# Primary Healthcare Staffing Needs Assessment—

# A Discrete Event Simulation Study

Tolulope Abe

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Kenneth Sherr

Richard Storch

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**Abstract**

Primary Healthcare Staffing Needs Assessment—
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Tolulope Abe

Chair of the Supervisory Committee:
Associate Professor Kenneth Sherr
Global Health

*Background:* Mozambique has a shortage of primary healthcare workers, effecting the quality of primary healthcare delivery. The specific aim of the proposed research is utilizing Industrial & Systems Engineering methods, specifically discrete event simulation, to identify strategies to improve primary healthcare delivery system performance in the Sofala Province of Mozambique. To improve primary healthcare delivery and assist facility-level management with decision-making, the research team decided to study staffing level effects on patient waiting time and develop a decision support tool that determines staffing level needs to maintain an average total wait time of less than 60minutes.

*Methods:* A discrete event simulation study was performed to model primary healthcare facility delivery systems using Arena Simulation software. What-if scenario experiments testing the impact health worker staffing level and patient demand fluctuations have on patient waiting time were designed using Statistical Analysis Software, and the experimental runs were performed using Arena Simulation Process Analyzer application. Minitab was used to perform a regression analysis to find mathematical models of wait time as a function of patient demand and staffing levels.

*Results:* The mathematical relationship of health worker staffing and patient demand levels with average patient wait time was estimated using regression analysis. The number of staff required to provide services was the aggregate of staffing needed for all patient types of a given facility. This approach produced staffing and wait time results that could not be validated and used to create a spreadsheet-based decision support tool.

*Conclusion:* The spreadsheet-based decision support tool aimed to bridge the gap between industrial and systems engineering methods and healthcare stakeholder knowledge of these methods while promoting implementation by allowing decision makers to perform simulations through a user-friendly tool. Although the proposed approach described in this study could not be validated, this method is beneficial when attempting to evaluate performance improvement strategy impacts on measures of performance. To create the spreadsheet-based decision support tool, it is recommended that an alternative approach be used to determine the relationship between wait time, patient demand, and staffing levels, such as queuing analysis.

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| | |
|---|---|
| ANC | Antenatal Care |
| DDCF | Doris Duke Charitable Foundation |
| DES | Discrete Event Simulation |
| GHI | Global Health Initiatives |
| HAI | Health Alliance International |
| ISE | Industrial and Systems Engineering |
| MOH | Ministry of Health |
| PAN | Process Analyzer |
| PHC | Primary Healthcare |
| RH | Rural Hospital |
| RHC | Rural Health Center |
| SAS | Statistical Analysis Software |
| UEM | University of Eduardo Mondlane |
| UHC | Urban Health Center |
| WHO | World Health Organization |
| WISN | Workload Indicators of Staffing Need |

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# DEDICATION

To Dad, Mom, James, & Michael

## Introduction

In Mozambique, the mission to understand complex primary healthcare (PHC) delivery systems is a complicated task partially due to human and technical resource shortages. One critical issue with PHC delivery systems, in developing countries especially, is health worker shortages. Since 2000, Global Health Initiatives (GHIs) have been developed and implemented to control the spread of communicable diseases and stren

Tanzania [6], India [7], Papua New Guinea [8], and East Africa [9]. Since facility, district, provincial, and national workload data may not be readily available, observational data collection, focus groups, and interviews with the assistance of doctors and nurses is required [5]. This can be a time-consuming process that interferes with accurate data collection while providing quality patient care.

In addition to WHO's WISN based calculations, Industrial & Systems Engineering (ISE) methods have been used to evaluate and manage staffing levels. ISE is defined as an engineering discipline:

> …concerned with the design, improvement, and installation of integrated systems of men, materials, and equipment. It draws upon specialized knowledge and skill in the mathematical, physical, and social sciences, together with the principles and methods of engineering analysis and design, to specify, predict and evaluate the results to be obtained from such systems [10].

Interdisciplinary teams consisting of health care stakeholders, frontline workers, and industrial & systems engineers have collaborated to apply ISE methods to manufacturing and service industries. Per work published between 2000-2014 describing ISE applications to the hospital setting in the Americas and Europe, the most common ISE methods that have been used to evaluate and manage staffing levels are deterministic modeling [11-59] and discrete event simulation [19, 33, 46, 60-77]. Compared to WISN, simulation and optimization models may require a greater amount of detailed data to be collected in order to analyze health worker needs. As these systems grow increasingly complex, accurate modeling tools require a greater deal of time and effort to create, validate, and verify [78]. Despite this, the aforementioned ISE methods remain powerful tools when analyzing complex health care systems.

Although ISE methods have been used in the healthcare industry of several industrialized countries, methods have been slower to spread in the healthcare industry of developing countries. This can be attributed to the lack of ISE awareness and knowledge. Another limitation of healthcare systems in both developed and developing countries is the ability to implement evidence-based performance improvement strategies. For simulation studies specifically, Brailsford suggests that overcoming this research challenge is based on the ability to balance a user-friendly simulation model with “scientific rigor and validity”. When describing the successful implementation of performance improvement strategies evaluated during a simulation study at a UK Hospital, he credits “the simplicity and interactive nature of the model” as a key factor for implementation [79].

The specific research question this study aims to answer is *how can discrete event simulation methods be used to determine primary healthcare staffing levels?* The objective of this study is to provide a description of a simulation study used to develop a decision support tool that determines healthcare staffing levels for PHC facilities in the Sofala Province in Mozambique. This study aims to provide 1) an industrial & systems engineering application in the primary health care setting and 2) a decision support tool to overcome user-friendliness barriers experienced when implementing improvement strategies observed during a simulation study. The spreadsheet-based decision support tool bridges the gap between ISE methods and PHC stakeholder and frontline staff knowledge of these methods.

**Methods**

The study method used to develop the PHC simulation model was based on a simulation study framework, illustrated in Figure 1 [80]. The steps in orange signify collaboration amongst simulation developers and PHC delivery system experts, while the steps in blue signify steps performed by simulation developers during this study. The chosen simulation method was discrete event simulation (DES). DES was chosen due to its advantages, which “stems from its flexibility, as well as the ability to handle variability, uncertainty, and complexity. It allows for an assessment of efficiency of a given system, performance of the ‘what-if’ analysis, as well as the possibility to design a new system” [81].

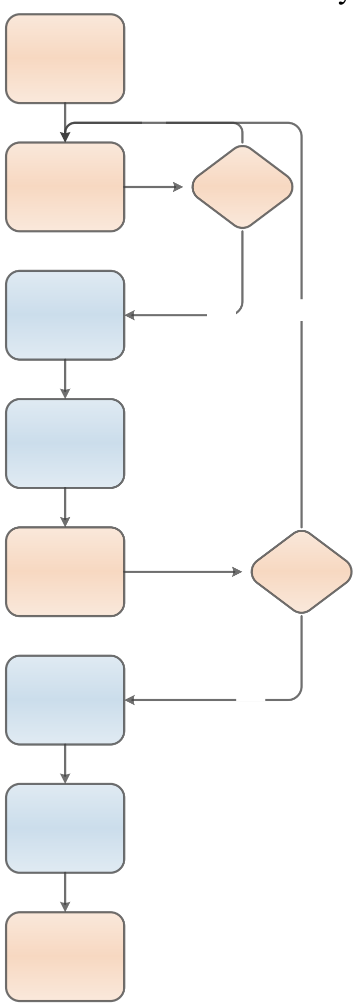


Figure 1. Simulation Study Framework

The following method subsections based on the simulation study framework steps describe the simulation study and spreadsheet-based decision support tool development.

*Formulate Problem & Plan Study*

To formulate the problem, the research team first set the objectives of the study: 1) strengthen integrated health systems management; 2) develop appropriate tools to facilitate decision-making; and 3) build capacity for conducting innovative ISE studies and operations research to guide system-strengthening efforts. In order to meet these objectives, the project team proposed the development of a DES to study the relationship between patient demand, health worker volume, and average total patient wait time in the PHC setting.  Average total patient wait time, the main performance measure of the study, is defined as the total amount of time a patient waits for services during a single PHC visit—from the time a patient arrives to a facility to the time that the patient leaves the facility—averaged for all patients of a given type.

Due to its poor health outcomes and high HIV prevalence, Sofala province was selected as the setting for this study. Sofala province has a variety of healthcare facilities offering different healthcare services. A simplifying assumption was that the majority of PHC services are sought from rural hospitals (RH), rural health centers (RHC), and urban health centers (UHC). The types of patients who typically seek PHC services at these facilities include adults receiving outpatient consultations, children receiving immunizations and/or outpatient consultations, and pregnant women receiving their first antenatal care. Additionally, laboratory and pharmacy services are available at each of the three facility types.

*Define Model & Collect Data*

A time study and health worker interviews were performed to collect service time data and define the conceptual model. The target population during the study were all patients who visit a rural health center, urban health center or rural hospital in the Sofala Province of Mozambique for PHC services. It was assumed that these patients were commonly adult and pediatric outpatients, some of whom require immunizations (well child patients), and pregnant patients seeking their first antenatal care visit (1$^{st}$ ANC patients). Data collection was performed on selected days during January – April 2011. To perform the on-site time study, data collectors were stationed at each service area and documented the start and end times for each service provided by health workers and times between services. Due to the limited number of data collectors, data was collected on two-four separate days, typically during the morning. Based on the data collected, the following is the margin of error for each patient type at each facility where data was collected (Appendix A). Table 1 shows the sample size and margin of error (95% confidence level) for each service at each health facility.

Table 1. Data Collection Sample Size and Corresponding Margin of Error

| | Outpatient | | | Well Child | | | Antenatal | | | Laboratory | | | Pharmacy | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rural Health Center | 63 | 30.70 | 7.58 | 34 | 5.20 | 1.75 | 27 | 13.49 | 5.09 | 90 | 6.06 | 1.25 | 176 | 9.39 | 1.39 |
| Urban Health Center | 50 | 27.81 | 7.71 | 79 | 40.68 | 8.97 | 61 | 28.71 | 7.20 | 219 | 14.10 | 1.87 | 162 | 9.87 | 1.52 |
| Rural Hospital | 54 | 20.17 | 5.38 | 56 | 46.75 | 12.24 | 56 | 40.47 | 10.60 | 197 | 17.54 | 2.45 | 286 | 27.21 | 3.15 |

The sample size (n) for each service ranged from 27 to 286 observations, while the margin of error (E) ranged from 1.25 to 12.24 (assuming the sample is normally distributed).  This may mean that the sample collected for outpatient, well child, and antenatal services did not accurately represent the population of patients who seek these services.

A conceptual model in the form of a basic process flow map (Appendix B) and list of assumptions (Appendix C) was created using the information gathered during the health worker interviews and time study. The basic process flow map illustrates the services each patient type received during a typical visit at each health facility. The list of assumptions provides more detail regarding patient flow, facility operations, and health worker staffing.

*Data Validation*

To validate that the data collected was an accurate representation of the service and waiting time experienced by patients, descriptive statistics of the collected data were presented to PHC frontline staff, managers, and stakeholders. Those who reviewed the data confirmed its accuracy.

*Construct Computer Simulation Model*

Model inputs and patient flow logic are required to construct the DES model. The model inputs for this simulation study were average number of arrivals that occur for each patient type during a workday, the service time probability distributions for each service, the patient flow logic, and the number and type of healthcare workers who provide PHC services. The software used to construct the DES model was Rockwell Automation's Arena® Simulation Software (v13.2).

A 2012 census report was the data source used to estimate the average daily visits for each patient type at each facility. Table 2 indicates the average daily visits used as an input for the model.

Table 2. Average Daily Patient Visits by Patient & Facility Type

| | Average Daily Visits | | |
|---|---|---|---|
| | ‡ | *A* | *A* *A* *A* |
| Rural Health Center | 75 | 17 | 4 |
| Rural Hospital | 351 | 127 | 14 |
| Urban Health Center | 912 | 102 | 19 |

‡

The data collected during the time study was used to determine the service time probability distributions for each service. Arena's® Input Analyzer application was used to find a probability distribution that best fit the observed data. Table 3 displays the service time distributions used in the model, measured in minutes unless otherwise stated.

Table 3. Service Time Probability Distributions by Service & Facility Type

| | Service Time Probability Distribtutions | | |
|---|---|---|---|
| | *A* *A* | *A* | *c* *A* *A* |
| Registration | n/a | Uniform(0,15)† | Uniform(0,15)† |
| Adult Outpatient Consultation | 0.5 + LOGN(3.51, 2.81) | 0.5 + LOGN(7.26, 6.15) | TRIA(0.5, 2.12, 9.5) |
| Pediatric Outpatient & Well Child Oupatient Consultation | 0.5 + LOGN(3.51, 2.81) | 0.5 + LOGN(7.26, 6.15) | TRIA(0.5, 2.12, 9.5) |
| Immunizations | 0.5 + LOGN(1.57, 1.58) | 0.5 + LOGN(4.25, 4.37) | 0.5 + 7 * BETA(0.653, 3.53) |
| Laboratory Services | 0.5 + 35 * BETA(0.525, 2.86) | 0.5 + 56 * BETA(0.649, 2.59) | 0.5 + 53 * BETA(0.71, 1.8) |
| Pharmacy Services Drop Off | Uniform(0.5, 1) | Uniform(0.5, 1) | Uniform(0.5, 1) |
| Pharmacy Service Delivery | Uniform(0.5, 1.5) | Uniform(0.5, 1.5) | Uniform(0.5, 1.5) |
| First Antenatal Care Visit | 1.5 + 19 * BETA(0.831, 1.52) | POIS(8.85) | 1.5 + LOGN(6.6, 8.3) |

† M

The patient flow logic of the model was based on the conceptual model process flow and PHC delivery system assumptions (Appendix B & C). Table 4 displays the number of healthcare workers at each facility based on a report of healthcare workers allocated to each healthcare facility.

Table 4. Healthcare Worker Volumes by Worker & Facility Type

| | Healthcare Worker Types and Volumes | | | |
|---|---|---|---|---|
| | A | A A | A | c A A |
| Registration Agent | A AA A c A A A | n/a | 3 | 1 |
| Outpatient Nurse | A A A | 2 | 14 | 9 |
| Outpatient Doctor | A A A | n/a | 1 | 1 |
| Immunization Agent | A A A A A Afb | 1 | 2 | 2 |
| Antenatal Care Nurse | A A A A | 2 | 5 | 5 |
| Laboratory Worker | A c A | 1 | 2 | 4 |
| Pharmacy Worker | A A | 1 | 3 | 6 |

*Perform a Pilot Run, Verification and Validation*

Once construction of the model was complete, the model was run so that output data could be verified and validated. While constructing the model, patients were "animated", or in other words assigned a picture, so patient flow through a PHC facility could be observed while the model was running to verify the patient logic was correctly constructed in the simulation model. To validate that the simulation model accurately represents the actual PHC delivery services at a given facility, hypothesis tests were performed comparing simulation output data results to actual system results. The performance measure compared for both the actual system and the model was the total time each patient type spends waiting during a visit, which is the performance measure of interest. This measure was not originally collected during the time study, so additional data was collected at each facility where the original data was collected and during the same months in order to minimize variability. Hypothesis testing comparing actual to model average total patient wait time found that the actual and model wait times are statistically different for each patient type at each facility except for 1st ANC patients who received care in a

Urban Health Center (Appendix D & E). This may be a result of the small sample size of the time study data collected due to limited data collection resources. A system expert reviewed and approved the conceptual model and summary wait times and concluded that although the model and time study data are statistically different, they had observed patient wait times in the field similar to the simulation model output. Table 5 summarizes the model output, including average total wait times, approved by the system expert.

Table 5. DES Model Output Validated by System Expert

| | % Requiring Lab and/or Pharmacy | Avg. Daily Arrivals | Avg Daily Departures | % LWBS | Total Wait Time (min) | Total Visit Time (min) |
|---|---|---|---|---|---|---|
| RHC Adult Outpatient | 60 | 53 | 52 | 2% | 184 | 193 |
| RHC Pediatric Outpatient | 45 | 23 | 22 | 4% | 115 | 123 |
| RHC 1st ANC Patient | 10 | 4 | 4 | 0% | 42 | 51 |
| RHC Well Child Patient | 0 | 17 | 17 | 0% | 47 | 50 |
| UHC Adult Outpatient | 60 | 639 | 509 | 20% | 197 | 205 |
| UHC Pediatric Outpatient | 45 | 274 | 186 | 32% | 183 | 190 |
| UHC 1st ANC Patient | 10 | 19 | 19 | 0% | 44 | 53 |
| UHC Well Child Patient | 0 | 102 | 101 | 1% | 242 | 246 |
| RH Adult Outpatient | 60 | 246 | 221 | 10% | 164 | 177 |
| RH Pediatric Outpatient | 45 | 106 | 95 | 10% | 143 | 155 |
| RH 1st ANC Patient | 10 | 14 | 14 | 0% | 42 | 51 |
| RH Well Child Patient | 0 | 127 | 127 | 0% | 160 | 167 |

*Design and Perform Experiments*

Following the validation, the simulation model was used to study what-if scenarios. In order to create the decision support tool that would provide information on the number of healthcare workers required as average daily visits fluctuated while aiming to reduce average total wait time, a simulation modeling experiment was designed. The what-if scenario tests determine average total wait time resulting from varying healthcare worker levels and patient demand. For the varying patient demand, average daily visits were increased by up to 100% and decreased by down to 90% at 10% intervals, making a total of 20 patient demand levels tested, including the current patient demand level (0% increase/decrease). The staffing level range for each type of healthcare worker was set at 6, for this was determined to be a potentially feasible staffing level range that could be fulfilled if necessary. Table 6 features the current and possible staffing minimum and maximum number of healthcare workers for each healthcare worker and facility type.

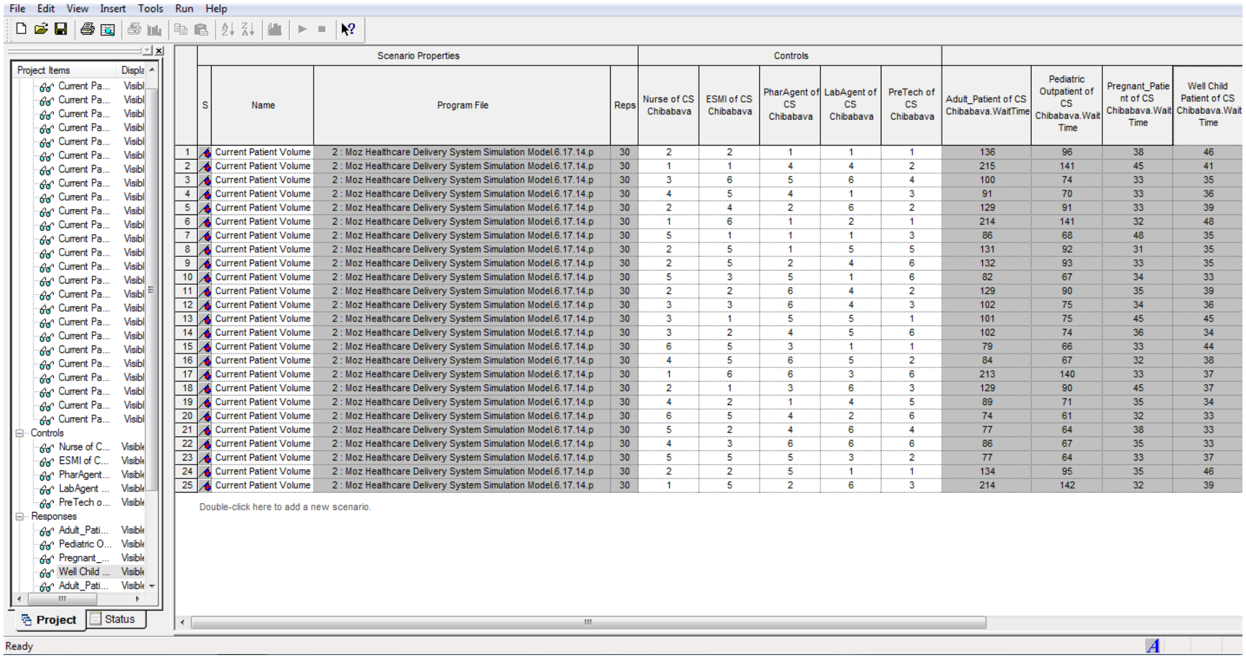
Table 6. Current and What-if Scenario Staffing Levels by Worker and Facility Type

| | Rural Health Center Experiment Staffing Levels | | | Urban Health Center Experiment Staffing Levels | | | Rural Hospital Experiment Staffing Levels | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Current** | **Min** | **Max** | **Current** | **Min** | **Max** | **Current** | **Min** | **Max** |
| Registration Agent (Primary) | n/a | n/a | n/a | 1 | 1 | 6 | 2 | 1 | 6 |
| Registration Agent (Secondary) | n/a | n/a | n/a | n/a | n/a | n/a | 1 | 1 | 6 |
| Outpatient RN | 2 | 1 | 6 | 9 | 7 | 12 | 14 | 12 | 17 |
| Outpatient MD | n/a | n/a | n/a | 1 | 1 | 6 | 1 | 1 | 6 |
| ANC (ESMI) RN | 2 | 1 | 6 | 5 | 3 | 8 | 5 | 3 | 8 |
| Pharm Worker | 1 | 1 | 6 | 6 | 4 | 9 | 3 | 1 | 6 |
| Lab Worker | 1 | 1 | 6 | 4 | 5 | 7 | 2 | 1 | 6 |
| Immunization (Pre) Tech | 1 | 1 | 6 | 2 | 1 | 6 | 2 | 1 | 6 |
| | **5 factors, 6 levels = $6^5$ = 7,776 Experiments** | | | **7 factors, 6 levels = $6^7$ = 279,936** | | | **8 factors, 6 levels = $6^8$ = 1,679,616** | | |

A single experiment is a combination of different levels of each healthcare worker to assess their impact on average total wait time at a specific patient demand level. A full-randomized experiment testing every combination of the staffing levels would require a total of 1,967,328 randomized experiments for each patient demand level at all three facilities. To reduce the number of experiments, balanced orthogonal arrays that would produce the similar statistical conclusions with fewer experiments were found using SAS Statistical Analysis Software (v9.4) (Appendix F-H). A total of 255 experiments for each volume level at all three facilities were designed using SAS.

*Analyze Output Data*

Arena's Process Analyzer (PAN) application was used to perform the what-if scenario experiments. Figure 2 displays an example of the first 25 experiments run in PAN for a Rural Health Center at the current (0% increase/decrease) patient demand level.



| | S | Name | Program File | Reps | Nurse of CS Chibabava | ESMI of CS Chibabava | PharAgent of CS Chibabava | LabAgent of CS Chibabava | PreTech of CS Chibabava | Adult_Patient of CS Chibabava.WaitTime | Pediatric Outpatient of CS Chibabava.Wait Time | Pregnant_Patient of CS Chibabava.Wait Time | Well Child Patient of CS Chibabava.Wait Time |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 2 | 2 | 1 | 1 | 1 | 136 | 96 | 38 | 46 |
| 2 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 1 | 1 | 4 | 4 | 2 | 215 | 141 | 45 | 41 |
| 3 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 3 | 6 | 5 | 6 | 4 | 100 | 74 | 33 | 35 |
| 4 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 4 | 5 | 4 | 1 | 3 | 91 | 70 | 33 | 36 |
| 5 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 2 | 4 | 2 | 6 | 2 | 129 | 91 | 33 | 39 |
| 6 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 1 | 6 | 1 | 2 | 1 | 214 | 141 | 32 | 48 |
| 7 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 5 | 1 | 1 | 1 | 3 | 86 | 68 | 48 | 35 |
| 8 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 2 | 5 | 1 | 5 | 5 | 131 | 92 | 31 | 35 |
| 9 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 2 | 5 | 2 | 4 | 6 | 132 | 93 | 33 | 35 |
| 10 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 5 | 3 | 5 | 1 | 6 | 82 | 67 | 34 | 33 |
| 11 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 2 | 2 | 6 | 4 | 2 | 129 | 90 | 35 | 39 |
| 12 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 3 | 3 | 6 | 4 | 3 | 102 | 75 | 34 | 36 |
| 13 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 3 | 1 | 5 | 5 | 1 | 101 | 75 | 45 | 45 |
| 14 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 3 | 2 | 4 | 5 | 6 | 102 | 74 | 36 | 34 |
| 15 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 6 | 5 | 3 | 1 | 1 | 79 | 66 | 33 | 44 |
| 16 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 4 | 5 | 6 | 5 | 2 | 84 | 67 | 32 | 38 |
| 17 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 1 | 6 | 6 | 3 | 6 | 213 | 140 | 33 | 37 |
| 18 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 2 | 1 | 3 | 6 | 3 | 129 | 90 | 45 | 37 |
| 19 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 4 | 2 | 1 | 4 | 5 | 89 | 71 | 35 | 34 |
| 20 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 6 | 5 | 4 | 2 | 6 | 74 | 61 | 32 | 33 |
| 21 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 5 | 2 | 4 | 6 | 4 | 77 | 64 | 38 | 33 |
| 22 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 4 | 3 | 6 | 6 | 6 | 86 | 67 | 35 | 33 |
| 23 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 5 | 5 | 5 | 3 | 2 | 77 | 64 | 33 | 37 |
| 24 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 2 | 2 | 5 | 1 | 1 | 134 | 95 | 35 | 46 |
| 25 | | Current Patient Volume | 2 : Moz Healthcare Delivery System Simulation Model.6.17.14.p | 30 | 1 | 5 | 2 | 6 | 3 | 214 | 142 | 32 | 39 |

Figure 2. Arena Process ANalyzer (PAN) Example

As shown in figure 2, the controls of the experiment are the combinations of healthcare worker staffing levels in the middle of the figure and the resulting average total wait time for each patient type are the experiment response variables at the right end of the figure. The what-if scenario experiments produced response data that can be used to determine the relationship between average total wait time, healthcare worker levels, and patient demand.

*Document, Present, and Implement Results*

The next step of the study was to create a decision support tool using the resulting what-if scenario experiment data. Once the relationship between average total patient wait time, health worker staffing levels, and patient demand was estimated, the staffing levels could be determined based on predicted average daily visits and a targeted average total patient wait time less than 60min. The aim of developing the decision support tool was to create a user-friendly interface accessible via any computer with Microsoft Excel macros-running capability.

The tool prompts a PHC staffing decision maker to select their given PHC health facility type, specify the expected number of visits for each patient type for an upcoming workday and a targeted average total wait time for all patient types (60min), and the macros outputs the number of healthcare workers based on the staffing level statistical relationship with these criteria (Appendix I).

To determine the statistical relationship between average total wait time, healthcare worker staffing level, and patient demand, Minitab Statistical Software was used to perform regression analysis and determine the regression models that would be used to create the decision support tool. A multiple regression analysis was performed for each patient type at each PHC facility. For the regression analysis performed for each patient type, patient demand and all healthcare workers who provide PHC services were the regressor variables for the regression model, and their average total wait times were the response variables. If the results showed that the p-values of the hypothesis test were greater than the selected $\alpha=0.05$, these independent variables were removed and the regression analysis was performed again, a stepwise regression analysis process known as backward elimination. Additionally, in order to meet the assumptions of regression analysis—residuals fit a $N(0,\sigma^2)$ distribution and residuals are independent of each other—a Box-Cox optimal power transformation was performed. Backward elimination of transformed regression models was performed when necessary as previously described. Based on backward elimination and transforming the response variable when needed, a total of 41 regression models were created. Minitab provided statistics to test the adequacy of each model. To determine the models that would be used for the decision support tool, the following statistics were analyzed to assess each regression models adequacy:

- ANOVA F-Test: Test how well independent variables predicts the response variable; *target: p-value<0.05*
- Lack-of-Fit: test how well the model fits the data; *target: p-value >0.05*
- $R^2$ adjusted: percent of response variable variation explained by the independent variable; *target: larger the better*
- Durbin Watson Statistic: test of residual correlation; *target: approximately equal to 2*
- Anderson Darling Statistic & p-value- hypothesis test of how well the residuals fit a normal distribution; *target: Anderson-Darlin Statistic for the smaller the better; p-value >0.05*

The statistics for each model were summarized and analyzed to determine the best regression model to use for the decision support tool [Appendix J]. None of the regression models met all target criteria, including models with an optimal Box-Cox transformation of the response variable. Therefore, regression models to include in the decision support tool were chosen for each patient type if they met most of the model adequacy target requirements listed above. Based on these criteria, the regression models most likely to meet all statistical requirements were regression models where the response variables were transformed via optimal Box-Cox transformation including all healthcare workers who provide services to the given patient type as the regressors. The exception to this was adult outpatient average total wait time at Urban Health Centers where the regression model chosen was the transformed model with backward elimination and well child care patients at Rural Hospitals where the regression model chosen was a non-transformed model with backward elimination.

To calculate the number of healthcare workers based on patient demand and average total wait time targets, the selected regression models were used as functions in a Microsoft Excel spreadsheet. The different staffing levels tested during the what-if scenario analysis served as the values for the independent variables of the regression models in the spreadsheet. Once average daily visit data is entered into the decision support tool for each patient type, the staffing level for each patient type was determined by finding the staffing level scenario resulting in the smallest difference between the expected average total wait time and the calculated average total wait time. For the selected health facility, the number of health workers needed is the aggregate of staffing levels for all patient types. The decision support tool outputs the aggregate staffing levels.

The average daily visits, healthcare worker volumes, and resulting average total wait time data from twenty randomly selected what-if scenarios were used to test the validity of the decision support tool for each health facility. The patient volumes and wait times for each individual patient type at each individual PHC facility were entered directly into the regression models. The staffing levels output by the decision support tool was compared to the what-if scenarios. The regression models could not be validated, meaning that staffing levels based on wait times and patient demand levels calculated with the regression models was not similar to the staffing levels for the wait times and patient demand levels found during the what-if scenario.

Upon further review of this method, the researchers have decided that identifying staffing needs for each facility based on average service time and average daily visits while controlling average total patient wait time can be performed using queuing analysis instead of a DES study.  DES was best used in this study to identify services where patients experience higher wait times and test strategies to alleviate these bottlenecks, like block scheduling strategies to smooth arrival patterns throughout the workday or reallocating a nurse to assist with registration during the peak hours of the day.

*Study Limitations*

The regression models used in the decision support tool are based on DES output data that was validated based on system expert approval, but the output data was not statistically valid. This may be due to the small sample size of data collected during the time study. Although the smaller sample size was attributed to the shortages in data collection resources during this study, future researchers interested in simulation studies in the healthcare setting should consider collecting a larger sample size. Additionally, a small sample of data should be set aside so it is not used as an input into the DES model and can therefore be used to validate the DES model output.

Another limitation of this study is that if any PHC system changes occur beyond changes in staffing levels and average daily volumes, such as PHC delivery performance improvement changes that impact service times or assumptions, the DES model would need to be updated to capture how these system changes impact average total patient wait times. In this case, a DES developer or healthcare decision maker familiar with DES and regression analysis is required to make decision support tool changes.

## Discussion

This study presented a simulation study performed remotely where the results were used to develop a spreadsheet-based decision support tool. The decision support tool aimed to identify the staffing level required to provide PHC services to an expected number of daily patient visits while maintaining a targeted average total patient wait time. The next step in this study is to use a different method to calculate staffing level needs for the decision support tool and implement the decision support tool amongst PHC facility management in the Sofala province.

To successfully implement a decision support tool in the PHC setting using the originally proposed method described in this study, the results of the simulation and the output featured in the study need to be reviewed with multiple PHC stakeholders, including frontline staff, at the provincial level to garner feedback to improve the decision support tool as needed as well as facilitate wide-spread support and utilization.

A limitation of the study is that frontline staff and end users were not involved in each step of the simulation study. Their involvement throughout the course of the study could assist with validation of the model as well as facilitate successful implementation of the decision support tool. To overcome this limitation for future studies, figure 3 proposes a simulation study in the healthcare setting framework based on literature of suggestions for successful simulation study implementation [80, 82].

Figure 3. Simulation Study Framework in the Global Health Setting

The revised framework proposes that a steering committee made up of end users, decision makers, and problem owners are involved with each step of the simulation study.  During this study, periodic meetings for data and model validation and for study status updates were held with system experts off-site, however future studies may consider performing these meetings on-site to promote study engagement amongst on-site steering committee members, which will ultimately increase implementation successfulness.

## Conclusion

This study aimed to develop a spreadsheet-based decision support tool accessible through Microsoft Excel. The tool would determine staffing needs based on the statistical relationship between staffing levels, patient demand, and wait time. Data produced from a discrete event simulation study was used to find the relationship amongst these variables. With a user-friendly interface, this decision support tool would support the implementation of industrial and systems engineering approaches in the primary health care setting.

The method proposed in this study could not be validated. The researcher suggests that future efforts to develop a decision support tool that determines staffing needs based on wait time and patient demand should use queuing analysis methods. To facilitate implementation of a revised decision support tool, end users, decision makers, and problem owners should be involved with each stage of the study and decision support tool development. Future work should determine how the decision support tool can be made more flexible to accurately capture structural changes, staffing level changes, and average daily visit fluctuations beyond the values tested during this study. Additionally, future work comparing the results from this study with other staffing methods, such as WISN and deterministic modeling, should be performed and reviewed with stakeholders to assess which method produces feasible staffing levels while achieving performance targets.

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Appendix A. Time Study Margin of Error Calculation

$$E \quad z\alpha_{\ 2} \frac{\sigma}{\sqrt{n}}$$

$where$

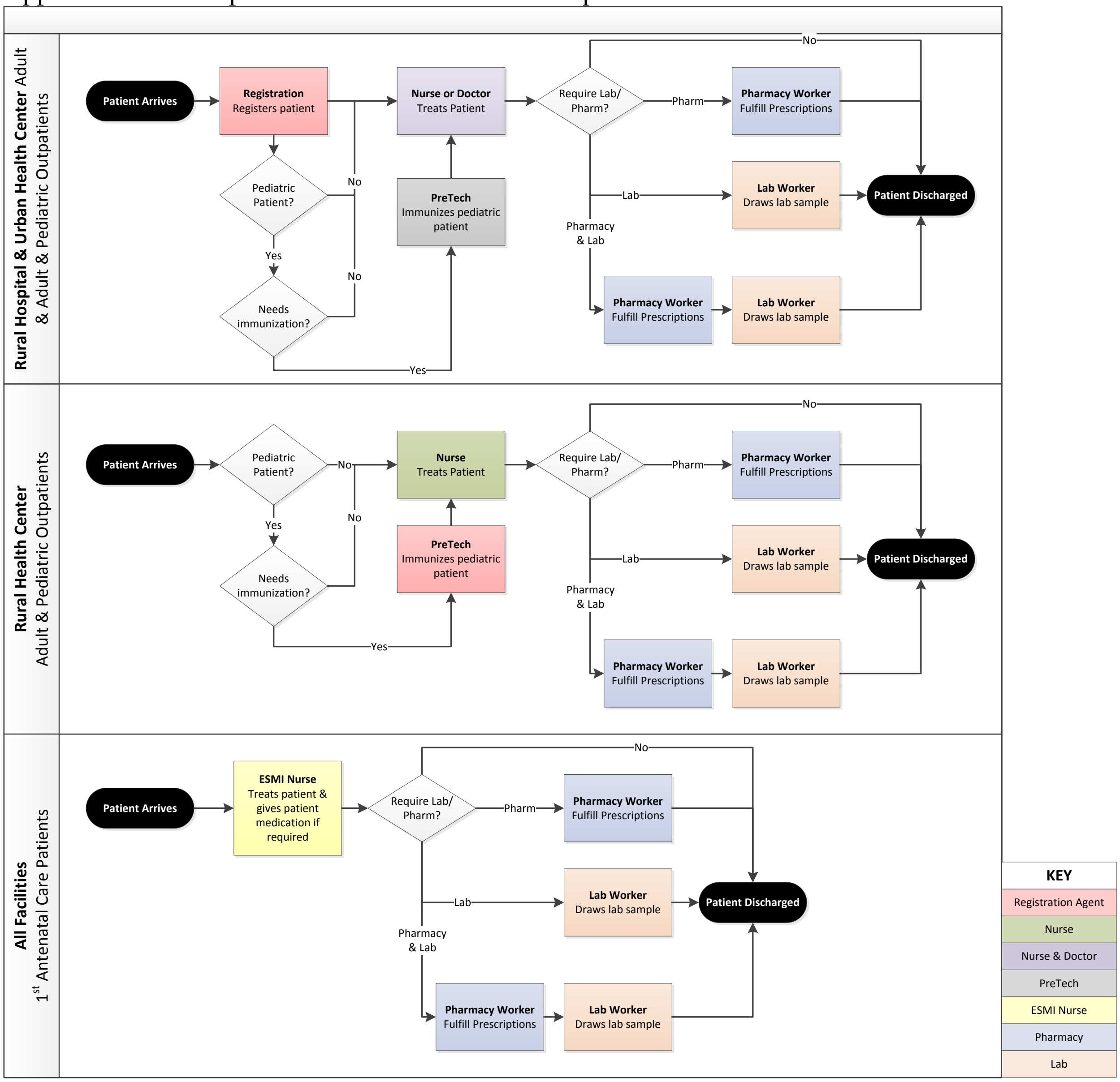
$z\alpha_{\ 2} \quad critical\ value\ of\ 95\%\ confidence\ level \quad 1.96$

$n \quad sample\ size\ of\ each\ patient\ type$

$E \quad margin\ of\ error$

$\sigma \quad standard\ deviation\ of\ consult\ time \quad min$

Appendix B. Conceptual Model: Process Flow Map of PHC Patient Flow



Appendix C. Conceptual Model: PHC Patient, Facility, & Worker Assumptions

| Category | Assumptions |
|---|---|
| Patient Assumptions | |
| Facility Assumptions | |
| Worker Assumptions | |

Appendix D. DES Model Validation Hypothesis Test

$For\ each\ type\ of\ patient\ i\ and\ for\ each\ facility\ j$
$let\ X_{ij}\quad model\ output\ average\ delay\ time$
$\mu_{ij}\quad actual\ system\ average\ delay\ time$

$Hypothesis\ Test$:
$H_0 : E\ \ X_{ij}\qquad \mu_{ij}$
$H_1 :\ E\ \ X_{ij}\qquad \mu_{ij}$
$reject\ H_0\ if\ |t_0|\quad t\alpha\ _{2,n-1}$

$Compute\ test\ statistic\quad t_0\quad \frac{X_{ij}\quad \mu_{ij}}{\frac{s}{\sqrt{n}}}$

$where\ model\ sample\ mean\quad X_{ij}\quad E\ \ X_{ij}\ \ , X_{ij}\quad \frac{1}{n}\sum_{i=1}^{n} X_{ij}$

$model\ sample\ standard\ deviation\quad s\quad \frac{\sum_{i=1}^{n}\ X_{ij}\quad X_{ij}\ \ ^{2}}{n\quad 1}$

$Per\ a\ 2\quad sided\ t\quad test\ and\ assuming\ \alpha\quad 0.05$
$critical\ value\ of\ t\quad t\alpha\ _{2,n-1}\quad t_{0.025,4}\quad 2.776$

# Appendix E. DES Model Validation Hypothesis Test Results Summary

**Rural Hospital**

| | | | |
|---|---|---|---|
| | 65 | | 157.56 |
| | 63 | | 142.49 |
| | 46 | | 152.69 |
| | 75 | | 143.40 |
| | 52 | | 137.16 |
| Actual Average = | 60.20 | Model Average = | 146.66 |
| $t_0$ = | 23.38 | Model St. Dev. = | 8.27 |
| **Conclusion:** | **Reject $H_0$** | | |
| | | | |
| | 18 | | 98.05 |
| | 28 | | 144.50 |
| | 36 | | 140.76 |
| | 37 | | 133.29 |
| | 20 | | 151.40 |
| Actual Average = | 27.80 | Model Average = | 133.60 |
| $t_0$ = | 11.31 | Model St. Dev. = | 20.92 |
| **Conclusion:** | **Reject $H_0$** | | |
| | | | |
| | 71 | | 41.86 |
| | 77 | | 36.02 |
| | 74 | | 42.34 |
| | 42 | | 38.52 |
| | 48 | | 42.15 |
| Actual Average = | 62.40 | Model Average = | 40.18 |
| $t_0$ = | -17.73 | Model St. Dev. = | 2.80 |
| **Conclusion:** | **Reject $H_0$** | | |
| | | | |
| | 43 | | 128.61 |
| | 38 | | 147.04 |
| | 16 | | 154.18 |
| | 14 | | 141.40 |
| | 9 | | 144.63 |
| Actual Average = | 24.00 | Model Average = | 143.17 |
| $t_0$ = | 28.35 | Model St. Dev. = | 9.40 |
| **Conclusion:** | **Reject $H_0$** | | |

**Rural Health Center**

| | | | |
|---|---|---|---|
| | 53 | | 134.09 |
| | 30 | | 137.59 |
| | 58 | | 138.59 |
| | 54 | | 130.00 |
| | 59 | | 133.87 |
| Actual Average = | 50.80 | Model Average = | 134.83 |
| $t_0$ = | 55.08 | Model St. Dev. = | 3.41 |
| **Conclusion:** | **Reject $H_0$** | | |
| | | | |
| | 67 | | 98.05 |
| | 55 | | 109.30 |
| | 46 | | 97.58 |
| | 51 | | 93.70 |
| | 64 | | 108.56 |
| Actual Average = | 56.60 | Model Average = | 101.44 |
| $t_0$ = | 14.22 | Model St. Dev. = | 7.05 |
| **Conclusion:** | **Reject $H_0$** | | |
| | | | |
| | 96 | | 45.12 |
| | 99 | | 48.46 |
| | 81 | | 63.19 |
| | 86 | | 46.98 |
| | 73 | | 32.72 |
| Actual Average = | 87.00 | Model Average = | 47.29 |
| $t_0$ = | -8.18 | Model St. Dev. = | 10.85 |
| **Conclusion:** | **Reject $H_0$** | | |
| | | | |
| | 47 | | 48.10 |
| | 37 | | 44.62 |
| | 62 | | 44.03 |
| | 40 | | 44.17 |
| | 62 | | 44.19 |
| Actual Average = | 49.60 | Model Average = | 45.02 |
| $t_0$ = | -5.89 | Model St. Dev. = | 1.74 |
| **Conclusion:** | **Reject $H_0$** | | |

**Urban Health Center**

| | | | |
|---|---|---|---|
| | 91 | | 207 |
| | 42 | | 195 |
| | 63 | | 203 |
| | 65 | | 197 |
| | 82 | | 193 |
| Actual Average = | 68.6 | Model Average = | 199.21 |
| $t_0$ = | 50.88 | Model St. Dev. = | 5.74 |
| **Conclusion:** | **Reject $H_0$** | | |
| | | | |
| | 45 | | 182 |
| | 40 | | 194 |
| | 38 | | 196 |
| | 63 | | 186 |
| | 46 | | 186 |
| Actual Average = | 46.4 | Model Average = | 188.81 |
| $t_0$ = | 52.40 | Model St. Dev. = | 6.08 |
| **Conclusion:** | **Reject $H_0$** | | |
| | | | |
| | 50 | | 43 |
| | 78 | | 40 |
| | 84 | | 46 |
| | 9 | | 41 |
| | 43 | | 56 |
| Actual Average = | 52.80 | Model Average = | 45.24 |
| $t_0$ = | -2.66 | Model St. Dev. = | 6.37 |
| **Conclusion:** | **Fail to reject $H_0$** | | |
| | | | |
| | 32 | | 99.31 |
| | 29 | | 101.24 |
| | 39 | | 97.3347 |
| | 47 | | 99.81 |
| | 41 | | 103.27 |
| Actual Average = | 37.60 | Model Average = | 100.19 |
| $t_0$ = | 63.13 | Model St. Dev. = | 2.22 |
| **Conclusion:** | **Reject $H_0$** | | |

# Appendix F. Rural Health Center Orthogonal Array for What-If Scenario Experiments

| | Rural Health Center Orthogonal Array for What-If Scenario Experiments | | | | |
|---|---|---|---|---|---|
| Exp # | Registration Agent | ANC RN | Pharm Worker | Lab Worker | Immunization Tech |
| | 2 | 2 | 1 | 1 | 1 |
| | 1 | 1 | 4 | 4 | 2 |
| | 3 | 6 | 5 | 6 | 4 |
| | 4 | 5 | 4 | 1 | 3 |
| | 2 | 4 | 2 | 6 | 2 |
| | 1 | 6 | 1 | 2 | 1 |
| | 5 | 1 | 1 | 1 | 3 |
| | 2 | 5 | 1 | 5 | 5 |
| | 2 | 5 | 2 | 4 | 6 |
| | 5 | 3 | 5 | 1 | 6 |
| | 2 | 2 | 6 | 4 | 2 |
| | 3 | 3 | 6 | 4 | 3 |
| | 3 | 1 | 5 | 5 | 1 |
| | 3 | 2 | 4 | 5 | 6 |
| | 6 | 5 | 3 | 1 | 1 |
| | 4 | 5 | 6 | 5 | 2 |
| | 1 | 6 | 6 | 3 | 6 |
| | 2 | 1 | 3 | 6 | 3 |
| | 4 | 2 | 1 | 4 | 5 |
| | 6 | 5 | 4 | 2 | 6 |
| | 5 | 2 | 4 | 6 | 4 |
| | 4 | 3 | 6 | 6 | 6 |
| | 5 | 5 | 5 | 3 | 2 |
| | 2 | 2 | 5 | 1 | 1 |
| | 1 | 5 | 2 | 6 | 3 |
| | 3 | 5 | 3 | 3 | 5 |
| | 3 | 1 | 3 | 4 | 6 |
| | 4 | 1 | 2 | 5 | 4 |
| | 4 | 6 | 3 | 4 | 1 |
| | 5 | 5 | 6 | 2 | 4 |
| | 4 | 1 | 5 | 6 | 5 |
| | 6 | 6 | 3 | 6 | 2 |
| | 4 | 3 | 5 | 2 | 3 |
| | 5 | 6 | 2 | 5 | 5 |
| | 6 | 1 | 2 | 2 | 2 |
| | 5 | 6 | 4 | 4 | 3 |
| | 1 | 4 | 1 | 5 | 4 |
| | 4 | 4 | 3 | 3 | 4 |
| | 1 | 2 | 3 | 5 | 3 |
| | 1 | 2 | 5 | 2 | 2 |
| | 6 | 4 | 6 | 5 | 3 |
| | 6 | 6 | 5 | 5 | 6 |
| | 3 | 4 | 6 | 2 | 5 |
| | 6 | 1 | 4 | 3 | 4 |
| | 6 | 3 | 1 | 4 | 4 |
| | 4 | 6 | 1 | 1 | 2 |
| | 1 | 1 | 6 | 1 | 5 |
| | 2 | 3 | 4 | 5 | 1 |
| | 6 | 3 | 2 | 1 | 5 |
| | 5 | 3 | 3 | 5 | 2 |
| | 4 | 4 | 4 | 2 | 1 |
| | 3 | 5 | 1 | 6 | 1 |
| | 3 | 2 | 2 | 1 | 4 |
| | 1 | 3 | 4 | 6 | 5 |
| | 2 | 6 | 4 | 3 | 5 |
| | 2 | 6 | 6 | 1 | 4 |
| | 5 | 1 | 6 | 3 | 1 |
| | 3 | 4 | 4 | 1 | 2 |
| | 3 | 3 | 1 | 3 | 2 |
| | 1 | 4 | 3 | 1 | 6 |
| | 1 | 3 | 2 | 3 | 1 |
| | 3 | 6 | 2 | 2 | 3 |
| | 6 | 4 | 5 | 4 | 5 |
| | 5 | 2 | 3 | 2 | 5 |
| | 2 | 4 | 5 | 3 | 3 |
| | 2 | 1 | 1 | 2 | 6 |
| | 5 | 4 | 1 | 6 | 6 |
| | 2 | 3 | 3 | 2 | 4 |
| | 4 | 2 | 2 | 3 | 6 |
| | 6 | 2 | 1 | 3 | 3 |
| | 6 | 2 | 6 | 6 | 1 |
| | 1 | 5 | 5 | 4 | 4 |
| | 5 | 4 | 2 | 4 | 1 |

# Appendix G. Urban Health Center Orthogonal Array for What-If Scenario Experiments

**Urban Health Center Orthogonal Array for What-If Scenario Experiments**

| Exp # | Registration Agent | Outpatient RN | Outpatient MD | ANC RN | Pharm Worker | Lab Worker | Immunization Tech |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 9 | 1 | 5 | 6 | 4 | 2 |
| 2 | 2 | 10 | 3 | 7 | 9 | 7 | 5 |
| 3 | 5 | 8 | 3 | 7 | 4 | 3 | 1 |
| 4 | 2 | 8 | 6 | 4 | 6 | 3 | 4 |
| 5 | 5 | 11 | 4 | 6 | 8 | 6 | 5 |
| 6 | 4 | 11 | 6 | 3 | 5 | 7 | 2 |
| 7 | 3 | 9 | 2 | 4 | 5 | 7 | 4 |
| 8 | 5 | 7 | 5 | 5 | 5 | 2 | 4 |
| 9 | 1 | 11 | 1 | 5 | 9 | 7 | 1 |
| 10 | 2 | 9 | 4 | 6 | 5 | 5 | 2 |
| 11 | 5 | 11 | 2 | 3 | 9 | 4 | 4 |
| 12 | 3 | 11 | 3 | 8 | 7 | 3 | 6 |
| 13 | 6 | 10 | 2 | 5 | 8 | 3 | 2 |
| 14 | 4 | 10 | 1 | 4 | 4 | 6 | 6 |
| 15 | 1 | 7 | 4 | 3 | 6 | 3 | 2 |
| 16 | 4 | 7 | 2 | 6 | 7 | 3 | 3 |
| 17 | 3 | 12 | 4 | 4 | 8 | 7 | 3 |
| 18 | 6 | 12 | 6 | 6 | 7 | 7 | 1 |
| 19 | 2 | 7 | 3 | 4 | 9 | 6 | 3 |
| 20 | 5 | 9 | 6 | 5 | 4 | 3 | 5 |
| 21 | 1 | 12 | 3 | 5 | 6 | 6 | 2 |
| 22 | 2 | 11 | 2 | 7 | 4 | 5 | 2 |
| 23 | 6 | 7 | 1 | 8 | 4 | 7 | 2 |
| 24 | 4 | 8 | 4 | 8 | 9 | 2 | 5 |
| 25 | 3 | 8 | 1 | 5 | 6 | 5 | 3 |
| 26 | 2 | 8 | 5 | 3 | 7 | 7 | 5 |
| 27 | 1 | 8 | 2 | 4 | 8 | 2 | 6 |
| 28 | 6 | 12 | 2 | 5 | 7 | 2 | 5 |
| 29 | 6 | 11 | 5 | 4 | 6 | 4 | 1 |
| 30 | 6 | 9 | 4 | 7 | 9 | 3 | 3 |
| 31 | 4 | 8 | 4 | 5 | 4 | 7 | 4 |
| 32 | 3 | 10 | 5 | 6 | 9 | 2 | 2 |
| 33 | 5 | 12 | 1 | 7 | 5 | 2 | 3 |
| 34 | 4 | 12 | 5 | 3 | 9 | 3 | 6 |
| 35 | 6 | 7 | 5 | 4 | 4 | 5 | 5 |
| 36 | 5 | 10 | 4 | 4 | 7 | 5 | 1 |
| 37 | 1 | 9 | 5 | 6 | 4 | 4 | 3 |
| 38 | 2 | 11 | 5 | 5 | 7 | 6 | 3 |
| 39 | 3 | 8 | 1 | 7 | 7 | 4 | 2 |
| 40 | 2 | 10 | 4 | 5 | 5 | 4 | 6 |
| 41 | 2 | 12 | 1 | 6 | 8 | 3 | 4 |
| 42 | 6 | 9 | 1 | 8 | 9 | 6 | 4 |
| 43 | 3 | 10 | 5 | 8 | 5 | 3 | 1 |
| 44 | 3 | 11 | 3 | 6 | 4 | 2 | 4 |
| 45 | 1 | 11 | 1 | 4 | 5 | 3 | 5 |
| 46 | 4 | 10 | 1 | 6 | 6 | 4 | 5 |
| 47 | 1 | 9 | 5 | 7 | 8 | 7 | 6 |
| 48 | 5 | 10 | 2 | 8 | 6 | 7 | 3 |
| 49 | 5 | 9 | 1 | 3 | 7 | 5 | 6 |
| 50 | 4 | 11 | 6 | 8 | 8 | 5 | 3 |
| 51 | 2 | 12 | 2 | 8 | 4 | 4 | 6 |
| 52 | 4 | 9 | 3 | 4 | 7 | 2 | 2 |
| 53 | 2 | 7 | 1 | 3 | 8 | 2 | 1 |
| 54 | 6 | 8 | 6 | 6 | 5 | 6 | 6 |
| 55 | 3 | 12 | 4 | 3 | 4 | 6 | 1 |
| 56 | 4 | 9 | 3 | 5 | 8 | 4 | 1 |
| 57 | 6 | 10 | 3 | 3 | 8 | 5 | 4 |
| 58 | 6 | 11 | 4 | 7 | 6 | 2 | 6 |
| 59 | 5 | 12 | 6 | 4 | 9 | 4 | 2 |
| 60 | 6 | 8 | 3 | 3 | 5 | 4 | 3 |
| 61 | 3 | 9 | 2 | 3 | 6 | 6 | 5 |
| 62 | 1 | 7 | 4 | 8 | 7 | 4 | 4 |
| 63 | 1 | 10 | 6 | 7 | 7 | 6 | 4 |
| 64 | 3 | 7 | 6 | 7 | 8 | 4 | 5 |
| 65 | 5 | 7 | 3 | 6 | 6 | 7 | 6 |
| 66 | 5 | 8 | 5 | 8 | 8 | 6 | 2 |
| 67 | 1 | 10 | 6 | 3 | 4 | 2 | 3 |
| 68 | 4 | 12 | 5 | 7 | 6 | 5 | 4 |
| 69 | 3 | 7 | 6 | 5 | 9 | 5 | 6 |
| 70 | 4 | 7 | 2 | 7 | 5 | 6 | 1 |
| 71 | 2 | 9 | 6 | 8 | 6 | 2 | 1 |
| 72 | 1 | 12 | 3 | 8 | 5 | 5 | 5 |
| 73 | 1 | 8 | 2 | 6 | 9 | 5 | 1 |

# Appendix H. Rural Hospital Orthogonal Array for What-If Scenario Experiments

**Rural Hospital Orthogonal Array for What-If Scenario Experiments**

| Exp # | Registration Agent (Primary) | Registration Agent (Secondary) | Outpatient RN | Outpatient MD | ANC RN | Pharm Worker | Lab Worker | Immunization Tech |
|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 1 | 14 | 1 | 5 | 3 | 2 | 2 |
| 2 | 2 | 4 | 16 | 3 | 3 | 2 | 4 | 5 |
| 3 | 6 | 6 | 12 | 4 | 6 | 3 | 1 | 2 |
| 4 | 2 | 4 | 12 | 1 | 5 | 6 | 1 | 6 |
| 5 | 3 | 1 | 15 | 1 | 8 | 2 | 6 | 4 |
| 6 | 1 | 6 | 16 | 3 | 5 | 6 | 5 | 1 |
| 7 | 4 | 2 | 16 | 1 | 7 | 4 | 2 | 1 |
| 8 | 3 | 6 | 14 | 6 | 7 | 2 | 5 | 5 |
| 9 | 6 | 1 | 14 | 2 | 3 | 3 | 5 | 6 |
| 10 | 3 | 5 | 17 | 4 | 5 | 4 | 5 | 6 |
| 11 | 5 | 5 | 15 | 1 | 5 | 1 | 3 | 3 |
| 12 | 1 | 5 | 14 | 1 | 4 | 5 | 4 | 4 |
| 13 | 3 | 6 | 15 | 3 | 6 | 6 | 4 | 6 |
| 14 | 5 | 1 | 13 | 5 | 7 | 6 | 2 | 6 |
| 15 | 2 | 3 | 14 | 5 | 7 | 1 | 6 | 3 |
| 16 | 6 | 1 | 15 | 5 | 5 | 4 | 4 | 1 |
| 17 | 3 | 4 | 13 | 2 | 6 | 3 | 4 | 3 |
| 18 | 2 | 3 | 15 | 4 | 6 | 2 | 3 | 2 |
| 19 | 1 | 1 | 13 | 3 | 6 | 5 | 2 | 1 |
| 20 | 1 | 5 | 17 | 3 | 6 | 4 | 5 | 2 |
| 21 | 3 | 1 | 17 | 6 | 3 | 6 | 3 | 3 |
| 22 | 6 | 5 | 12 | 2 | 6 | 1 | 2 | 6 |
| 23 | 6 | 6 | 16 | 5 | 7 | 5 | 4 | 3 |
| 24 | 5 | 4 | 14 | 6 | 4 | 1 | 4 | 6 |
| 25 | 4 | 6 | 14 | 5 | 4 | 6 | 3 | 2 |
| 26 | 2 | 3 | 17 | 2 | 4 | 6 | 2 | 4 |
| 27 | 4 | 5 | 13 | 4 | 5 | 2 | 5 | 3 |
| 28 | 5 | 4 | 17 | 1 | 6 | 6 | 5 | 5 |
| 29 | 2 | 1 | 13 | 4 | 8 | 6 | 1 | 4 |
| 30 | 5 | 6 | 16 | 6 | 8 | 3 | 3 | 4 |
| 31 | 4 | 3 | 12 | 1 | 3 | 2 | 5 | 1 |
| 32 | 5 | 5 | 17 | 6 | 8 | 2 | 2 | 2 |
| 33 | 3 | 1 | 14 | 3 | 5 | 1 | 2 | 2 |
| 34 | 1 | 2 | 13 | 4 | 3 | 1 | 4 | 2 |
| 35 | 6 | 4 | 13 | 1 | 3 | 4 | 3 | 4 |
| 36 | 4 | 2 | 12 | 6 | 6 | 5 | 6 | 5 |
| 37 | 2 | 6 | 17 | 5 | 8 | 4 | 6 | 6 |
| 38 | 6 | 3 | 17 | 1 | 7 | 2 | 4 | 6 |
| 39 | 4 | 3 | 13 | 6 | 5 | 6 | 4 | 5 |
| 40 | 3 | 6 | 17 | 1 | 4 | 1 | 1 | 1 |
| 41 | 5 | 2 | 15 | 5 | 8 | 5 | 5 | 6 |
| 42 | 2 | 1 | 12 | 5 | 5 | 2 | 4 | 2 |
| 43 | 2 | 5 | 13 | 3 | 7 | 4 | 6 | 5 |
| 44 | 3 | 5 | 15 | 5 | 3 | 3 | 1 | 5 |
| 45 | 4 | 5 | 16 | 2 | 8 | 6 | 4 | 2 |
| 46 | 5 | 3 | 16 | 5 | 6 | 3 | 5 | 4 |
| 47 | 4 | 1 | 14 | 1 | 7 | 3 | 5 | 2 |
| 48 | 4 | 1 | 17 | 3 | 4 | 5 | 1 | 3 |
| 49 | 5 | 1 | 12 | 2 | 4 | 2 | 3 | 5 |
| 50 | 5 | 2 | 14 | 2 | 5 | 4 | 1 | 5 |
| 51 | 2 | 2 | 14 | 1 | 6 | 4 | 1 | 3 |
| 52 | 6 | 5 | 16 | 4 | 7 | 6 | 3 | 5 |
| 53 | 1 | 2 | 12 | 5 | 8 | 6 | 5 | 3 |
| 54 | 2 | 2 | 15 | 6 | 4 | 5 | 5 | 2 |
| 55 | 2 | 2 | 17 | 3 | 7 | 3 | 4 | 4 |
| 56 | 5 | 1 | 16 | 4 | 6 | 1 | 6 | 1 |
| 57 | 1 | 4 | 14 | 5 | 6 | 2 | 2 | 4 |
| 58 | 6 | 4 | 16 | 6 | 5 | 5 | 2 | 3 |
| 59 | 1 | 3 | 15 | 2 | 8 | 4 | 3 | 1 |
| 60 | 3 | 5 | 14 | 2 | 8 | 5 | 4 | 1 |
| 61 | 6 | 2 | 15 | 1 | 3 | 6 | 2 | 2 |
| 62 | 1 | 6 | 13 | 6 | 3 | 2 | 1 | 6 |
| 63 | 6 | 2 | 17 | 6 | 5 | 1 | 6 | 4 |
| 64 | 2 | 6 | 14 | 4 | 3 | 5 | 3 | 1 |
| 65 | 2 | 1 | 16 | 2 | 3 | 1 | 5 | 3 |
| 66 | 6 | 3 | 15 | 3 | 4 | 1 | 5 | 5 |
| 67 | 1 | 6 | 12 | 1 | 8 | 1 | 4 | 5 |
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| 70 | 3 | 2 | 12 | 2 | 7 | 6 | 6 | 1 |
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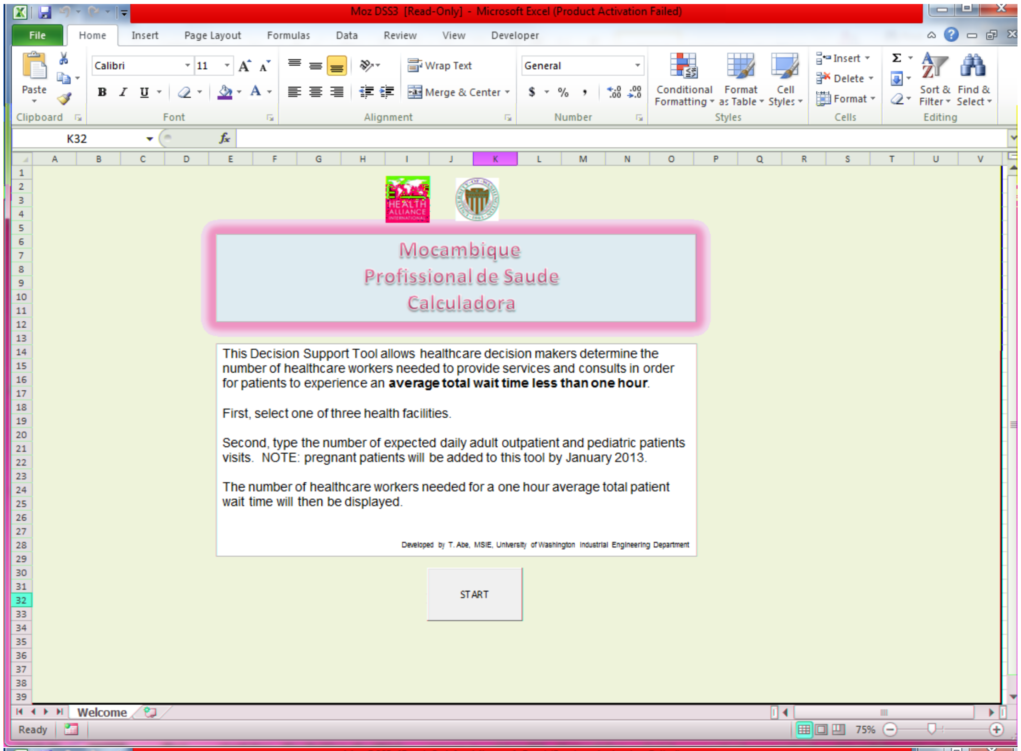
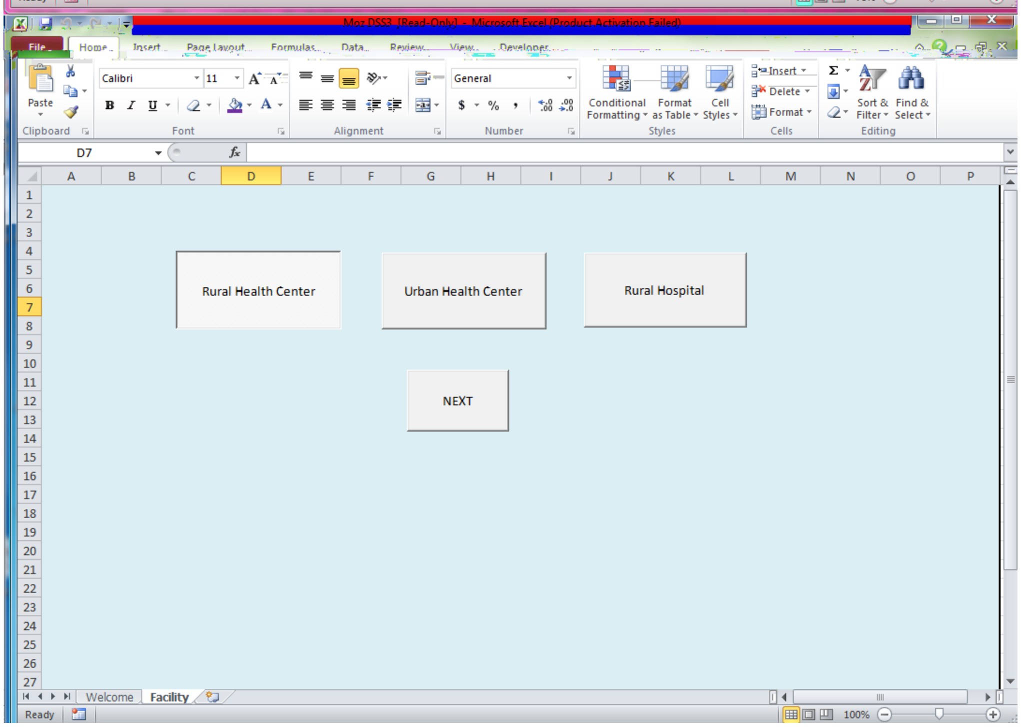
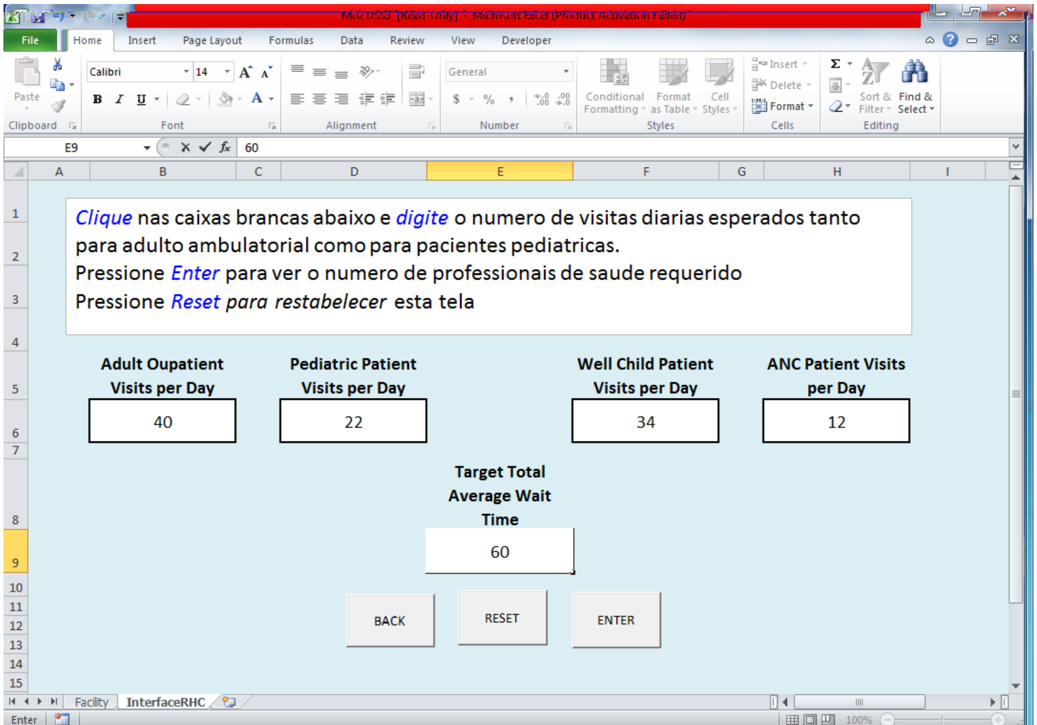
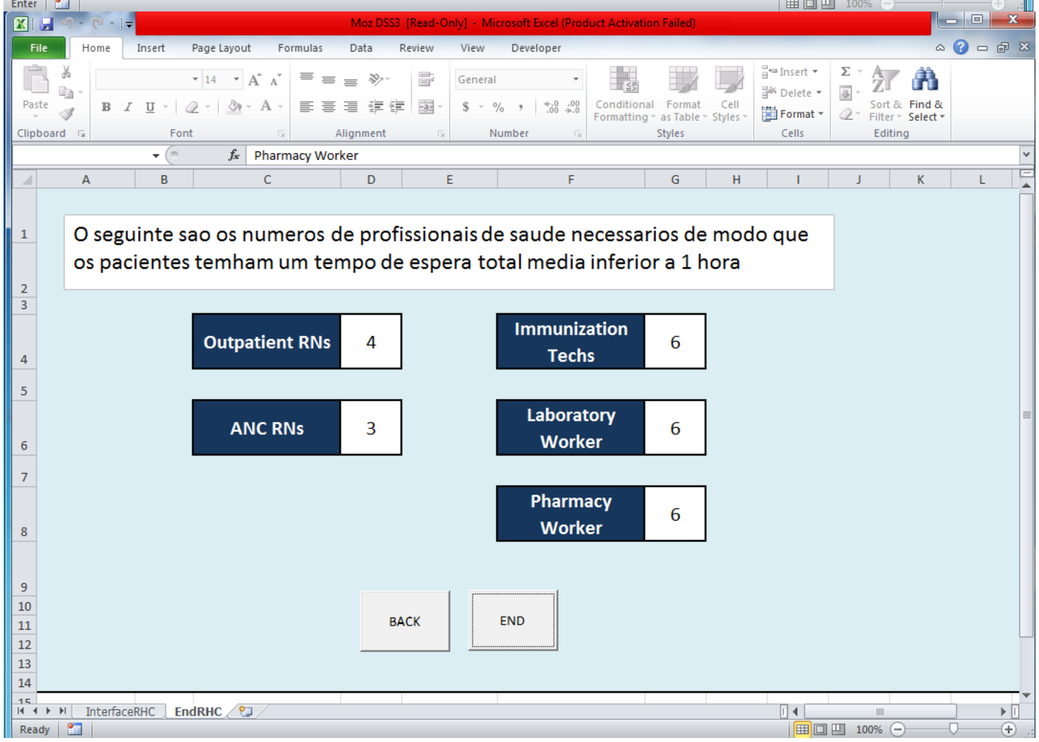
| 79 | 1 | 3 | 17 | 5 | 3 | 5 | 2 | 5 |
| 80 | 1 | 1 | 16 | 1 | 4 | 3 | 6 | 5 |
| 81 | 3 | 4 | 16 | 5 | 4 | 4 | 1 | 2 |
| 82 | 3 | 4 | 12 | 4 | 7 | 5 | 5 | 4 |
| 83 | 4 | 2 | 13 | 3 | 4 | 3 | 3 | 6 |
| 84 | 6 | 1 | 17 | 4 | 8 | 5 | 1 | 5 |
| 85 | 2 | 4 | 13 | 6 | 8 | 1 | 5 | 1 |
| 86 | 5 | 6 | 13 | 1 | 5 | 5 | 6 | 2 |
| 87 | 6 | 3 | 14 | 6 | 6 | 6 | 1 | 1 |
| 88 | 4 | 6 | 15 | 4 | 7 | 1 | 2 | 4 |
| 89 | 4 | 1 | 15 | 6 | 6 | 4 | 4 | 4 |
| 90 | 4 | 6 | 17 | 2 | 6 | 2 | 6 | 3 |
| 91 | 1 | 2 | 16 | 2 | 5 | 2 | 1 | 4 |
| 92 | 4 | 4 | 14 | 4 | 8 | 4 | 2 | 5 |
| 93 | 1 | 3 | 14 | 4 | 5 | 3 | 6 | 6 |
| 94 | 2 | 6 | 15 | 2 | 5 | 3 | 2 | 5 |
| 95 | 2 | 5 | 12 | 6 | 4 | 3 | 2 | 1 |
| 96 | 5 | 5 | 14 | 3 | 3 | 6 | 6 | 4 |
| 97 | 1 | 1 | 12 | 6 | 7 | 4 | 3 | 6 |
| 98 | 4 | 3 | 16 | 3 | 8 | 1 | 1 | 6 |
| 99 | 5 | 3 | 13 | 2 | 7 | 5 | 1 | 2 |
| 100 | 6 | 6 | 13 | 2 | 4 | 4 | 5 | 4 |
| 101 | 3 | 2 | 16 | 4 | 4 | 2 | 2 | 6 |
| 102 | 2 | 5 | 16 | 1 | 6 | 5 | 3 | 6 |
| 103 | 5 | 3 | 12 | 4 | 4 | 4 | 4 | 3 |
| 104 | 1 | 4 | 15 | 4 | 4 | 6 | 6 | 3 |
| 105 | 4 | 4 | 17 | 5 | 5 | 3 | 3 | 1 |
| 106 | 6 | 5 | 13 | 5 | 4 | 2 | 6 | 1 |
| 107 | 6 | 4 | 12 | 3 | 8 | 3 | 6 | 2 |
| 108 | 1 | 5 | 15 | 6 | 7 | 3 | 1 | 3 |
| 109 | 3 | 3 | 16 | 6 | 3 | 4 | 6 | 2 |

Appendix I. Spreadsheet-based Decision Support Tool Example




Moz DSS3 [Read-Only] - Microsoft Excel (Product Activation Failed)
Clique nas caixas brancas abaixo e digite o numero de visitas diarias esperados tanto para adulto ambulatorial como para pacientes pediatricas.
Pressione Enter para ver o numero de professionais de saude requerido
Pressione Reset para restabelecer esta tela
Adult Oupatient Visits per Day
40
Pediatric Patient Visits per Day
22
Well Child Patient Visits per Day
34
ANC Patient Visits per Day
12
Target Total Average Wait Time
60
BACK
RESET
ENTER
Facility
InterfaceRHC


Moz DSS3 [Read-Only] - Microsoft Excel (Product Activation Failed)
Pharmacy Worker
O seguinte sao os numeros de profissionais de saude necessarios de modo que os pacientes temham um tempo de espera total media inferior a 1 hora
Outpatient RNs
4
Immunization Techs
6
ANC RNs
3
Laboratory Worker
6
Pharmacy Worker
6
BACK
END
InterfaceRHC
EndRHC

# Appendix J. Regression Models and Statistical Summaries

| Response Variable | Model | Lack-of-fit | ANOVA F Test | $R^2$ adj. | Durbin-Watson Statistic | Anderson Darlin [p-value] |
|---|---|---|---|---|---|---|
| ***Rural Heatlh Center*** | | | | | | |
| Adult Outpatient Wait Time | AWT = 120.667 + 1.10595 AV - 19.1836 BRNV - 0.696486 LabV - 0.557691 PharmV | P>0.05 | p<0.05 | 83.49% | 1.73 | 25.12 [p<0.005] |
| Adult Outpatient Wait Time [BE] | AWT = 118.814 + 1.106 AV - 19.1923 BRNV - 0.711789 LabV | p<0.05 | p<0.05 | 83.47% | 1.73 | 24.60 [p<0.005] |
| Transformed Adult Outpatient Wait Time | AWT^0.227453 = 2.8627 + 0.00718114 AV - 0.10564 BRNV - 0.00453417 LabV - 0.00397788 PharmV | P>0.05 | p<0.05 | 86.78% | 1.09 | 22.72 [p<0.005] |
| Pediatric Outpatient Wait Time | PWT = 94.0721 + 1.94099 PV - 14.6733 BRNV - 0.344633 LabV - 0.267091 PharmV | P>0.05 | p<0.05 | 75.68% | 1.91 | 47.39 [p<0.005] |
| Pediatric Outpatient Wait Time [BE] | PWT = 91.9837 + 1.94109 PV - 14.6833 BRNV | p<0.05 | p<0.05 | 75.67% | 1.9 | 46.34 [p<0.005] |
| Transformed Ped. Outpatient Wait Time | PWT^-0.0680245 = -0.744201 + 0.00119551 PV - 0.00731516 BRNV - 0.000272647 LabV - 0.000243344 PharmV | P>0.05 | p<0.05 | 83.95% | 1.10 | 20.60 [p<0.005] |
| Transformed Ped. Outpatient Wait Time [BE] | PWT^-0.0673181 = -0.747284 + 0.00118675 PV - 0.00726617 BRNV - 0.000277242 Lab V | p<0.05 | p<0.05 | 83.92% | 1.10 | 20.26 [p<0.005] |
| Well Child Care Patient | WCWT = 40.2754 + 0.453931 WCV - 0.914471 BRNV - 0.0599932 LabV - 0.0562125PharmV - 1.97145 PreTV | P>0.05 | p<0.05 | 78.65% | 2.04 | 33.43 [p<0.005] |
| Well Child Care Patient [BE] | WCWT = 39.8895 + 0.453956 WCV - 1.97461 PreTV - 0.916315 BRNV | p<0.05 | p<0.05 | 78.63% | 2.04 | 33.77 [p<0.005] |
| Transformed Well Child Care Patient | (WCWT^L-1)/(L*g^(L-1)) = 146085 + 0.434451 WCV - 1.47802 PreTV - 0.850668 BRNV - 0.0012703 PharmV - 0.0333537 LabV \| L = Lambda = -2.53882, g = 37.4774 is the geometric mean of WCWT | P>0.05 | p<0.05 | 88.63% | 1.61 | 3.85 [p<0.005] |
| Transformed Well Child Care Patient [BE] | (WCWT^L-1)/(L*g^(L-1)) = 146085 + 0.434457 WCV - 1.47897 PreTV - 0.851227 BRNV \| L = Lambda = -2.53882, g = 37.4774 is the geometric mean of WCWT | p<0.05 | p<0.05 | 88.63% | 1.61 | 4.09 [p<0.005] |
| Pregnant Patient Wait Time | PregWT = 38.6559 + 1.48583 PRV - 2.43632 ERNV - 0.0481731 PharmV - 0.036288 LabV | p<0.05 | p<0.05 | 62.97% | 2.05 | 40.24 [p<0.005] |
| Pregnant Patient Wait Time [BE] | PregWT = 38.3682 + 1.48592 PRV - 2.43789 ERNV | p<0.05 | p<0.05 | 63.00% | 2.05 | 40.19 [p<0.005] |
| Transformed Preg. Patient Wait Time | (PregWT^L-1)/(L*g^(L-1)) = 535023 + 1.26618 PRV - 1.64813 ERNV - 0.0606347PharmV - 0.0654934 LabV \| L = Lambda = -3, g = 35.5939 is the geometric mean of PregWT | p<0.05 | p<0.05 | 70.43% | 1.84 | 4.04 [p<0.005] |
| Transformed Preg. Patient Wait Time [BE] | (PregWT^L-1)/(L*g^(L-1)) = 535022 + 1.26631 PRV - 1.65048 ERNV \| L = Lambda = -3, g = 35.5939 is the geometric mean of PregWT | p<0.05 | p<0.05 | 70.37% | 1.84 | 3.86 [p<0.005] |
| ***Urban Heatlh Center*** | | | | | | |
| **Response Variable** | **Model** | **Lack-of-fit** | | **$R^2$ adj.** | **Durbin-Watson Statistic** | **Anderson Darlin [p-value]** |
| Adult Outpatient Wait Time | AWT = 128.727 + 0.121836 AV - 0.0843473 RegV - 3.91733 BRNV - 3.90924 MDV - 0.376547 PharmV + 0.135669 LabV | p>0.05 | p<0.05 | 84.88% | 0.29 | 34.68 [p<0.005] |
| Adult Outpatient Wait Time [BE] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] |
| Transformed Adult Outpatient Wait Time | (AWT^L-1)/(L*g^(L-1)) = 61.62 + 0.118828 AV - 0.0750188 RegV - 4.49829 BRNV - 4.5089 MDV - 0.481781 PharmV + 0.493463 LabV \| L = Lambda = 2.58286, g = 146.180 is the geometric mean of AWT | p>0.05 | p<0.05 | 91.52% | 0.93 | 8.74 [p<0.005] |
| Transformed Adult Outpatient Wait Time [BE] | (AWT^L-1)/(L*g^(L-1)) = 61.3739 + 0.118828 AV - 4.49873 BRNV - 4.51107 MDV - 0.482164 PharmV + 0.49504 LabV \| L = Lambda = 2.58288, g = 146.130 is the geometric mean of AWT | p>0.05 | p<0.05 | 91.52% | 0.93 | 8.71 [p<0.005] |
| Pediatric Outpatient Wait Time | PWT = 125.118 + 0.293655 PV - 0.0920016 RegV - 4.19844 BRNV - 4.20444 MDV - 0.265244 PharmV + 0.128185 LabV | p>0.05 | p<0.05 | 87.50% | 0.35 | 24.73 [p<0.005] |
| Pediatric Outpatient Wait Time [BE] | PWT = 123.671 + 0.293655 PV - 4.19912 BRNV - 4.20784 MDV | p<0.05 | p<0.05 | 87.52% | 0.35 | 24.17 [p<0.005] |
| Transformed Ped. Outpatient Wait Time | (PWT^L-1)/(L*g^(L-1)) = 65.3777 + 0.28858 PV - 0.0823304 RegV - 4.69906 BRNV-4.70601 MDV - 0.322257 PharmV + 0.340038 LabV \| L = Lambda = 2.25076, g = 142.067 is the geometric mean of PWT | p>0.05 | p<0.05 | 91.80% | 0.90 | 8.29 [p<0.005] |
| Transformed Ped. Outpatient Wait Time [BE] | (PWT^L-1)/(L*g^(L-1)) = 64.5921 + 0.288538 PV - 4.69722 BRNV - 4.70596 MDV \| L = Lambda = 2.24704, g = 142.067 is the geometric mean of PWT | p<0.05 | p<0.05 | 91.78% | 0.91 | 7.21 [p<0.005] |
| Well Child Care Patient | WCWT = 94.0701 + 0.446264 WCV - 3.75518 RegV - 0.764232 BRNV + 0.295787 [illegible] | p>0.05 | p<0.05 | 77.32% | 1.96 | 54.56 [p<0.005] |
| Well Child Care Patient [BE] | WCWT = 96.0686 + 0.446264 WCV - 3.74594 RegV - 0.762384 BRNV - 12.2255 PreTV - 0.743447 LabV | p>0.05 | p<0.05 | 77.33% | 1.96 | 55.44 [p<0.005] |
| Transformed Well Child Care Patient | WCWT^-0.340488 = -0.236239 + 0.000483037 WCV - 0.00302548 RegV - 0.0103864 PreTV - 0.000474143 BRNV + 0.000335128 MDV - 0.000129612 PharmV - 0.000655445 LabV | p>0.05 | p<0.05 | 89.92% | 1.13 | 8.33 [p<0.005] |
| Transformed Well Child Care Patient [BE] | WCWT^-0.340429 = -0.23605 + 0.000483073 WCV - 0.00301704 RegV - 0.010382 PreTV - 0.000472447 BRNV - 0.000653759 LabV | p>0.05 | p<0.05 | 89.91% | 1.13 | 8.60 [p<0.005] |
| Pregnant Patient Wait Time | PregWT = 47.8384 + 0.829958 PRV - 3.26423 ERNV - 0.0456434 PharmV - 0.361975 LabV | p>0.05 | p<0.05 | 88.49% | 1.91 | 30.26 [p<0.005] |
| Pregnant Patient Wait Time [BE] | PregWT = 47.5426 + 0.829958 PRV - 3.26429 ERNV - 0.362029 LabV | p<0.05 | p<0.05 | 88.49% | 1.91 | 30.07 [p<0.005] |
| Transformed Preg. Patient Wait Time | PregWT^-0.713901 = -0.0685864 + 0.000905954 PRV - 0.00296484 ERNV - 5.83559e-005 PharmV - 0.000390646 LabV | p>0.05 | p<0.05 | 93.51% | 1.35 | 6.59 [p<0.005] |
| Transformed Preg. Patient Wait Time [BE] | PregWT^-0.713506 = -0.0690655 + 0.000906793 PRV - 0.00296778 ERNV - 0.000391078 LabV | p<0.05 | p<0.05 | 93.51% | 1.35 | 6.52 [p<0.005] |
| ***Rural Hospital*** | | | | | | |
| **Response Variable** | **Model** | **Lack-of-fit** | | **$R^2$ adj.** | **Durbin-Watson Statistic** | **Anderson Darlin [p-value]** |
| Adult Outpatient Wait Time | AWT = 143.52 + 0.325805 AV - 4.48906 RegV1 - 3.55044 BRNV - 3.43398 MDV - 2.02939 PharmV - 0.53778 LabV | p>0.05 | p<0.05 | 90.86% | 1.39 | 11.90 [p<0.005] |
| Transformed Adult Wait Time | AWT^1.26787 = 573.101 + 1.51659 AV - 22.1621 RegV1 - 17.415 BRNV - 16.9099 MDV - 9.43802 PharmV - 1.95441 LabV | p>0.05 | p<0.05 | 91.35% | 1.73 | 6.00 [p<0.005] |
| Pediatric Outpatient Wait Time | PWT = 84.2908 + 0.617292 PV + 10.0146 RegV1 - 3.38159 BRNV - 3.85698 MDV - 2.34554 PharmV - 1.29786 LabV | p>0.05 | p<0.05 | 80.91% | 1.99 | 19.03 [p<0.005] |
| Transformed Ped. Outpatient Wait Time | PWT^0.433749 = 6.5857 + 0.0193667 PV + 0.286226 RegV1 - 0.0945083 BRNV - 0.103485 MDV - 0.0703437 PharmV - 0.0487926 LabV | p>0.05 | p<0.05 | 83.15% | 1.56 | 6.16[p<0.005] |
| Well Child Care Patient | WCWT = 115.839 + 0.490139 WCV - 1.23523 RegV2 - 18.1671 PreTV - 0.0863572 BRNV - 0.489667 MDV - 0.0303029 PharmV - 0.525024 LabV | p>0.05 | p<0.05 | 88.17% | 1.80 | 19.48 [p<0.005] |
| Well Child Care Patient [BE] | WCWT = 114.486 + 0.490139 WCV - 1.23567 RegV2 - 18.1674 PreTV - 0.490103 MDV - 0.525285 LabV | p>0.05 | p<0.05 | 88.18% | 1.80 | 19.33 [p<0.005] |
| Transformed Well Child Care Patient | WCWT^0.397467 = 6.2631 + 0.0125831 WCV - 0.0256401 RegV2 - 0.420784 PreTV - 0.00230074 BRNV - 0.0110497 MDV + 0.000265971 PharmV - 0.0137362 LabV | p>0.05 | p<0.05 | 89.64% | 1.35 | 28.42 [p<0.005] |
| [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] |
| Pregnant Patient Wait Time | PregWT = 45.5047 + 0.962978 PRV - 2.61967 ERNV - 0.207573 PharmV - 0.3907 LabV | p<0.05 | p<0.05 | 88.36% | 1.68 | 27.21[p<0.005] |
| Transformed Preg. Patient Wait Time | PregWT^-0.218378 = -0.44138 + 0.00217199 PRV - 0.00516606 ERNV - 0.000414973 PharmV - 0.000834499 LabV | p<0.05 | p<0.05 | 90.69% | 1.44 | 7.10 [p<0.005] |

BE=Backwards Elimination: the resulting model and statistic after independent variables with a p-value >0.05 were removed and the regression was performed again

Selectied for decision support tool