosstabulation

Count

		P2B					Total
		2	3	4	5	6	
P1B	1	2	4	0	0	0	6
	2	4	2	1	0	0	7
	3	5	4	13	3	0	25
	4	2	6	6	2	1	17
	5	1	1	5	16	0	23
	6	2	0	7	2	1	12
Total		16	17	32	23	2	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.179	.059	3.568	.000
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

```
CROSSTABS
  /TABLES=N1A BY N2A
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
N1A * N2A	90	100.0%	0	0.0%	90	100.0%

N1A * N2A Crosstabulation

Count

		N2A						Total
		1	2	3	4	5	6	
N1A	1	3	4	0	0	0	0	7
	2	1	7	1	3	3	0	15
	3	2	2	8	3	3	2	20
	4	0	3	6	6	2	0	17
	5	1	5	0	5	7	4	22
	6	0	1	0	1	3	4	9
Total		7	22	15	18	18	10	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.253	.063	5.187	.000
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

```
CROSSTABS
  /TABLES=N1B BY N2B
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
N1B * N2B	90	100.0%	0	0.0%	90	100.0%

N1B * N2B Crosstabulation

Count

		N2B						Total
		1	2	3	4	5	6	
N1B	1	3	0	2	0	0	0	5
	2	0	6	9	1	4	0	20
	3	0	3	3	6	1	0	13
	4	1	1	7	12	4	4	29
	5	0	0	4	1	1	4	10
	6	0	0	9	0	3	1	13
Total		4	10	34	20	13	9	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.129	.057	2.722	.006
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

```
CROSSTABS
  /TABLES=AdjustedAvgPA BY AdjustedAvgNA
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
AdjustedAvgPA * AdjustedAvgNA	90	100.0%	0	0.0%	90	100.0%

AdjustedAvgPA * AdjustedAvgNA Crosstabulation

Count

		AdjustedAvgNA						Total
		1	2	3	4	5	6	
AdjustedAvgPA	2	2	5	6	2	0	0	15
	3	0	2	7	6	0	0	15
	4	0	6	4	10	9	2	31
	5	1	0	1	7	7	4	20
	6	0	0	0	3	1	5	9
Total		3	13	18	28	17	11	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.204	.067	3.811	.000
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

```
CROSSTABS
  /TABLES=NEDOCS BY AdjustedAvgClin
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
NEDOCS * AdjustedAvgClin	90	100.0%	0	0.0%	90	100.0%

NEDOCS * AdjustedAvgClin Crosstabulation

Count

		AdjustedAvgClin					Total
		2	3	4	5	6	
NEDOCS	1	4	4	2	0	0	10
	2	3	6	7	1	0	17
	3	3	12	10	4	1	30
	4	1	0	15	4	0	20
	5	0	0	0	9	3	12
	6	0	0	0	1	0	1
Total		11	22	34	19	4	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.276	.061	5.296	.000
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

```
CROSSTABS
  /TABLES=P1 BY P2
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
P1 * P2	90	100.0%	0	0.0%	90	100.0%

P1 * P2 Crosstabulation

Count

		P2					Total
		1	2	3	4	5	
P1	1	2	2	0	0	0	4
	2	2	7	3	0	0	12
	3	0	4	10	4	1	19
	4	0	1	11	18	4	34
	5	0	0	3	6	12	21
Total		4	14	27	28	17	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.394	.070	6.811	.000
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

```
CROSSTABS
  /TABLES=N1 BY N2
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
N1 * N2	90	100.0%	0	0.0%	90	100.0%

N1 * N2 Crosstabulation

Count

		N2					Total
		1	2	3	4	5	
N1	1	2	2	0	0	0	4
	2	2	8	3	1	0	14
	3	0	4	25	1	1	31
	4	1	0	2	13	3	19
	5	0	1	2	6	13	22
Total		5	15	32	21	17	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.572	.064	9.907	.000
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

```
CROSSTABS
  /TABLES=AdjustedAvgP BY AdjustedAvgN
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
AdjustedAvgP * AdjustedAvgN	90	100.0%	0	0.0%	90	100.0%

AdjustedAvgP * AdjustedAvgN Crosstabulation

Count

		AdjustedAvgN						Total
		1	2	3	4	5	55	
AdjustedAvgP	1	1	1	0	0	0	0	2
	2	0	5	5	1	0	0	11
	3	0	4	11	1	2	0	18
	4	1	2	12	12	10	0	37
	5	0	0	6	6	9	1	22
Total		2	12	34	20	21	1	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.239	.067	4.229	.000
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

```
CROSSTABS
  /TABLES=EDWIN BY AdjustedAvrg
  /FORMAT=AVALUE TABLES
  /STATISTICS=KAPPA
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
EDWIN * AdjustedAvrg	90	100.0%	0	0.0%	90	100.0%

EDWIN * AdjustedAvrg Crosstabulation

Count

		AdjustedAvrg			Total
		1	2	3	
EDWIN	1	4	11	4	19
	2	1	35	21	57
	3	0	3	11	14
Total		5	49	36	90

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.235	.079	3.347	.001
N of Valid Cases		90			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

APPENDIX I UCF IRB RESPONSE

RE: Quantifying and Managing Overcrowding in Healthcare Facilities

Joanne Muratori <Joanne.Muratori@ucf.edu>

Tue 11/17/2015 7:54 AM

Inbox

To: Abdulrahman Albar <aalbar@knights.ucf.edu>;

Cc: Patria Davis <Patria.Davis@ucf.edu>; Kamille Chaparro <Kamille.Chaparro@ucf.edu>; Gillian Morien <Gillian.Morien@ucf.edu>; Sophia Dziegielewski <Sophia.Dziegielewski@ucf.edu>;

2 attachments (80 KB)

Part One.docx; Part Two..docx;

TO: Abdulrahman Albar

I am happy to confirm our conversation about your study, "A Framework for Quantifying and Managing Overcrowding in Healthcare Facilities." Per your summary below and the attached documents, you plan to obtain expert opinions regarding healthcare facilities and overcrowding. Studies that obtain facts (number of patients in waiting rooms, number of ED physicians and nurses, ER occupancy rate, etc.) from subject matter experts do not have to be submitted to the IRB for approval as this does not meet the federal definition of "human subjects research." We are making a distinction here between "research" and "human subjects research."

If you have additional questions, please feel free to phone me at 407-823-2901.

Best wishes on the success of your research.

Regards,

Joanne Muratori, M.A., CIP
IRB Manager

University of Central Florida
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, FL 32826-3246
Phone: 407-823-2901
Fax: 407-823-3299
joanne.muratori@ucf.edu

APPENDIX J EXPERT KNOWLEDGE ACQUISITION

Emergency Department Overcrowding Study – Expert Knowledge - Part One

Question 1: Suppose that an Emergency Room (ER) capacity is 50 beds, and assume that the current ER occupancy rate is 100%, what is the range number of patients in Emergency Department (ED) waiting area that describes each patient demand level in the first column?

Patient Demand	Number of patients in ED waiting area **(0=Minimum to 100= Maximum)**	
	Lower value	Upper value
Low		
Medium		
High		
Very high		

Question 2: Suppose that an ED capacity is 50 beds, what is the range number of ED physicians that describes each physician staffing level in the first column?

Physician staffing level	Number of ED physicians	
	Lower value	Upper value
Inadequate		
Partially adequate		
Adequate		

Question 3: Suppose that an ED capacity is 50 beds, what is the range number of ED nurses that describes each nurse staffing level in the first column?

Nurse staffing level	Number of ED nurses	
	Lower value	Upper value
Inadequate		
Partially adequate		
Adequate		

Question 4: what is the ER occupancy rate that describes the subjective level of each occupancy rate in the first column?

ER Occupancy Rate	Occupancy Rate **(0%=Minimum to 100%= Maximum)**	
	Lower value	Upper value
Low		
Medium		
High		
Very High		

Question 5: Suppose that an Emergency Room (ER) capacity is 50 beds, what is the range number of boarded patients in Emergency Department (ED) that describes each ED patient boarding status in the first column?

ED Patient Boarding Status	Number of boarded patients **(0=Minimum to 20= Maximum)**	
	Lower value	Upper value
Low		
Medium		
High		
Very high		

Emergency Department Overcrowding Study – Expert Knowledge – Part Two

Section 1: ED Demand Status

The aim of this section is to determine the Emergency Department (ED) demand status based on the following two factors:

- **Ratio of patients to ED capacity** (This factor links the number of patients waiting for ED care services to the ED size. e.g. when the ratio is 0.2, it means that there is 10 patients waiting for service in a 50 beds emergency room)

- **Average Patients Complexity** (This factor is constructed based on Emergency Severity Index (ESI) which divides patient severity into five categories namely; resuscitation, emergent, urgent, less urgent, and nonurgent. The resuscitation, and emergent are considered high complex cases, the complexity of urgent cases are considered medium, while the complexity of less urgent and nonurgent cases are considered low).

Based on your expertise, please evaluate the consequence "THEN column" of each condition in the table below. For example: Rule FLS1-01 states that "**IF** Ratio of Patients to ED Capacity is *Low* **AND** Patient Complexity is *Low* **THEN** ED Demand Status is ………….. ". Your answer should determine the ED Demand Status whether it is *Very Low, Low, Medium, High,* or *Very High.*

Rule Code	**IF** Ratio of Patients to ED Capacity **is**	**AND** Patient Complexity **is**	**THEN** ED Demand Status **is**
FLS1-01	Low	Low	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-02	Low	Medium	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-03	Low	High	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-04	Medium	Low	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-05	Medium	Medium	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-06	Medium	High	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High

FLS1-07	High	Low	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-08	High	Medium	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-09	High	High	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-10	Very High	Low	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-11	Very High	Medium	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High
FLS1-12	Very High	High	☐ Very Low ☐ Low ☐ Medium ☐ High ☐ Very High

Section 2: ED Staffing Status

The aim of this section is to determine the Emergency Department (ED) staffing status based on the following two factors:

- **ED Physician staffing**
- **ED Nurse Staffing**

Based on your expertise, please evaluate the consequence "THEN column" of each condition in the table below. For example: Rule FLS2-01 states that "**IF** ED Physician Staffing is *Inadequate* **AND** ED Nurse Staffing is *Inadequate* **THEN** ED Staffing Status is ………….." Your answer should determine the ED staffing Status whether it is *Inadequate, Partially adequate, or adequate*.

Rule Code	IF ED Physician Staffing **is**	AND ED Nurse Staffing **is**	THEN ED Staffing Status **is**
FLS2-01	Inadequate	Inadequate	☐ Inadequate ☐ Partially Adequate ☐ Adequate
FLS2-02	Inadequate	Partially adequate	☐ Inadequate ☐ Partially Adequate ☐ Adequate
FLS2-03	Inadequate	Adequate	☐ Inadequate ☐ Partially Adequate ☐ Adequate
FLS2-04	Partially adequate	Inadequate	☐ Inadequate ☐ Partially Adequate ☐ Adequate
FLS2-05	Partially adequate	Partially adequate	☐ Inadequate ☐ Partially Adequate ☐ Adequate
FLS2-06	Partially adequate	Adequate	☐ Inadequate ☐ Partially Adequate ☐ Adequate
FLS2-07	Adequate	Inadequate	☐ Inadequate ☐ Partially Adequate ☐ Adequate
FLS2-08	Adequate	Partially adequate	☐ Inadequate ☐ Partially Adequate ☐ Adequate
FLS2-09	Adequate	Adequate	☐ Inadequate ☐ Partially Adequate ☐ Adequate

Section 3: ED Workload

The aim of this section is to determine the Emergency Department (ED) Workload based on the following three factors:

- **ED Staffing Status**
- **ED Occupancy Rate**
- **Patients Complexity**

Based on your expertise, please evaluate the consequence "THEN column" of each condition in the table below. For example: Rule FLS3-01 states that "**IF** ED Staffing Status is *Inadequate* **AND** ED Occupancy Rate is *Low* **AND** Patient Complexity is *Low* **THEN** ED Workload is …………..". Your answer should determine the ED Workload whether it is *Low, Medium, High,* or *Very High.*

Rule Code	IF ED Staffing Status is	AND ED Occupancy Rate is	AND Patient Complexity is	THEN ED Workload is
FLS3-01	Inadequate	Low	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-02	Inadequate	Low	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-03	Inadequate	Low	High	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-04	Inadequate	Medium	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-05	Inadequate	Medium	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-06	Inadequate	Medium	High	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-07	Inadequate	High	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-08	Inadequate	High	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-09	Inadequate	High	High	☐ Low ☐ Medium ☐ High ☐ Very High

FLS3-10	Inadequate	Very High	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-11	Inadequate	Very High	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-12	Inadequate	Very High	High	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-13	Partially adequate	Low	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-14	Partially adequate	Low	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-15	Partially adequate	Low	High	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-16	Partially adequate	Medium	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-17	Partially adequate	Medium	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-18	Partially adequate	Medium	High	☐ Low ☐ Medium ☐ High ☐ Very High

FLS3-19	Partially adequate	High	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-20	Partially adequate	High	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-21	Partially adequate	High	High	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-22	Partially adequate	Very High	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-23	Partially adequate	Very High	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-24	Partially adequate	Very High	High	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-25	Adequate	Low	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-26	Adequate	Low	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-27	Adequate	Low	High	☐ Low ☐ Medium ☐ High ☐ Very High

FLS3-28	Adequate	Medium	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-29	Adequate	Medium	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-30	Adequate	Medium	High	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-31	Adequate	High	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-32	Adequate	High	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-33	Adequate	High	High	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-34	Adequate	Very High	Low	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-35	Adequate	Very High	Medium	☐ Low ☐ Medium ☐ High ☐ Very High
FLS3-36	Adequate	Very High	High	☐ Low ☐ Medium ☐ High ☐ Very High

Section 4: ED Crowding Level

The aim of this section is to determine the Emergency Department (ED) Crowding Level based on the following three factors:

- **ED Demand Status**
- **ED Workload**
- **ED Boarding Status** (The boarding status refers to the number of boarded patients in the ED.)

Based on your expertise, please evaluate the consequence "THEN column" of each condition in the table below. For example: Rule FLS4-01 states that "**IF** ED Demand Status is *Very Low* **AND** ED Workload is *Low* **AND** ED Boarding Status is *Low* **THEN** ED Crowding Level is ………….". Your answer should determine the ED staffing Status whether it is *Insignificant*, *Low, Medium, High,* or *Extreme*.

Rule Code	IF ED Demand Status **is**	AND ED Workload **is**	AND Boarding Status **is**	THEN ED Crowding Level **is**
FLS4-01	Very Low	Low	Low	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-02	Very Low	Low	Medium	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-03	Very Low	Low	High	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-04	Very Low	Low	Very High	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-05	Very Low	Medium	Low	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-06	Very Low	Medium	Medium	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-07	Very Low	Medium	High	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-08	Very Low	Medium	Very High	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-09	Very Low	High	Low	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-10	Very Low	High	Medium	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-11	Very Low	High	High	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-12	Very Low	High	Very High	☐Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-13	Very Low	Very High	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-14	Very Low	Very High	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-15	Very Low	Very High	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-16	Very Low	Very High	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-17	Low	Low	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-18	Low	Low	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-19	Low	Low	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-20	Low	Low	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-21	Low	Medium	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-22	Low	Medium	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-23	Low	Medium	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-24	Low	Medium	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-25	Low	High	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-26	Low	High	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-27	Low	High	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-28	Low	High	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-29	Low	Very High	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-30	Low	Very High	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-31	Low	Very High	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-32	Low	Very High	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-33	Medium	Low	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-34	Medium	Low	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-35	Medium	Low	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-36	Medium	Low	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-37	Medium	Medium	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-38	Medium	Medium	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-39	Medium	Medium	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-40	Medium	Medium	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-41	Medium	High	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-42	Medium	High	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-43	Medium	High	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-44	Medium	High	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-45	Medium	Very High	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-46	Medium	Very High	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-47	Medium	Very High	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-48	Medium	Very High	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-49	High	Low	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-50	High	Low	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-51	High	Low	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-52	High	Low	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-53	High	Medium	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-54	High	Medium	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-55	High	Medium	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-56	High	Medium	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-57	High	High	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-58	High	High	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-59	High	High	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-60	High	High	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-61	High	Very High	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-62	High	Very High	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-63	High	Very High	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-64	High	Very High	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-65	Very High	Low	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-66	Very High	Low	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-67	Very High	Low	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-68	Very High	Low	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-69	Very High	Medium	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-70	Very High	Medium	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-71	Very High	Medium	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-72	Very High	Medium	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-73	Very High	High	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-74	Very High	High	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-75	Very High	High	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-76	Very High	High	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-77	Very High	Very High	Low	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-78	Very High	Very High	Medium	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

FLS4-79	Very High	Very High	High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme
FLS4-80	Very High	Very High	Very High	☐ Insignificant ☐ Low ☐ Medium ☐ High ☐ Extreme

APPENDIX K RELIABILITY ANALYSIS FOR EXPERT EVALUATION

Reliability Analysis for Expert Evaluation of Fuzzy Rules of Subsystem I

```
RELIABILITY
  /VARIABLES=HCE01 HCE02 HCE03 HCE04 HCE05 HCE06 HCE07 HCE08 HCE09 HCE10
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL
  /ICC=MODEL(MIXED) TYPE(ABSOLUTE) CIN=95 TESTVAL=0.
```

Reliability

```
[DataSet1] \\Client\C$\SPSS\System 1.sav
```

Warnings

The determinant of the covariance matrix is zero or approximately zero. Statistics based on its inverse matrix cannot be computed and they are displayed as system missing values.

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	12	100.0
	Excluded[a]	0	.0
	Total	12	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.977	.979	10

Inter-Item Correlation Matrix

	HCE01	HCE02	HCE03	HCE04	HCE05	HCE06	HCE07	HCE08	HCE09	HCE10
HCE01	1.000	.756	.864	.575	.813	.856	.799	.780	.898	.869
HCE02	.756	1.000	.900	.434	.803	.902	.954	.854	.907	.841
HCE03	.864	.900	1.000	.653	.924	.980	.912	.853	.972	.931
HCE04	.575	.434	.653	1.000	.629	.630	.358	.754	.703	.788
HCE05	.813	.803	.924	.629	1.000	.943	.810	.821	.877	.853
HCE06	.856	.902	.980	.630	.943	1.000	.883	.870	.951	.912
HCE07	.799	.954	.912	.358	.810	.883	1.000	.785	.879	.827
HCE08	.780	.854	.853	.754	.821	.870	.785	1.000	.885	.945
HCE09	.898	.907	.972	.703	.877	.951	.879	.885	1.000	.949
HCE10	.869	.841	.931	.788	.853	.912	.827	.945	.949	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HCE01	28.75	101.114	.870	.	.975
HCE02	29.25	96.932	.897	.	.975
HCE03	28.83	100.152	.979	.	.972
HCE04	28.67	112.788	.634	.	.982
HCE05	29.17	100.879	.906	.	.974
HCE06	28.92	97.902	.970	.	.972
HCE07	29.00	99.091	.885	.	.975
HCE08	28.92	108.629	.909	.	.976
HCE09	28.92	100.447	.980	.	.972
HCE10	29.08	103.538	.956	.	.973

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
32.17	125.788	11.216	10

Intraclass Correlation Coefficient

	Intraclass Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.806[a]	.656	.926	43.746	11	99	.000
Average Measures	.976[c]	.950	.992	43.746	11	99	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type A intraclass correlation coefficients using an absolute agreement definition.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Reliability Analysis for Expert Evaluation of Fuzzy Rules of Subsystem II

```
RELIABILITY
  /VARIABLES=HCE01 HCE02 HCE03 HCE04 HCE05 HCE06 HCE07 HCE08 HCE09 HCE10
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL
  /ICC=MODEL(MIXED) TYPE(ABSOLUTE) CIN=95 TESTVAL=0.
```

Reliability

```
[DataSet2] \\Client\C$\SPSS\System 2.sav
```

Warnings

The determinant of the covariance matrix is zero or approximately zero. Statistics based on its inverse matrix cannot be computed and they are displayed as system missing values.

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	9	100.0
	Excluded[a]	0	.0
	Total	9	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.972	.975	10

Inter-Item Correlation Matrix

	HCE01	HCE02	HCE03	HCE04	HCE05	HCE06	HCE07	HCE08	HCE09	HCE10
HCE01	1.000	.895	.688	.659	.639	.746	.811	.895	.895	.895
HCE02	.895	1.000	.688	.639	.845	.803	.892	1.000	1.000	1.000
HCE03	.688	.688	1.000	.539	.539	.750	.707	.688	.688	.688
HCE04	.659	.639	.539	1.000	.742	.651	.826	.639	.639	.639
HCE05	.639	.845	.539	.742	1.000	.763	.889	.845	.845	.845
HCE06	.746	.803	.750	.651	.763	1.000	.884	.803	.803	.803
HCE07	.811	.892	.707	.826	.889	.884	1.000	.892	.892	.892
HCE08	.895	1.000	.688	.639	.845	.803	.892	1.000	1.000	1.000
HCE09	.895	1.000	.688	.639	.845	.803	.892	1.000	1.000	1.000
HCE10	.895	1.000	.688	.639	.845	.803	.892	1.000	1.000	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HCE01	15.67	36.250	.867	.	.969
HCE02	15.56	35.528	.959	.	.966
HCE03	15.11	39.611	.715	.	.974
HCE04	15.00	35.500	.723	.	.976
HCE05	15.22	34.194	.857	.	.971
HCE06	15.33	37.000	.853	.	.970
HCE07	15.44	35.778	.956	.	.966
HCE08	15.56	35.528	.959	.	.966
HCE09	15.56	35.528	.959	.	.966
HCE10	15.56	35.528	.959	.	.966

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17.11	44.361	6.660	10

Intraclass Correlation Coefficient

	Intraclass Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.729[a]	.516	.912	35.665	8	72	.000
Average Measures	.964[c]	.914	.990	35.665	8	72	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type A intraclass correlation coefficients using an absolute agreement definition.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Reliability Analysis for Expert Evaluation of Fuzzy Rules of Subsystem III

```
GET
  FILE='\\Client\C$\SPSS\System 3.sav'.
DATASET NAME DataSet3 WINDOW=FRONT.
RELIABILITY
  /VARIABLES=HCE01 HCE02 HCE03 HCE04 HCE05 HCE06 HCE07 HCE08 HCE09 HCE10
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL
  /ICC=MODEL(MIXED) TYPE(ABSOLUTE) CIN=95 TESTVAL=0.
```

Reliability

```
[DataSet3] \\Client\C$\SPSS\System 3.sav
```

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	36	100.0
	Excluded[a]	0	.0
	Total	36	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.975	.975	10

Inter-Item Correlation Matrix

	HCE01	HCE02	HCE03	HCE04	HCE05	HCE06	HCE07	HCE08	HCE09	HCE10
HCE01	1.000	.764	.822	.724	.799	.838	.697	.577	.815	.776
HCE02	.764	1.000	.886	.838	.903	.833	.834	.750	.898	.884
HCE03	.822	.886	1.000	.758	.869	.892	.824	.697	.847	.842
HCE04	.724	.838	.758	1.000	.853	.764	.786	.603	.743	.751
HCE05	.799	.903	.869	.853	1.000	.825	.823	.708	.840	.842
HCE06	.838	.833	.892	.764	.825	1.000	.866	.706	.825	.863
HCE07	.697	.834	.824	.786	.823	.866	1.000	.706	.784	.875
HCE08	.577	.750	.697	.603	.708	.706	.706	1.000	.758	.753
HCE09	.815	.898	.847	.743	.840	.825	.784	.758	1.000	.881
HCE10	.776	.884	.842	.751	.842	.863	.875	.753	.881	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HCE01	22.47	66.999	.831	.813	.974
HCE02	22.64	62.066	.936	.917	.970
HCE03	22.72	63.978	.916	.880	.971
HCE04	22.42	65.450	.832	.790	.974
HCE05	22.94	64.797	.919	.877	.971
HCE06	22.64	62.066	.911	.885	.971
HCE07	23.06	63.997	.885	.851	.972
HCE08	22.72	66.206	.759	.646	.976
HCE09	22.58	63.793	.909	.876	.971
HCE10	22.81	63.533	.921	.880	.971

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
25.22	79.149	8.897	10

Intraclass Correlation Coefficient

	Intraclass Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.770[a]	.673	.856	40.119	35	315	.000
Average Measures	.971[c]	.954	.983	40.119	35	315	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type A intraclass correlation coefficients using an absolute agreement definition.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Reliability Analysis for Expert Evaluation of Fuzzy Rules of Subsystem IV

```
RELIABILITY
  /VARIABLES=HCE01 HCE02 HCE03 HCE04 HCE05 HCE06 HCE07 HCE08 HCE09 HCE10
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL
  /ICC=MODEL(MIXED) TYPE(ABSOLUTE) CIN=95 TESTVAL=0.
```

Reliability

```
[DataSet4] \\Client\C$\SPSS\System 4.sav
```

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	80	100.0
	Excluded[a]	0	.0
	Total	80	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.973	.974	10

Inter-Item Correlation Matrix

	HCE01	HCE02	HCE03	HCE04	HCE05	HCE06	HCE07	HCE08	HCE09	HCE10
HCE01	1.000	.735	.664	.744	.859	.828	.806	.786	.813	.800
HCE02	.735	1.000	.809	.672	.756	.785	.822	.814	.798	.825
HCE03	.664	.809	1.000	.629	.688	.669	.779	.737	.786	.758
HCE04	.744	.672	.629	1.000	.854	.811	.748	.698	.776	.696
HCE05	.859	.756	.688	.854	1.000	.854	.831	.794	.855	.819
HCE06	.828	.785	.669	.811	.854	1.000	.833	.816	.842	.817
HCE07	.806	.822	.779	.748	.831	.833	1.000	.866	.879	.855
HCE08	.786	.814	.737	.698	.794	.816	.866	1.000	.855	.859
HCE09	.813	.798	.786	.776	.855	.842	.879	.855	1.000	.877
HCE10	.800	.825	.758	.696	.819	.817	.855	.859	.877	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HCE01	31.18	68.855	.866	.787	.970
HCE02	30.65	65.977	.859	.796	.971
HCE03	30.89	71.519	.796	.729	.973
HCE04	30.74	68.778	.812	.769	.972
HCE05	30.70	65.327	.903	.869	.969
HCE06	30.84	69.404	.897	.834	.969
HCE07	30.91	68.866	.917	.852	.969
HCE08	30.81	69.268	.890	.823	.970
HCE09	30.76	68.133	.925	.871	.968
HCE10	30.78	68.683	.901	.843	.969

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
34.25	84.291	9.181	10

Intraclass Correlation Coefficient

	Intraclass Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.769[a]	.706	.828	36.989	79	711	.000
Average Measures	.971[c]	.960	.980	36.989	79	711	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type A intraclass correlation coefficients using an absolute agreement definition.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Reliability Analysis for Expert Evaluation of All Fuzzy Rules

```
RELIABILITY
  /VARIABLES=HCE01 HCE02 HCE03 HCE04 HCE05 HCE06 HCE07 HCE08 HCE09 HCE10
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL
  /ICC=MODEL(MIXED) TYPE(ABSOLUTE) CIN=95 TESTVAL=0.
```

Reliability

```
[DataSet4] \\Client\C$\SPSS\Whole System.sav
```

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	137	100.0
	Excluded[a]	0	.0
	Total	137	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.979	.979	10

Inter-Item Correlation Matrix

	HCE01	HCE02	HCE03	HCE04	HCE05	HCE06	HCE07	HCE08	HCE09	HCE10
HCE01	1.000	.756	.745	.741	.802	.832	.773	.757	.836	.799
HCE02	.756	1.000	.858	.727	.830	.843	.867	.842	.871	.877
HCE03	.745	.858	1.000	.711	.794	.824	.851	.788	.855	.839
HCE04	.741	.727	.711	1.000	.844	.800	.757	.733	.792	.760
HCE05	.802	.830	.794	.844	1.000	.865	.861	.819	.871	.863
HCE06	.832	.843	.824	.800	.865	1.000	.878	.828	.879	.871
HCE07	.773	.867	.851	.757	.861	.878	1.000	.852	.880	.890
HCE08	.757	.842	.788	.733	.819	.828	.852	1.000	.874	.883
HCE09	.836	.871	.855	.792	.871	.879	.880	.874	1.000	.914
HCE10	.799	.877	.839	.760	.863	.871	.890	.883	.914	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HCE01	27.66	91.565	.846	.748	.978
HCE02	27.43	86.026	.904	.842	.977
HCE03	27.53	91.545	.877	.802	.977
HCE04	27.34	91.445	.824	.739	.979
HCE05	27.51	86.531	.914	.856	.976
HCE06	27.50	89.164	.923	.860	.976
HCE07	27.66	88.460	.923	.867	.976
HCE08	27.52	90.266	.892	.821	.977
HCE09	27.45	88.485	.944	.899	.975
HCE10	27.53	88.515	.934	.890	.975

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
30.57	109.865	10.482	10

Intraclass Correlation Coefficient

	Intraclass Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.817[a]	.777	.854	47.088	136	1224	.000
Average Measures	.978[c]	.972	.983	47.088	136	1224	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type A intraclass correlation coefficients using an absolute agreement definition.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Expert Consensus Rate on Consequences of Fuzzy Conditions of Subsystem I

Rule Code	Very Low	Low	Medium	High	Very High	Total	Consensus Rate
FLS1-01	8	2				10	80%
FLS1-02	3	6	1			10	60%
FLS1-03	1	1	7	1		10	70%
FLS1-04		8	2			10	80%
FLS1-05		1	9			10	90%
FLS1-06			1	9		10	90%
FLS1-07		1	8		1	10	80%
FLS1-08		2	8			10	80%
FLS1-09				6	4	10	60%
FLS1-10			6	4		10	60%
FLS1-11				10		10	100%
FLS1-12					10	10	100%
Total	12	21	42	30	15	120	79%

Expert Consensus Rate on Consequences of Fuzzy Conditions of Subsystem II

Rule Code	Inadequate	Partially adequate	Adequate	Total	Consensus Rate
FLS2-01	10			10	100%
FLS2-02	8	2		10	80%
FLS2-03	5	4	1	10	50%
FLS2-04	9	1		10	90%
FLS2-05		9	1	10	90%
FLS2-06		8	2	10	90%
FLS2-07	8	2		10	80%
FLS2-08	1	8	1	10	80%
FLS2-09			10	10	100%
FLS2-10	41	34	15	90	84%

Expert Consensus Rate on Consequences of Fuzzy Conditions of Subsystem III

Rule Code	Low	Medium	High	Very High	Total	Consensus Rate
FLS3-01	8	2			10	80%
FLS3-02	5	4	1		10	50%
FLS3-03	2	1	7		10	70%
FLS3-04	1	7	2		10	70%
FLS3-05		4	6		10	60%
FLS3-06			8	2	10	80%
FLS3-07		2	8		10	80%
FLS3-08		2	6	2	10	60%
FLS3-09				10	10	100%
FLS3-10			7	3	10	70%
FLS3-11			6	4	10	60%
FLS3-12			1	9	10	90%
FLS3-13	9	1			10	90%
FLS3-14	6	4			10	60%
FLS3-15	1	7	2		10	70%
FLS3-16	4	6			10	60%
FLS3-17		7	3		10	70%
FLS3-18		3	7		10	70%
FLS3-19		8	2		10	80%
FLS3-20			10		10	100%
FLS3-21			3	7	10	70%
FLS3-22		4	6		10	60%
FLS3-23			8	2	10	80%
FLS3-24				10	10	100%
FLS3-25	9			1	10	90%
FLS3-26	10				10	100%
FLS3-27	3	7			10	70%
FLS3-28	8	2			10	80%
FLS3-29		9	1		10	90%
FLS3-30		6	4		10	60%
FLS3-31		10			10	100%
FLS3-32		2	8		10	80%
FLS3-33			7	3	10	70%
FLS3-34		7	3		10	70%
FLS3-35			7	3	10	70%
FLS3-36			1	9	10	90%
Total	66	105	124	65	360	76%

Expert Consensus Rate on Consequences of Fuzzy Conditions of Subsystem IV

Rule Code	Insignificant	Low	Medium	High	Extreme	Total	Consensus Rate
FLS4-01	10					10	100%
FLS4-02	6	3	1			10	60%
FLS4-03		10				10	10%
FLS4-04		2	7	1		10	70%
FLS4-05	2	8				10	80%
FLS4-06		8	2			10	80%
FLS4-07			10			10	100%
FLS4-08			7	3		10	70%
FLS4-09		3	7			10	70%
FLS4-10			8	2		10	80%
FLS4-11			4	6		10	60%
FLS4-12			1	7	2	10	70%
FLS4-13		1	8	1		10	80%
FLS4-14			4	6		10	60%
FLS4-15			1	6	3	10	60%
FLS4-16				5	5	10	50%
FLS4-17	8	2				10	80%
FLS4-18	2	8				10	80%
FLS4-19		8	2			10	80%
FLS4-20		2	7	1		10	70%
FLS4-21	2	6	2			10	60%
FLS4-22		5	5			10	50%
FLS4-23		1	8	1		10	80%
FLS4-24			7	3		10	70%
FLS4-25		1	9			10	90%
FLS4-26			9	1		10	90%
FLS4-27			3	7		10	70%
FLS4-28			2	6	2	10	60%
FLS4-29		4	5	1		10	50%
FLS4-30			7	3		10	70%
FLS4-31			1	8	1	10	80%
FLS4-32				6	4	10	60%
FLS4-33	3	7				10	70%
FLS4-34		7	3			10	70%
FLS4-35		2	8			10	80%
FLS4-36			3	7		10	70%
FLS4-37		3	7			10	70%
FLS4-38			9	1		10	90%
FLS4-39			7	3		10	70%

FLS4-40			3	6	1	10	60%
FLS4-41			3	7		10	70%
FLS4-42			3	6	1	10	60%
FLS4-43			1	8	1	10	80%
FLS4-44				6	4	10	60%
FLS4-45			3	7		10	70%
FLS4-46			5	4	1	10	50%
FLS4-47				8	2	10	80%
FLS4-48				6	4	10	60%
FLS4-49		5	5			10	50%
FLS4-50		1	9			10	90%
FLS4-51			4	6		10	60%
FLS4-52			5	5		10	50%
FLS4-53		1	6	3		10	60%
FLS4-54			6	3	1	10	60%
FLS4-55			2	6	2	10	60%
FLS4-56				7	3	10	70%
FLS4-57			5	5		10	50%
FLS4-58			2	7	1	10	70%
FLS4-59				9	1	10	90%
FLS4-60				2	8	10	80%
FLS4-61			3	6	1	10	60%
FLS4-62			1	8	1	10	80%
FLS4-63				4	6	10	60%
FLS4-64					10	10	100%
FLS4-65		2	8			10	80%
FLS4-66			10			10	100%
FLS4-67			8	2		10	80%
FLS4-68			7	1	2	10	70%
FLS4-69			8	2		10	80%
FLS4-70			1	8	1	10	80%
FLS4-71			1	7	2	10	70%
FLS4-72				5	5	10	50%
FLS4-73			1	7	2	10	70%
FLS4-74			1	4	5	10	50%
FLS4-75				2	8	10	80%
FLS4-76					10	10	100%
FLS4-77			1	8	1	10	80%
FLS4-78				5	5	10	50%
FLS4-79				1	9	10	90%
FLS4-80					10	10	100%
Total	33	100	276	266	125	800	71%

APPENDIX L FUZZY LOGIC COMPUTER CODING

Fuzzy Logic Subsystem I (ED Demand Status)

```
(IOM, 2007)
Name='Demand'
Type='mamdani'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=12
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Patient-Demand'
Range=[0 2]
NumMFs=4
MF1='Low':'trapmf',[0 0 0.2 0.5]
MF2='Medium':'trapmf',[0.2 0.5 0.6 0.8]
MF3='High':'trapmf',[0.6 0.8 0.9 1.2]
MF4='Very-High':'trapmf',[0.9 1.2 2 2]

[Input2]
Name='Patient-Complexity'
Range=[1 5]
NumMFs=3
MF1='Low':'trapmf',[1 1 2 2.5]
MF2='Medium':'trapmf',[2 2.5 3.5 4]
MF3='High':'trapmf',[3.5 4 5 5]

[Output1]
Name='ED-Demand'
Range=[0 100]
NumMFs=5
MF1='Very-Low':'trimf',[0 0 25]
MF2='Low':'trimf',[0 25 50]
MF3='Medium':'trimf',[25 50 75]
MF4='High':'trimf',[50 75 100]
MF5='Very-High':'trimf',[75 100 100]

[Rules]
1 1, 1 (1) : 1
1 2, 2 (1) : 1
1 3, 3 (1) : 1
2 1, 2 (1) : 1
2 2, 3 (1) : 1
2 3, 4 (1) : 1
3 1, 3 (1) : 1
3 2, 4 (1) : 1
3 3, 5 (1) : 1
4 1, 3 (1) : 1
```

```
4 2, 4 (1) : 1
4 3, 5 (1) : 1
```

Fuzzy Logic Subsystem II (ED Staffing Status)

```
(IOM, 2007)
Name='Staffing'
Type='mamdani'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Physician-Staffing'
Range=[0 0.32]
NumMFs=3
MF1='Inadequate':'trapmf',[0 0 0.06 0.12]
MF2='Partially-Adequate':'trapmf',[0.06 0.12 0.16 0.24]
MF3='Adequate':'trapmf',[0.16 0.24 0.32 0.32]

[Input2]
Name='Nurse-Staffing'
Range=[0 0.5]
NumMFs=3
MF1='Inadequate':'trapmf',[0 0 0.08 0.18]
MF2='Partially-Adequate':'trapmf',[0.08 0.18 0.24 0.32]
MF3='Adequate':'trapmf',[0.24 0.32 0.5 0.5]

[Output1]
Name='ED-Staffing'
Range=[0 100]
NumMFs=3
MF1='Inadequate':'trapmf',[0 0 25 35]
MF2='Partially-Adequate':'trapmf',[25 35 65 75]
MF3='Adequate':'trapmf',[65 75 100 100]

[Rules]
1 1, 1 (1) : 1
1 2, 1 (1) : 1
1 3, 1 (1) : 1
2 1, 1 (1) : 1
2 2, 2 (1) : 1
2 3, 2 (1) : 1
3 1, 1 (1) : 1
3 2, 2 (1) : 1
3 3, 3 (1) : 1
```

Fuzzy Logic Subsystem III (ED Staffing Status)

```
(IOM, 2007)
Name='WorkloadV.100'
Type='mamdani'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=36
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='ED-Staffing'
Range=[0 100]
NumMFs=3
MF1='Iadequate':'trapmf',[0 0 25 35]
MF2='Partially-Adequate':'trapmf',[25 35 65 75]
MF3='Adequate':'trapmf',[65 75 100 100]

[Input2]
Name='ER-Occupancy-Rate'
Range=[0 100]
NumMFs=4
MF1='Low':'trapmf',[0 0 20 35]
MF2='Medium':'trapmf',[20 35 45 65]
MF3='High':'trapmf',[45 65 70 90]
MF4='Very-High':'trapmf',[70 90 100 100]

[Input3]
Name='Patient-Complexity'
Range=[1 5]
NumMFs=3
MF1='Low':'trapmf',[1 1 2 2.5]
MF2='Medium':'trapmf',[2 2.5 3.5 4]
MF3='High':'trapmf',[3.5 4 5 5]

[Output1]
Name='ED-Workload'
Range=[0 100]
NumMFs=4
MF1='Low':'trimf',[0 0 33.34]
MF2='Medium':'trimf',[0 33.34 66.67]
MF3='High':'trimf',[33.34 66.67 100]
MF4='Very-High':'trimf',[66.67 100 100]

[Rules]
1 1 1, 1 (1) : 1
1 1 2, 1 (1) : 1
```

```
1 1 3, 3 (1) : 1
1 2 1, 2 (1) : 1
1 2 2, 3 (1) : 1
1 2 3, 3 (1) : 1
1 3 1, 3 (1) : 1
1 3 2, 3 (1) : 1
1 3 3, 4 (1) : 1
1 4 1, 3 (1) : 1
1 4 2, 3 (1) : 1
1 4 3, 4 (1) : 1
2 1 1, 1 (1) : 1
2 1 2, 1 (1) : 1
2 1 3, 2 (1) : 1
2 2 1, 2 (1) : 1
2 2 2, 2 (1) : 1
2 2 3, 3 (1) : 1
2 3 1, 2 (1) : 1
2 3 2, 3 (1) : 1
2 3 3, 4 (1) : 1
2 4 1, 3 (1) : 1
2 4 2, 3 (1) : 1
2 4 3, 4 (1) : 1
3 1 1, 1 (1) : 1
3 1 2, 1 (1) : 1
3 1 3, 2 (1) : 1
3 2 1, 1 (1) : 1
3 2 2, 2 (1) : 1
3 2 3, 2 (1) : 1
3 3 1, 2 (1) : 1
3 3 2, 3 (1) : 1
3 3 3, 3 (1) : 1
3 4 1, 2 (1) : 1
3 4 2, 3 (1) : 1
3 4 3, 4 (1) : 1
```

Fuzzy Logic Subsystem IV (ED Staffing Status)

```
(IOM, 2007)
Name='CrowdingV.101'
Type='mamdani'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=80
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Demand'
Range=[0 100]
NumMFs=5
MF1='Very-Low':'trimf',[0 0 25]
MF2='Low':'trimf',[0 25 50]
MF3='Medium':'trimf',[25 50 75]
MF4='High':'trimf',[50 75 100]
MF5='Very-High':'trimf',[75 100 100]

[Input2]
Name='Workload'
Range=[0 100]
NumMFs=4
MF1='Low':'trimf',[0 0 33.34]
MF2='Medium':'trimf',[0 33.34 66.67]
MF3='High':'trimf',[33.34 66.67 100]
MF4='Very-High':'trimf',[66.67 100 100]

[Input3]
Name='Boarding'
Range=[0 0.4]
NumMFs=4
MF1='Low':'trapmf',[0 0 0.04 0.12]
MF2='Medium':'trapmf',[0.04 0.12 0.16 0.24]
MF3='High':'trapmf',[0.16 0.24 0.26 0.32]
MF4='Very-High':'trapmf',[0.26 0.32 0.4 0.4]

[Output1]
Name='Crowding'
Range=[0 100]
NumMFs=5
MF1='Insignificant':'trimf',[0 0 25]
MF2='Low':'trimf',[0 25 50]
MF3='Medium':'trimf',[25 50 75]
MF4='High':'trimf',[50 75 100]
MF5='Extreme':'trimf',[75 100 100]
```

```
[Rules]
1 1 1, 1 (1) : 1
1 1 2, 1 (1) : 1
1 1 3, 2 (1) : 1
1 1 4, 3 (1) : 1
1 2 1, 2 (1) : 1
1 2 2, 2 (1) : 1
1 2 3, 3 (1) : 1
1 2 4, 3 (1) : 1
1 3 1, 3 (1) : 1
1 3 2, 3 (1) : 1
1 3 3, 4 (1) : 1
1 3 4, 4 (1) : 1
1 4 1, 3 (1) : 1
1 4 2, 4 (1) : 1
1 4 3, 4 (1) : 1
1 4 4, 4 (1) : 1
2 1 1, 1 (1) : 1
2 1 2, 2 (1) : 1
2 1 3, 2 (1) : 1
2 1 4, 3 (1) : 1
2 2 1, 2 (1) : 1
2 2 2, 2 (1) : 1
2 2 3, 3 (1) : 1
2 2 4, 3 (1) : 1
2 3 1, 3 (1) : 1
2 3 2, 3 (1) : 1
2 3 3, 4 (1) : 1
2 3 4, 4 (1) : 1
2 4 1, 3 (1) : 1
2 4 2, 3 (1) : 1
2 4 3, 4 (1) : 1
2 4 4, 4 (1) : 1
3 1 1, 2 (1) : 1
3 1 2, 2 (1) : 1
3 1 3, 3 (1) : 1
3 1 4, 3 (1) : 1
3 2 1, 3 (1) : 1
3 2 2, 3 (1) : 1
3 2 3, 3 (1) : 1
3 2 4, 4 (1) : 1
3 3 1, 3 (1) : 1
3 3 2, 4 (1) : 1
3 3 3, 4 (1) : 1
3 3 4, 4 (1) : 1
3 4 1, 4 (1) : 1
3 4 2, 3 (1) : 1
3 4 3, 4 (1) : 1
3 4 4, 4 (1) : 1
4 1 1, 2 (1) : 1
4 1 2, 3 (1) : 1
4 1 3, 3 (1) : 1
4 1 4, 4 (1) : 1
4 2 1, 3 (1) : 1
4 2 2, 3 (1) : 1
4 2 3, 4 (1) : 1
```

```
4 2 4, 4 (1) : 1
4 3 1, 3 (1) : 1
4 3 2, 4 (1) : 1
4 3 3, 4 (1) : 1
4 3 4, 5 (1) : 1
4 4 1, 4 (1) : 1
4 4 2, 4 (1) : 1
4 4 3, 5 (1) : 1
4 4 4, 5 (1) : 1
5 1 1, 3 (1) : 1
5 1 2, 3 (1) : 1
5 1 3, 3 (1) : 1
5 1 4, 3 (1) : 1
5 2 1, 3 (1) : 1
5 2 2, 4 (1) : 1
5 2 3, 4 (1) : 1
5 2 4, 4 (1) : 1
5 3 1, 4 (1) : 1
5 3 2, 5 (1) : 1
5 3 3, 5 (1) : 1
5 3 4, 5 (1) : 1
5 4 1, 4 (1) : 1
5 4 2, 5 (1) : 1
5 4 3, 5 (1) : 1
5 4 4, 5 (1) : 1
```

APPENDIX M GIEDOC VALIDATION DATA SHEET

Hospital Capacity	
ED Capacity	

Observation No.	No. of Patients in Waiting Area	Patient Complexity (Waiting Area)	No. of ED Physicians	No. of ED Nurses	No. of Patients in Emergency Room	Patient Complexity (Emergency Room)	No. of Patients in Boarding Area	Expert Assessment of Crowding Level *1= Insignificant* *2= Low* *3= Medium* *4= High* *5= Extreme*
1								
2								
3								
4								
5								
6								
7								
8								
9								
10								
11								
12								
13								
14								
15								
16								
17								
18								
19								
20								
21								
22								
23								
24								

APPENDIX N GIEDOC RELIABILITY ANALYSIS

CROSSTAB

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
GIEDOC * Expert	24	100.0%	0	0.0%	24	100.0%

GIEDOC * Expert Crosstabulation

Count

		Expert			Total
		2	3	4	
GIEDOC	2	2	2	0	4
	3	1	11	3	15
	4	0	0	5	5
Total		3	13	8	24

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	.562	.152	3.772	.000
N of Valid Cases		24			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

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