

## A Comparative Analysis of Extended Resource Utilization and Resource Allocation on Patient Waiting Time: A Simulation-Based Approach

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### Abstract

*Globally, patient waiting time is an ongoing healthcare issue, with patients waiting longer hours to receive medical attention at healthcare facilities. Applying Queuing Theory and Dynamic Capability Theory (DCT), this study examines the varying extent of implementing flexibility configuration strategies, namely Extended Resource Utilization and Resource Allocation, both in isolation and in combination, on Patient Waiting Time. A time motion data collection method was used to collect process data, and a discrete event simulation (DES) approach was used for modeling the patient flow. The findings reveal that combining extended resource utilisation and resource utilisation has the most substantial improvement (22.09 percent) on patient waiting time, followed by extended resource utilisation at 15.42 percent and resource allocation at 6.67 percent. However, to leverage flexibility aimed at reducing patient waiting time, in the interim, the study recommends extended resource utilisation since resource allocation has a cost implication. The study advances the understanding of improving patient waiting time by linking QT and DCT and offers insights into how resources, particularly the healthcare providers, can be configured to respond to the challenge of prolonged PWT along the patient treatment process.*

**Keywords:** Waiting time, flexibility, resource allocation, resource utilisation, simulation

### Introduction

Patient waiting time defined as the time spent (both actual waiting and service times) by a patient at the different service points (such as registration, laboratory) that a patient visits for care within a healthcare facility, is an emerging healthcare issue in many national healthcare settings (Edrisa et al., 2020; Kyarisiima et al., 2024). While patients recognise that some degree of waiting is inherent in accessing healthcare services, institutions such as the Institute of Medicine recommend patients be seen within 30 minutes (Biya et al., 2022). Unfortunately, patients across various national healthcare settings often experience prolonged waiting times in healthcare facilities, with the situation argued to be dire in developing economies where patients often wait between 2 and 4 hours before receiving treatment (Edrisa et al., 2020; Kyarisiima et al., 2024). Reviewed studies further illustrate this challenge, reporting mean waiting times of 6.6 hours in Uganda, 4 hours in Haiti, 3.5 hrs in Rwanda, 2.8 hours in both Ghana and Tanzania, and 2.7 hours in Pakistan (Altema et al., 2020; Appiah, 2019; Edrisa et al., 2020; Kyarisiima et al., 2024; Msengwa et al., 2020; Sarwat, 2021). This may imply that many healthcare facilities in developing economies are inefficient, unresponsive, and unsafe. Prolonged PWTs are mostly the result of a disparity between patient needs for a service and the available resources to meet the

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current patient needs, with Africa expected to bear approximately 52 percent of the global health workforce deficit by 2030 (Ahmat et al., [2022](#); Boniol et al., [2022](#); Kam et al., [2021](#); Zhang et al., [2023](#)). Consequently, some patients must wait, since not all patients can be attended to immediately. Available evidence shows that the patient waiting time challenge is more prevalent in outpatient clinics such as the Antenatal care (ANC) (Abdus-salam et al., [2021](#); Berihun et al., [2023](#); Datta et al., [2023](#); Edrisa et al., [2020](#); Kyarisiima et al., [2024](#)).

Several operation-based measures, such as block appointment, transition from paper to electronic medical record, the acquisition of modern diagnostic equipment and maximum waiting time guarantee have been implemented; however, prolonged waiting times remains an ongoing healthcare issue (Boniol et al., [2022](#); Mwanswila et al., [2024](#); OECD, [2020](#); Tagimacruz et al., [2025](#)). Given societal trends such as rapid population growth and an aging population often suffering from multiple and complex diseases, it is anticipated that patient numbers will improve significantly (McIntyre & Chow, [2020](#); Naiker et al., [2018](#)). As a result, healthcare facilities continue to face operational capacity constraints, particularly healthcare providers such as doctors and nurses, who have a critical role to play, forcing some patients to wait (Kyarisiima et al., [2024](#)). In contrast to other sectors, prolonged patient waiting time presents unique and severe implications in the health sector, such as death in adverse circumstances. As posited by Edrisa et al. ([2020](#)), more emphasis needs to be put on lowering patient waiting time as government and other relevant institutions strive to attain top-notch health outcomes.

In striving to meet several healthcare operational needs, healthcare policymakers are becoming more proactive and looking beyond traditional strategies. For instance, literature presents the application of supply chain operational strategies in healthcare among the contemporary proactive strategies advocated for. These include absorptive, adaptive, and restorative strategies applied before, during, and after a disruptive event occurs, respectively (Gaudenzi & Pellegrino, [2023](#); Rojo et al., [2018](#)). Since healthcare facilities operate daily, incorporating adaptive strategies in their daily operations is crucial in responding to fluctuating patient needs. Among the adaptive strategies highlighted in the literature is agile, which relates to the ability of organisations to respond promptly to fluctuations (Gaudenzi & Pellegrino, [2023](#); Sindhvani et al., [2019](#)). One of the key attributes of agile is flexibility (Olsson & Aronsson, [2015](#); Sindhvani et al., [2019](#)). A multidimensional concept studied across various managerial levels, namely tactical, operational, and strategic (Kumar & Singh, [2020](#)). Unfortunately, at the operational level, the assessment of flexibility within the health sector, particularly healthcare operations along the patient treatment process, has been overlooked in the literature (Bera et al., [2022](#); Kumar & Singh, [2020](#)). Thus, a comprehensive and process wide perspective on patient care is often lacking and this increases the need for adoption of a holistic view of the patient care spectrum, from arrival to discharge, while adopting flexible strategies to achieve better patient outcomes.

Contrary to various scholarly perspectives on flexibility, at the operational level, flexibility calls for adjusting the available resources and processes in response to the diverse patient needs (Alolayyan & Alyahya, [2023](#); Bera et al., [2022](#)). This alleviates several bottlenecks along the patient flow. Several studies highlight the critical contribution of flexibility in improving healthcare outcomes such as patient waiting time (Chahal et al., [2018](#); El-Khalil & Mezher, [2020](#); Lucianetti et al., [2018](#); Ministry of Health, [2022](#)). Literature suggests that creating flexibility in available resources, such as healthcare providers, can be achieved either by changing the quantity of resources (resource allocation) or by extending their use (extended resource utilization) (Bera

et al., [2022](#); Olsson & Aronsson, [2015](#)). In this study, resource allocation is defined based on the understanding of Bera et al. ([2022](#)) and Daniels et al. (2004) as the ability of the healthcare facility to adjust the number of available resources at different stages of the patient care process. Additionally, Choe et al. (2022) and Kornelakis (2014) define extended resource utilization as the capability to vary working hours of the available healthcare providers in bottleneck areas. To wholly achieve the benefits of integrating flexibility into healthcare operational processes, recent studies have recommended exploration of how the different flexibility configuration strategies improve healthcare outcomes (Alolayyan & Alyahya, [2023](#); Kumar & Singh, [2020](#); Yousuf et al., [2019](#)).

Extant literature shows that discussions on resource allocation and extended resource utilization have considered each of the strategies independently in disregard of the varying extent of pursuing either or both on patient waiting time (Bera et al., [2022](#); Hassanzadeh et al., [2023](#); Msengwa et al., [2020](#); Masrom et al., 2023). This explains the inadequate knowledge of the benefits that could accrue from pursuit of either or both strategies. Besides the argument in literature is that a combination of strategies may outperform individual strategies (Alolayyan & Alyahya, [2023](#); Alolayyan & Ibrahim, 2021; Yousuf et al., [2019](#)). In addressing this gap, this study investigates the varying extent of pursuing either resource allocation or extended resource utilization or both on patient waiting time. Available evidence suggests that even a small amount of flexibility, when properly configured, can lead to better operational outcomes, however, this may require testing before actual implementation (El-Khalil & Mezher, [2020](#); Wang et al., 2021). Simulation offers an opportunity to replicate reality and investigate the effects of operational changes in advance before actual implementation (Forbus & Berleant, [2022](#); Volochtchuk & Leite, [2022](#)). Discrete Event Simulation (DES), as one of the simulation approaches, is applicable at the operational level (Hejazi, 2021; Law, 2015; Vázquez-Serrano et al., 2021) and suitable for modelling PWTs, since PWT involves queuing for different services, and entities such as patients change at discrete instances of time (Bera et al., [2022](#)).

### **Literature review**

Patient waiting times are a dynamic phenomenon fluctuating with variations in patient demand, resource availability, and operational conditions such as disruptions in the flow of patients. This may necessitate the adoption of a mix of different but complementary theoretical perspectives. Consequently, this study draws on two complementary theories (Queuing Theory and Dynamic Capability Theory) to provide a more comprehensive understanding of the patient waiting time phenomenon. Whereas Queuing Theory provides the analytical basis for identifying and analyzing system bottlenecks, the theory ignores the human behavioural aspect of the servers since not all servers are machines (Marin et al., 2007; Rathore, 2022; Wichansky, 1976). Accordingly, QT is complemented with the Dynamic Capability Theory (DCT) which posits that organizations must adapt, integrate and reconfigure resources and capabilities in as they respond to changes in their operating environment (Bleady et al., 2018; Furnival et al., 2019; Mittal, 2019; Teece, 2018). Among the capabilities is flexibility (Heikinheimo et al., 2025). The severe mismatch between patient expectation of less waiting time and the available resources poses a critical challenge to healthcare providers since the delivery and consumption of healthcare occur concurrently. Besides, the patient waiting time challenge mirrors inefficiencies in the patient flow processes resulting from operational constraints (Kyarisiima et al., [2024](#)). As a result, healthcare providers must develop strategies as a response mechanism aimed at improving patient waiting time. Among the response mechanisms is flexibility. Unfortunately, this phenomenon remains

understudied within the health sector (Kumar & Singh, [2020](#)). Healthcare practitioners and scholars have thus argued for incorporation of flexibility in healthcare operations (Alolayyan et al., [2022](#); Bera et al., [2022](#); Ministry of Health, [2022](#)). This could be through dealing with fluctuating patient volumes, and capacity utilization (Kumar, [2022](#); Wise et al., [2020](#)). Contemporary studies contend that the response rate to patient needs is partly dependent on the flexibility of healthcare providers (Bera et al., [2022](#); Kumar & Singh, [2020](#)). From the literature, flexibility is created by either altering the amount of resources or extending their use (Bera et al., [2022](#); Olsson & Aronsson, [2015](#); Simwita & Helgheim, [2016](#)).

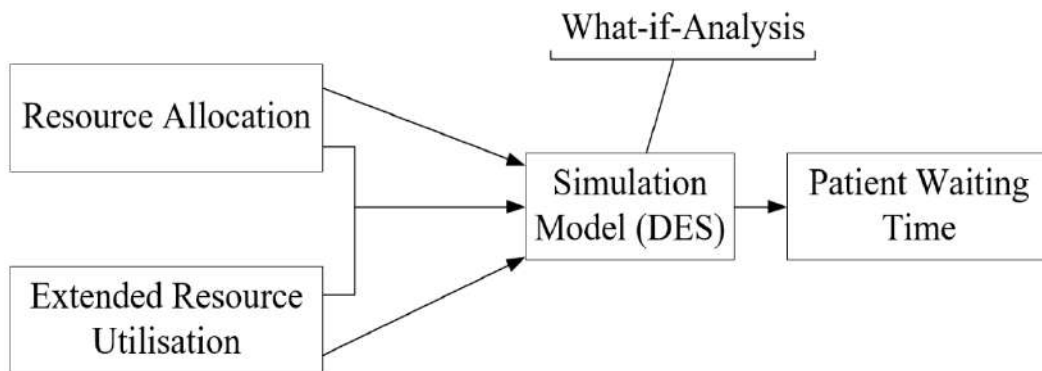
Empirical evidence shows that either decision, if implemented, has the potential to improve patient waiting time. For example, Msengwa et al. ([2020](#)) in their study on outpatient department waiting times and resource allocation, posited that the introduction of a physician and a registration staff member, reduced average patient waiting time to 38 minutes. Bera et al. ([2022](#)) contended that, allocating additional resources to bottleneck areas significantly reduced patient waiting times in the cardiology department. Relatedly, in a study utilising discrete event simulation to enhance operating theatre efficiency, Hassanzadeh et al. ([2023](#)) established that extending theatre operating hours by just one hour resulted in a 50 percent reduction in turnaround time. Bahadori et al. ([2014](#)), in their study found that the addition of a staff member at the dispensing unit led to a reduction of average waiting time by approximately 8 minutes and 44 seconds. Reducing patient waiting time may call for careful alignment of healthcare providers across the patient treatment flow. Thus, necessitating the need to assess patient flow from a flexibility perspective. Unfortunately, there is a dearth of research allowing flexibility in a service capacity along the patient care treatment (Bera et al., [2022](#)). Specifically, there is a notable gap in research addressing the varying extent to which various flexibility configurations (extended resource utilisation and resource allocation) in available resources improve patient waiting time. Yet, studies emphasize that flexibility aspects should not be considered in isolation, since they may vary in importance, and combining multiple flexibility configurations may yield better outcomes than applying individual strategies independently (Al-Hakimi et al., [2022](#); Alolayyan & Alyahya, [2023](#); Bera et al., [2022](#); Kumar & Singh, [2020](#); Rechel et al., [2010](#); Yousuf et al., [2019](#)).

Similarly, available evidence shows that the patient waiting time challenge is more prevalent in outpatient clinics such as the Antenatal care (Datta et al., [2023](#); Edrisa et al., [2020](#); Kyarisiima et al., [2024](#)). However, despite the significance placed on antenatal healthcare, there is limited scholarly attention on patient waiting times in antenatal clinics (Abdus-salam et al., [2021](#); Berihun et al., [2023](#)). Besides, the majority of patient waiting time studies are not done in specialised clinics, which raises a question of generalizability (Edrisa et al., [2020](#)). Thus, this study aims to address this knowledge gap by employing discrete event simulation to illustrate the differential impact of resource utilization, resource allocation, and their combined implementation on patient waiting time.

### **Conceptual model**

The study aim, as described in the introduction section, was to inquire into the relative importance of implementing flexibility strategies (resource allocation and extended resource utilisation) on patient waiting time. Therefore, a conceptual model was developed to help measure the relative importance of the aforementioned flexibility strategies, tested through simulation and supported

by what-if analysis, on patient waiting times. [Figure 1](#) below provides the layout of the conceptual model.



**Figure 1. The Conceptual Model**

*Source: Developed from synthesis of Literature.*

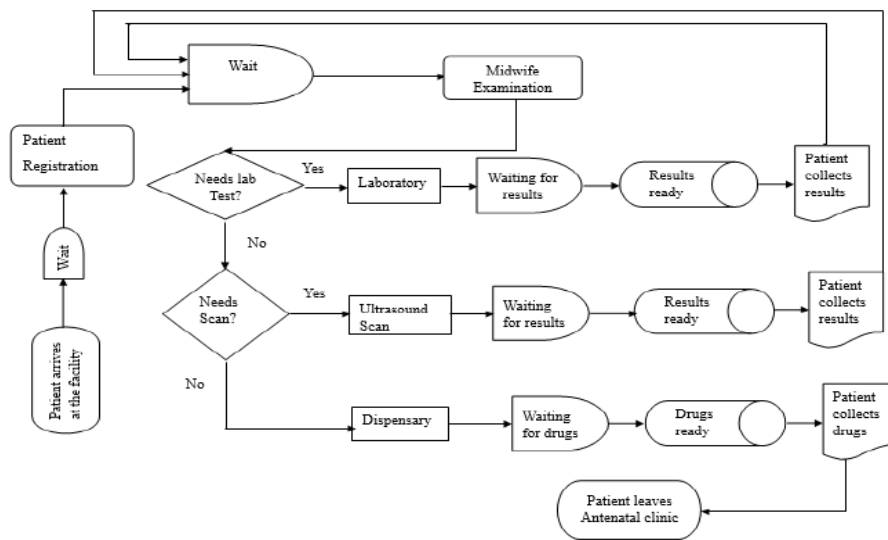
### Material and Methods

Uganda has five national referral hospitals: Butabika, Kawempe, Kiruddu, China-Uganda Friendship Hospital (CUFH), and Mulago National Specialized Hospital (Ministry of Health, 2020). The selection of CUFH as the focus of this study is informed by several factors. Located in Kampala, CUFH serves an estimated population of 10 million people (Ministry of Health, 2021b). As a national referral facility, CUFH consumes substantial resources, surpassing lower tier healthcare facilities. Available evidence shows that, between FY 2019/20 and FY 2021/22, CUFH recorded a 30 percent increase in general outpatient visits (Naguru Referral Hospital, [2020](#), [2022](#)). Furthermore, the Ministry of Health. (2021a) states that CUFH had the highest number of healthcare providers among Uganda’s national referral hospitals at 83 percent with Butabika at 73 percent, Kawempe at 37 percent, and Kiruddu at 29 percent. This gives CUFH greater operational flexibility than facilities with lower staffing levels. Besides, patients are more likely to flock healthcare facilities with a high likelihood of finding a healthcare provider. Although Mulago National Referral Hospital met the stated selection criteria, it was excluded from this study due to its designation as a higher-tier national and specialised hospital, which distinguishes it from the other referral facilities under consideration.

Available evidence shows that the patient waiting time challenge is more prevalent in outpatient clinics (Datta et al., 2023; Edrisa et al., [2020](#); Kyarisiima et al., [2024](#)). As a result, the antenatal clinic was considered. The choice of clinic was based on the following criteria. Antenatal care (ANC) is a planned medical intervention designed to safeguard the health of pregnant women and their unborn children (Ministry of Health, [2022](#)). Despite the significance placed on antenatal healthcare, there is limited scholarly attention on patient waiting times in antenatal clinics (Abdusalam et al., [2021](#); Berihun et al., [2023](#)). Yet, it is not unusual to find expectant mothers waiting in hallways for medical care. Similarly, majority of patient waiting time studies are not done in specialised clinics which raises a question of generalizability (Edrisa et al., [2020](#)).

The ANC clinic is mainly operated by six midwives. CUFH also has a central laboratory and a scan section, which serve the entire hospital. The scan on average has 3 radiographers, and the laboratory has at least three lab technicians. To fully understand the clinical operations, interviews

were held with the in-charges of the various units involved in providing ANC services (laboratory, ultrasound scan, and the antenatal clinic). Information obtained from the interviews was used in mapping and developing the process map of the antenatal care, as shown in [Figure 2](#). [Figure 2](#) is detailed as follow: ANC mothers often arrive as early as 6:00 a.m. Upon arrival, they self-register by writing their names on a sheet of paper, a practice aimed at facilitating a first-come, first-served discipline. The combination of high client volume and the adherence to a first-come first-served principle largely explains why many ANC mothers arrive at the clinic very early in the morning. The clinic opens at 8 am, and soon patient registration starts, followed by the first midwife examination. Midwives are responsible for initiating ancillary investigations, including laboratory tests and obstetric ultrasound, based on the clinical need. ANC mothers are sent to either the ultrasound scan or the laboratory. Once the results are ready, they return to the midwife for the subsequent examination after which they are sent to the dispensing section and finally discharged.



**Figure 2. The process map of Antenatal Care.**

*Source: Field Data*

### Data collection and Analysis

Ethical approval for this study was granted by the Research and Ethics Committee of CUFH. Patient written consent, was deemed unnecessary and data collection was conducted anonymously to ensure participant confidentiality since this was a process improvement study. To support data collection, four enumerators were recruited and oriented about the study's objective and data collection procedure. A time-motion approach was employed where ANC mothers were followed from the moment of arrival at the clinic through to the point of discharge, utilising stopwatches and structured data sheet previously used by other scholars such as (Msengwa et al., 2020; Musinguzi, 2015) where each column represented either waiting or assessment time of a particular observed patient activity. During the data collection period, a total of 384 ANC mothers who completed the entire process were included in the study. Patients who did not undergo the entire process were excluded as the study specifically focused on capturing the entire ANC process. Healthcare records show that the clinic attends to an average of 80 ANC mothers daily. Relatedly, ANC mothers that required emergency care did not form part of this study.

The analysis followed a structured procedure. Starting with data independence which was assessed using scatter plots and linear correlation analysis to ensure that observations were not autocorrelated. Candidate distribution families were hypothesized based on descriptive statistics, visual inspection through histograms and box plots. Subsequently, chi-square goodness-of-fit tests were conducted to evaluate the adequacy of each candidate distribution and to identify the best-fitting model for the observed data. Discrete-event simulation (DES) was employed as the primary methodological approach for this study. The simulation model was developed using Arena software (Version 13.0). Probability distribution parameters were derived using both Minitab (Version 22.0) and Arena’s Input Analyzer. Table 1 provides a summary of the selected probability distributions incorporated into the simulation model.

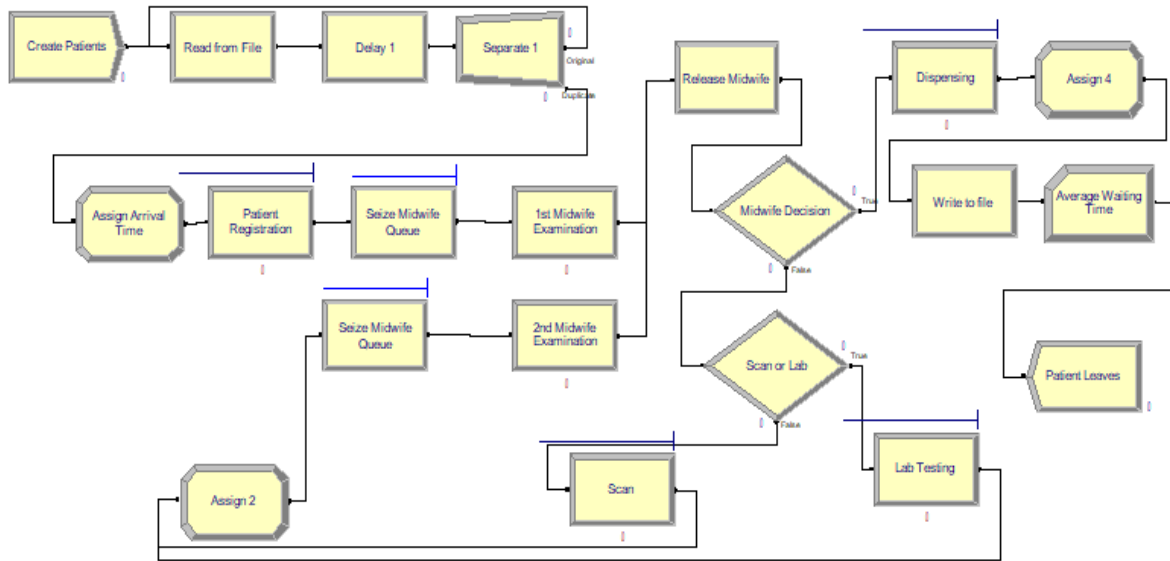
**Table 1: Simulation model input based on current antenatal care process (minutes)**

Patient flow	Type	Parameter	$\chi^2$ -test (P-value)
Arrival Time	Constant	1	
Registration Time	Expression	NORM (3.98, 1.14)	17.8 (0.09)
1st Midwife Examination Time	Expression	5.28 + WEIB (1.97, 3.7)	14.7 (0.1)
Lab Testing Time	Expression	15.1 + LOGN (5.36, 2.32)	11.7 (0.07)
Ultrasound Scan	Expression	11 + GAMM (1.78, 3.05)	6.44 (0.27)
2nd Midwife Examination Time	Expression	1.45 + WEIB (1.46, 3.85)	15.4 (0.09)
Dispensing Time	Expression	NORM (2, 0.0756)	14.9 (0.095)

*Source: Field Data*

**Model development and assumptions**

Development of a simulation model requires thorough understanding of the system’s operational behavior (van Hulzen et al., 2022). This may involve understanding the flow of activities, how long they take and the resources allocated. However, replicating healthcare processes involving human behavior is not a straightforward phenomenon. At an individual level, they have intrinsic motivators and may make irrational decisions, which can be difficult to model (Forbus & Berleant, 2022). Thus, a number of assumptions were made during simulation model development. First, the study focuses on the operational hours between 6:00 a.m. and 3:30 p.m., as patient arrivals begin as early as 6:00 a.m. Second, given that the primary objective of the study is to examine the complete ANC treatment process, the analysis was limited to clients who underwent the full care pathway from arrival to discharge. Third, ANC mothers are treated on first-come first-served basis. Fourth, resources are available to ANC mothers from Monday to Friday. Fifth, as part of the outpatient department, the antenatal clinic begins and ends the day empty. Sixth, this study assumes no priority in queues. Seven, the decision on whether to do resource allocation or extend resource utilisation is based on identifying bottlenecks within the patient treatment flow. The simulation model was developed based on the aforementioned assumptions and executed for 384 independent replications, with the system reinitialized between each run. Each replication represented a single operational day at the clinic. Figure 3 shows the developed simulation model for the antenatal care process



**Figure 3. The developed Simulation Model for the Antenatal Care Process**

*Source: Field Data*

**Model verification and validation**

Model verification was performed to confirm that the model was implemented correctly, while validation assessed the degree to which the model accurately reflected real-world system behaviour. The developed model was verified using Arena debugging tools, animation and Little’s Law to ensure the model is free from logical error (Fonseca, 2023; Masrom et al., 2023).

Little's Law states that:

$$L = \lambda W$$

Where;

L=the average number of patients in a stationary system/work in progress

$\lambda$  = the average effective arrival rate

W= the average time an entity spends in the system

**Real Data**

$$\begin{aligned} \lambda &= \frac{\text{Total number of entities (patients) arriving}}{\text{Total Hour (simulation time)}} \\ &= 80 / (9.5 * 60) \\ &= \mathbf{0.1404} \end{aligned}$$

**Simulation Data**

$$\begin{aligned} L &= \lambda W \\ 55.6841 &= \lambda(379.03) \\ &= \mathbf{0.1404} \end{aligned}$$

To validate the simulation model, the following measures were considered. High face validity, paired t-test, average number of ANC mothers, average patient waiting time, and a percentage difference of less than 10 percent. High face validity was maintained by involving the section heads during model development. A paired t-test was used to compare means for waiting time between the observed waiting time and the simulation value at a 95 percent confidence interval. It can be deduced that the two reported average waiting times are not significantly different, as shown in Table 2. The average number of ANC mothers attended to per day at the clinic is 80,

and the DES model output shows 80 ANC mothers per day, as shown in Figure 4. In addition, the difference percentage in Table 3 indicates that the simulation model was considered verified and validated.

**Table 2: The paired sample t-test results for both real and simulation data**

		Mean	N	Std. Dev		
Pair 1	Real Data	379.06	80	42.46		
	Simulation Data	379.35	80	43.78		
<b>Paired Differences</b>						
		Mean	Std. Dev	Std. Error	t	Sig
Pair 1	Real Data - Simulation Data	-.2905	2.1059	.2355	-1.234	.221

Replications: 384 Time Units: Minutes

**Key Performance Indicators**

**System** Average  
Number Out 80

The difference percentage must be less than 10 percent (Ahmad et al., 2021).

$$\text{Difference \%} = \frac{|\text{Simulation data} - \text{Actual Data}|}{|\text{Actual Data}|}$$

**Figure 4. Average number of ANC Entities per day**

**Table 3. Summarises the average service time per entity (in minutes) for both empirical and simulated data, along with the verification percentage difference**

Patient Flow	Real Data	Simulation Data	% of Verification
Patient Registration	3.9930	3.9766	0.4107
1st Midwife Examination	7.0412	7.0559	0.2088
Lab Testing	19.9100	20.4511	2.7177
Scan	16.2005	16.3912	1.1771
2nd Midwife Examination	2.7826	2.7727	0.3558
Dispensing	1.9954	1.994	0.0702

**Simulation results, System bottlenecks, alternative solutions and evaluation of alternatives**

The primary objective of this study was to examine the extent to which resource allocation, extended resource utilisation, and their combined application influence patient waiting time. To achieve this, a discrete-event simulation (DES) model was developed to replicate the baseline antenatal care (ANC) process. The study then employed the model to examine the different possible configuration scenarios of Resource Allocation and Extended Resource Utilisation aimed at reducing patient waiting time. Unresolved bottlenecks within the patient treatment flow remain a critical driver of prolonged waiting times, undermining both operational efficiency and patient satisfaction in healthcare facilities. Since mitigating a bottleneck at one point in the service chain can inadvertently create new constraints downstream, this study explored the complete ANC process and assessed how resource allocation and utilization could improve patient waiting time.

Figure 5 shows the simulation results for the average service time at each service point across the entire patient treatment flow process. Laboratory testing and Scan had the highest average service times of 20.45 minutes and 16.39 minutes, respectively. The least average service time was at the dispensing service point, with an average service time of 2 minutes.

Replications: 384    Time Units: Minutes

Process						
Time per Entity						
VA Time Per Entity	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
1st Midwife Examination	7.0559	< 0.01	6.8788	7.2459	5.4211	8.9218
2nd Midwife Examination	2.7727	< 0.00	2.6331	2.8983	1.5407	4.2477
Dispensing	1.9994	< 0.00	1.9741	2.0189	1.7028	2.3368
Lab Testing	20.4511	< 0.03	19.7516	21.6668	16.1074	38.2327
Patient Registration	3.9766	< 0.01	3.6437	4.2989	0.00	8.4698
Scan	16.3912	< 0.08	14.6920	18.5459	11.6974	37.0741

Figure 5. Simulated average service times (in minutes) per entity

Figure 6, shows the average waiting time in queues at each service point along the patient treatment flow process. The longest patient waiting time was witnessed at the patient registration and Midwife Examination service points, with an average patient waiting time of approximately 275.42 minutes and 34.42 minutes, respectively. The service point with the shortest waiting time was dispensing, with an average patient waiting time of approximately 2.25 minutes. As illustrated in Figure 6, the primary bottlenecks within the ANC clinic occurred at the patient registration and the midwife examination point.

Queue						
Time						
Waiting Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Dispensing.Queue	2.2488	< 0.06	0.6828	4.0247	0.00	9.7910
Lab Testing.Queue	8.0901	< 0.42	0.6681	21.1573	0.00	50.5503
Midwife Examination.Queue	34.4193	< 0.12	30.6000	37.9549	0.00	73.5070
Patient Registration.Queue	275.42	< 0.02	274.92	276.07	255.00	292.73
Scan.Queue	14.8667	< 0.94	0.5680	45.0495	0.00	83.4511

Figure 6. Simulated average waiting time per entity at each service point

Table 4 presents the different Resource Allocation (RA) scenarios that were evaluated during the simulation. A total of six RA scenarios were evaluated at the identified bottleneck points (patient registration and midwife examination). 1 and 2 in Table 4 indicate the number of resources that were added to a bottleneck service area, while 0 implies that no resource was added to a bottleneck area. Additionally, during simulation, Extended Resource Utilisation (ERU), was actualised by

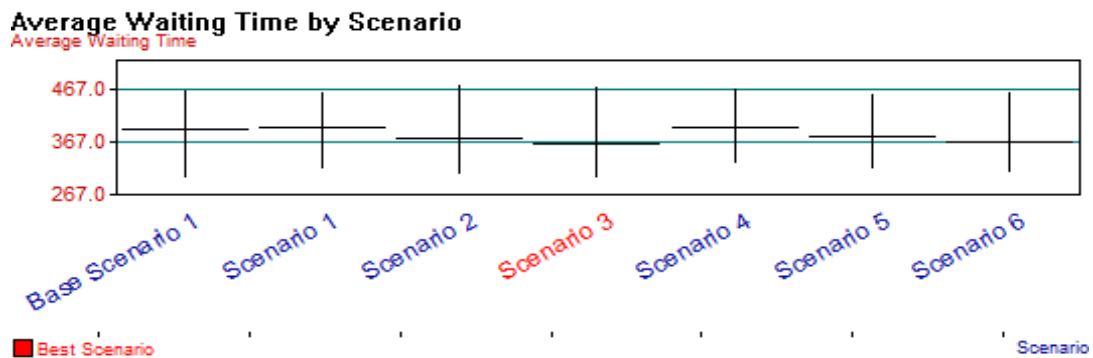
adjusting the start time of activities at the bottleneck areas by 1 hour. Lastly, a combination of both RA and ERU was also evaluated.

**Table 4. Different simulated scenarios on patient waiting Time**

	Additional staff at the Registration	Additional staff at Midwife Examination
<b>Resource Allocation (RA) Scenarios</b>		
Scenario 1	1	0
Scenario 2	1	1
Scenario 3	1	2
Scenario 4	2	0
Scenario 5	2	1
Scenario 6	2	2
Extended Resource Utilisation (ERU)	< 60 minutes	
RA and ERU	Combined	

**Resource allocation**

One of the key objectives of the study was to examine the extent to which patient waiting time in the antenatal care could be reduced by resource allocation. As illustrated in [Table 4](#) and [Figure 7](#), distinct configurations of resource allocation reflect the several scenarios that were simulated. The base scenario in [Figure 7](#) reflects the current system prior to any configuration whereas scenarios 1, 2, 4, 5, and 6 indicate several resource allocation configurations intended to reduce patient waiting time. With the exception of scenario 1, scenarios 2, 4, 5 and 6, demonstrate varying extents in the reduction of average patient waiting time. Additionally, scenario 3, demonstrates the lowest average waiting time among all scenarios. This outlook underscores resource allocation as a critical approach for reducing patient waiting time.

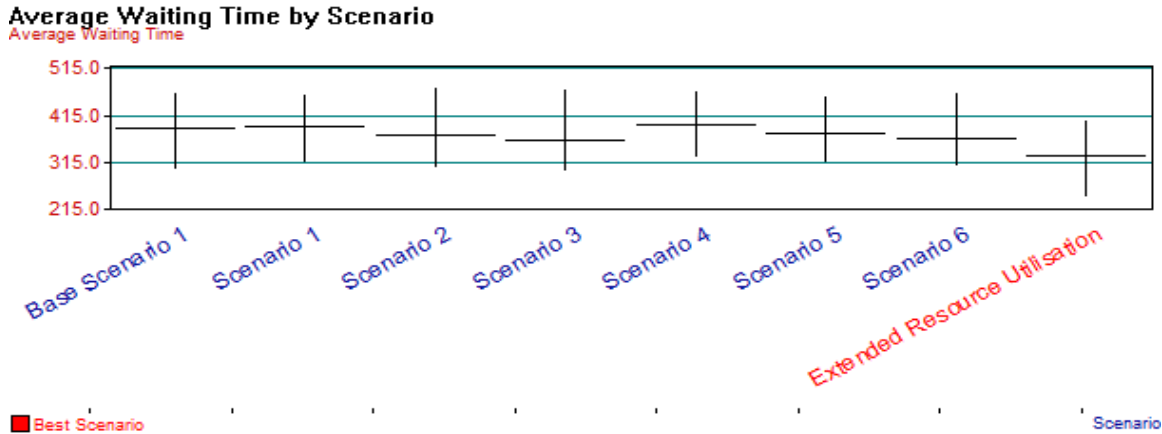


**Figure 7. Simulated resource allocation scenarios on patient waiting time**

**Extended resource utilisation**

In addition to examining the extent to which resource allocation could reduce patient waiting time, the study further sought to investigate the varying extent of either pursuing resource allocation or extended resource utilisation. This was purposed to establish which of the two configuration strategies offers better results in terms of reducing patient waiting time. [Figure 8](#) illustrates the simulation results that compare both resource allocation (scenarios 1, 2, 4, 5 and 6) and extended resource utilisation (Scenario 7). As per the illustration, extended resource

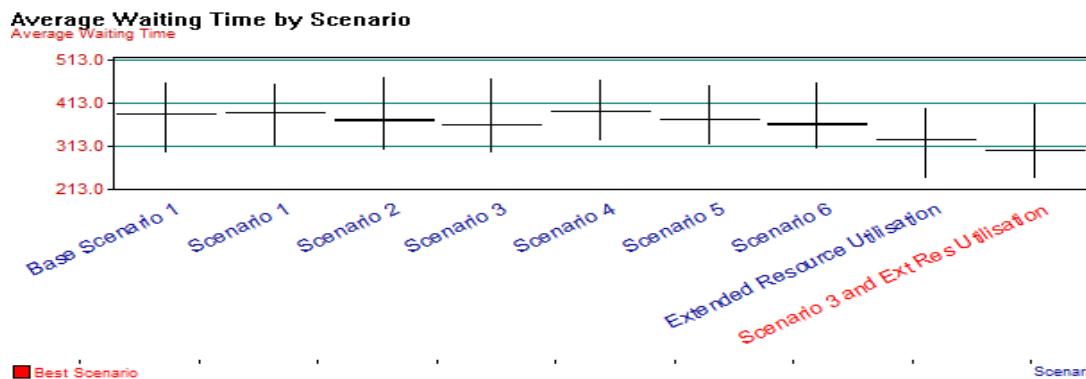
utilization (Scenario 7) presented the lowest average patient waiting time, outperforming both the base scenario and resource allocation configurations. This demonstrated how critical time-related flexibility is, as a mechanism for addressing the patient waiting time challenge in the wake of budget and infrastructure limitations.



**Figure 8. Simulated scenarios of resource allocation and extended resource utilisation on patient waiting time**

### Combining Resource Allocation and Extended Resource Utilisation

Further still, the study sought to examine the extent of pursuing either or both configuration strategies. As per [Figure 9](#), while resource allocation and extended resource utilisation individually reduce patient waiting time, their combination presents the lowest average patient waiting times across all simulated scenarios, outperforming both the base scenario and the individual scenarios of resource allocation and extended resource utilisation. These findings demonstrate that a strategy combining resource allocation and extended resource utilization is more effective for improving patient waiting time.



**Figure 9. Simulated scenarios of resource allocation, extended resource utilisation and their combination on patient waiting**

[Table 5](#) compares the base scenario with the results after implementing Resource Allocation, Extended Resource Utilisation and their combination. As shown in [Table 5](#), Resource Allocation and Extended Resource Utilisation when implemented in isolation will result in approximately 6.67 and 15.42 percent improvement in patient waiting time, respectively. However, their combination had the highest improvement of approximately 22.09 percent in patient waiting time.

This implies that, Resource Allocation and Extended Resource Utilisation when implemented in isolation and combination will result in improvement in patient waiting time.

**Table 5. The improvement percentage for each alternative solution on patient waiting time**

	<b>Base Scenario</b>	<b>After</b>	<b>Improvement Percentage</b>
Resource allocation (RA)	389.22	363.25	6.67
Extended resource utilisation (ERU)	389.22	329.22	15.42
Combining RA and ERU	389.22	303.25	22.09

### **Discussion**

This study intended to explore the extent to which flexibility configuration strategies in the healthcare sector can reduce patient waiting time, specifically within the antenatal care process. Particularly, the study focused on examining the varying extent of pursuing either or both resource allocation and extended resource utilisation on patient waiting time. The study employed DES to model the baseline antenatal care (ANC) process and examine the possible flexibility configuration scenarios along the identified bottleneck areas across the patient flow. The principal objective was to establish the most effective strategy for reducing patient waiting time. The simulation results demonstrate that introducing flexibility in available resources across different stages of the ANC process significantly improves patient waiting times. These findings are consistent with those reported by Bera et al. (2022), who similarly emphasise the significance of implementing flexibility along different stages of healthcare processes aimed at reducing patient waiting time. The significant reduction in patient waiting time clearly indicates that various forms of flexibility can be used to improve healthcare outcomes, such as patient waiting time. However, combining the two strategies has a very substantial improvement compared to individual strategies. This finding is in line with a claim that combining strategies outperforms individual strategies (Alolayyan & Alyahya, 2023; Alolayyan & Ibrahim, 2021; Yousuf et al., 2019). Interestingly, combining the two strategies may not practically translate into the best scenario at a given point in time. The prevailing context renders extended resource utilisation as the better scenario since resource allocation may have a cost implication. Unfortunately, healthcare funding in Uganda remains consistently below the Abuja Declaration target of 15 percent of the national budget (Uganda Bureau of Statistics, 2023).

### **Contribution to Literature**

The literature review established that there is a dearth of research in healthcare allowing flexibility in a service capacity (Bera et al., 2022). The study filled this gap by exploring how allowing flexibility in available healthcare resources along the different service points, from when the patient arrives to the point of discharge, may improve patient waiting times. The literature review also established that despite a consistent focus of researchers, there is a dearth of information regarding the assessment of flexibility in service operation, particularly how several kinds of flexibilities could vary for increased performance outcomes (Kumar & Singh, 2020). The study filled this gap by investigating the varying extent to which flexibility configuration strategies on available resources improves patient waiting time in isolation and in combination. The study established that flexibility configurations on available resources do vary in improving healthcare outcomes such as PWT.

### **Contribution to Theory**

From the literature, the study of waiting time is synonymous with Queuing Theory (QT). However, patient waiting time is a dynamic phenomenon fluctuating with variations in patient need and resource availability. Available evidence shows that QT alone cannot fully address the PWT challenge. Besides, QT has been critiqued for failure to consider server behaviours since not all servers are machines. (Marin et al., 2007; Rathore, 2022; Wichansky, 1976). In addressing this gap, the study complements QT with DCT, an indication that no theory can entirely address the patient waiting time challenge.

### **Practical Implications**

This study provides practical and fundamental insights in implementing flexibility to achieve better healthcare outcomes, specifically reduction of patient waiting time. Findings reveal that which flexibility configuration strategy healthcare providers choose to implement will deliver significant improvements in patient waiting time. Relatedly, findings present the priority in which the studied flexibility configuration strategies could be implemented. For instance, the combination of RA and ERU would be prioritized, followed by ERU and RA respectively.

### **Conclusion and Recommendations**

From the study results, it is revealed that both strategies RA, ERU and a combination of the two have a significant contribution towards the reduction of patient waiting time. Noticeably, a combination of RA and ERU presents the most effective improvement. However, ERU emerges as the most feasible alternative owing to the fact that RA comes with cost implications in terms of recruiting more healthcare providers.

### **References**

- Abdus-Salam, R. A., Adeniyi, A. A., & Bello, F. A. (2021). Antenatal clinic waiting time, patient satisfaction, and preference for staggered appointment—a cross-sectional study. *Journal of patient experience*, 8, 23743735211060802.
- Agaba, P., Magadi, M., Onukwugha, F., & Misinde, C. (2021). Factors Associated with the Timing and Number of Antenatal Care Visits among Unmarried Compared to Married Youth in Uganda between 2006 and 2016. *Social Sciences (2076-0760)*, 10(12).
- Ahmad, S. S. S., Kasim, A. S. A., Masood, I., Ho, F. H., & Abdullah, H. (2021). Capacity study of a food processing company using Arena simulation software. *Research progress in mechanical and manufacturing engineering*, 2(1), 166-173.
- Ahmat, A., Okoroafor, S. C., Kazanga, I., Asamani, J. A., Millogo, J. J. S., Illou, M. M. A., ...& Nyoni, J. (2022). The health workforce status in the WHO African Region: findings of a cross-sectional study. *BMJ Global Health*, 7(Suppl 1), e008317.
- Ajisehiri, W. S., Abimbola, S., Tesema, A. G., Odusanya, O. O., Peiris, D., & Joshi, R. (2023). “We just have to help”: Community health workers' informal task-shifting and task-sharing practices for hypertension and diabetes care in Nigeria. *Frontiers in public health*, 11, 1038062.
- Al-Hakimi, M. A., Goail, M. M., Al-Hattami, H. M., Murshid, M. A., Saleh, M. H., & Moghalles, S. A. M. (2023). Improving operational performance of manufacturing SMEs: the interactive effect of technical and human lean practices. *International Journal of Quality & Reliability Management*, 40(4), 1092-1110.
- Alolayyan, M., Al-Rwaidan, R., Hamadneh, S., Ahmad, A., AlHamad, A., Al-Hawary, S., & Alshurideh, M. (2022). The mediating role of operational flexibility on the relationship

- between quality of health information technology and management capability. *Uncertain Supply Chain Management*, 10(4), 1131-1140.
- Alolayyan, M. N., & Alyahya, M. S. (2023). Operational flexibility impact on hospital performance through the roles of employee engagement and management capability. *BMC health services research*, 23(1), 19.
- Alolayyan, M. N., & Ibrahim, A. S. (2021). Proposed mathematical model to study and analyze the relationship between operational flexibility dimensions and hospital performance. *Global Journal of Flexible Systems Management*, 22(4), 289-305.
- Altema, J., Bien-Aime, K., Roger, M. C., & Blaise, W. (2020). Causes of long wait time in health consultation services and strategies to reduce them: an observational study in rural Haiti. *The Lancet Global Health*, 8, S33.
- Appiah, K. W. A. B. E. N. A. (2019). Patient satisfaction with waiting time at the out patient department (OPD), holy family hospital, techiman. *Journal of Social Science Management*, 4(3), 165-176.
- Bahadori, M., Mohammadnejhad, S. M., Ravangard, R., & Teymourzadeh, E. (2014). Using queuing theory and simulation model to optimize hospital pharmacy performance. *Iranian red crescent medical Journal*, 16(3), e16807.
- Bera, S., Kumar, P., & Bhattacharya, S. (2023). A study on how to achieve flexibility in healthcare process: a simulation-based approach. *International Journal of Productivity and Performance Management*, 72(8), 2292-2316.
- Berihun, A., Abebo, T. A., Aseffa, B. M., Simachew, Y., Jisso, M., & Shiferaw, Y. (2023). Third delay and associated factors among women who gave birth at public health facilities of Gurage zone, southern Ethiopia. *BMC Women's Health*, 23(1), 369.
- Biya, M., Gezahagn, M., Birhanu, B., Yitbarek, K., Getachew, N., & Beyene, W. (2022). Waiting time and its associated factors in patients presenting to outpatient departments at Public Hospitals of Jimma Zone, Southwest Ethiopia. *BMC Health Services Research*, 22(1), 107.
- Bleady, A., Ali, A. H., & Ibrahim, S. B. (2018). Dynamic capabilities theory: pinning down a shifting concept. *Academy of Accounting and Financial Studies Journal*, 22(2), 1-16.
- Boniol, M., Kunjumen, T., Nair, T. S., Siyam, A., Campbell, J., & Diallo, K. (2022). The global health workforce stock and distribution in 2020 and 2030: a threat to equity and 'universal' health coverage?. *BMJ global health*, 7(6).
- Bwire, A., Sama, D. J., Mirano, J., Nyachae, P., Owino, K., Nabukeera, J., ... & Bose, K. (2024). Boosting contraceptive uptake in urban Uganda: older women benefit when layering adolescent and youth interventions onto existing family planning programming. *Global Health: Science and Practice*, 12(Supplement 2).
- Chahal, H., Gupta, M., & Lonial, S. (2018). Operational flexibility in hospitals: Scale development and validation. *International Journal of Production Research*, 56(10), 3733-3755.
- Choe, H., Kim, Y., & Moon, S. (2022). The effect of labor flexibility on financial performance in Korea: The moderating effect of labor relations climate. *Sustainability*, 14(4), 2121.
- Daniels, R. L., Mazzola, J. B., & Shi, D. (2004). Flow shop scheduling with partial resource flexibility. *Management science*, 50(5), 658-669.
- Datta, S., Kapoor, R., & Mehta, P. (2023). A multi-objective optimization model for outpatient care delivery with service fairness. *Business process management journal*, 29(3), 630-652.

- Edrisa, M., Esther, B., Fredrick, N., Martin, M., Peace, B., & Daniel, K. (2020). Injury Timespan at a Specialized Outpatient Clinic of the National Referral Hospital, Uganda. *J Community Med Health Educ* 10: 701
- El-Khalil, R., & Ali Mezher, M. (2020). A study of the relation between flexibility dimensions and performance metrics: Literature review. In *Proceedings of the 5th NA International Conference on Industrial Engineering and Operations Management* (pp. 1307-1318).
- Fonseca, I. C. P. (2023). A continuous process for validation, verification, and accreditation of simulation models. *Mathematics*, 11(4), 845.
- Forbus, J. J., & Berleant, D. (2022). Discrete-event simulation in healthcare settings: a review. *Modelling*, 3(4), 417-433.
- Furnival, J., Boaden, R., & Walshe, K. (2019). A dynamic capabilities view of improvement capability. *Journal of Health Organization and Management*, 33(7-8), 821-834.
- Gaudenzi, B., Pellegrino, R., & Confente, I. (2023). Achieving supply chain resilience in an era of disruptions: a configuration approach of capacities and strategies. *Supply Chain Management: An International Journal*, 28(7), 97-111.
- Hassanzadeh, H., Boyle, J., Khanna, S., Biki, B., Syed, F., Sweeney, L., & Borkwood, E. (2023). A discrete event simulation for improving operating theatre efficiency. *The International Journal of Health Planning and Management*, 38(2), 360-379.
- Hejazi, T. H. (2021). *State-dependent resource reallocation plan for health care systems: A simulation optimization approach*. *Computers & Industrial Engineering*, 159, 107502.
- Kam, A. W., Collins, S., Park, T., Mihail, M., Stanaway, F. F., Lewis, N. L., ... & Smith, J. E. (2021). Using Lean Six Sigma techniques to improve efficiency in outpatient ophthalmology clinics. *BMC Health Services Research*, 21(1), 38.
- Kornelakis, A. (2014). Balancing flexibility with security in organizations? Exploring the links between flexicurity and human resource development. *Human Resource Development Review*, 13(4), 398-412.
- Kumar, P. (2022). Internal flexibility in health-care organizations: a value-laden perspective on sustainability. *International Journal of Organizational Analysis*, 30(3), 721-742.
- Kumar, P., & Singh, A. P. (2020). Flexibility in service operations: review, synthesis and research agenda. *Benchmarking: An International Journal*, 27(7), 2108-2129.
- Kyarisiiima, I., Nzayirambaho, M., Nkurunziza, A., & Twagirayezu, I. (2024). Assessment of Patient Waiting Time in Primary Health Care Settings in Rwanda: A Mixed-Method Study. *Rwanda Journal of Medicine and Health Sciences*, 7(1), 6-21.
- Law, A. M. (2015). *Simulation Modeling and Analysis*. Fifth Edit. *Tucson: McGraw-Hill*.
- Lucianetti, L., Jabbour, C. J. C., Gunasekaran, A., & Latan, H. (2018). Contingency factors and complementary effects of adopting advanced manufacturing tools and managerial practices: Effects on organizational measurement systems and firms' performance. *International Journal of Production Economics*, 200, 318-328.
- Marin, C. V., Drury, C. G., Batta, R., & Lin, L. (2007, October). Human factors contributes to queuing theory: Parkinson's law and security screening. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 51, No. 10, pp. 602-606). Sage CA: Los Angeles, CA: SAGE Publications.
- McIntyre, D., & Chow, C. K. (2020). Waiting time as an indicator for health services under strain: a narrative review. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, 57, 0046958020910305.
- Ministry of Health. (2020). *Annual Health Sector Performance Report*
- Ministry of Health. (2021a). *Humman Resources for Health Audit Report 2019/2020*

- Ministry of Health. (2021b). *Statement to Parliament on the State of Public Healthcare Service Delivery in Uganda*
- Ministry of Health. (2022). *Essential Maternal and Newborn Clinical Care Guidelines for Uganda*
- Mittal, S. (2019). How organizations implement new practices in dynamic context: role of deliberate learning and dynamic capabilities development in health care units. *Journal of Knowledge Management*, 23(6), 1176-1195.
- Msengwa, A. S., Rashidi, J., & Mniachi, R. A. (2020). Waiting time and resource allocation for out-patient department: a case of Mwananyamala Hospital in Dar es Salaam, Tanzania. *Tanzania Journal for Population studies and Development*, 27(1), 64-81.
- Mwanswila, M. J., Mollel, H. A., & Mushi, L. D. (2024). Outcome evaluation of technical strategies on reduction of patient waiting time in the outpatient department at Kilimanjaro Christian Medical Centre—Northern Tanzania. *BMC Health Services Research*, 24(1), 785.
- Naguru Referral Hospital. (2020). *Ministerial Policy Statement FY 2020/21*.
- Naguru Referral Hospital. (2022). *Ministerial Policy Statement FY 2022/23*.
- Naiker, U., FitzGerald, G., Dulhunty, J. M., & Rosemann, M. (2018). Time to wait: a systematic review of strategies that affect out-patient waiting times. *Australian Health Review*, 42(3), 286-293.
- Ochen, A. M., & Primus, C. C. (2023). Family planning uptake and its associated factors among women of reproductive age in Uganda: An insight from the Uganda Demographic and Health Survey 2016. *PLOS Global Public Health*, 3(12), e0001102.
- OECD. (2020). *Waiting Times for Health Services : Next in Line*.
- Olsson, O., & Aronsson, H. (2015). Managing a variable acute patient flow—categorising the strategies. *Supply Chain Management: An International Journal*, 20(2), 113-127.
- Masrom, S. N. F., Ngor, P. Y., & Rani, R. M. (2023). Simulating and Analysing Patients' Waiting Time in Outpatient Department at Public Clinic in Johor Using Arena Software.
- Rathore, R. (2022). A Review on Study of application of queueing models in Hospital sector. *International Journal for Global Academic & Scientific Research*.
- Rechel, B., Wright, S., Barlow, J., & McKee, M. (2010). Hospital capacity planning: from measuring stocks to modelling flows. *Bulletin of the World Health Organization*, 88, 632-636.
- Rajo, A., Stevenson, M., Llorens Montes, F. J., & Perez-Arostegui, M. N. (2018). Supply chain flexibility in dynamic environments: The enabling role of operational absorptive capacity and organisational learning. *International Journal of Operations & Production Management*, 38(3), 636-666.
- Sarwat, A. (2021). The Effects of waiting time and satisfaction among patients visiting medical outpatient department of a tertiary care hospital. *Journal of Pakistan Psychiatric Society*, 18(03), 25-29.
- Simwita, Y. W., & Helgheim, B. I. (2016). Simulation analysis of resource flexibility on healthcare processes. *Journal of Multidisciplinary Healthcare*, 519-528.
- Sindhvani, R., Singh, P. L., Prajapati, D. K., Iqbal, A., Phanden, R. K., & Malhotra, V. (2019). Agile system in health care: literature review. *Advances in industrial and production engineering: select proceedings of FLAME 2018*, 643-652.
- Tagimacruz, T., Cepoiu-Martin, M., & Marshall, D. A. (2025). Exploratory analysis using discrete event simulation modelling of the wait times and service costs associated with the maximum wait time guarantee policy applied in a rheumatology central intake clinic. *Health Systems*, 14(1), 1-11.

- Teece, D. J. (2018). Dynamic capabilities as (workable) management systems theory. *Journal of Management & Organization*, 24(3), 359-368.
- Uganda Bureau of Statistics. (2023). *Statistical Abstract*.
- van Hulzen, G., Martin, N., Depaire, B., & Souverijns, G. (2022). Supporting capacity management decisions in healthcare using data-driven process simulation. *Journal of Biomedical Informatics*, 129, 104060.
- Vázquez-Serrano, J. I., Peimbert-García, R. E., & Cárdenas-Barrón, L. E. (2021). Discrete-event simulation modeling in healthcare: a comprehensive review. *International journal of environmental research and public health*, 18(22), 12262.
- Volochtchuk, A. V. L., & Leite, H. (2022). Process improvement approaches in emergency departments: a review of the current knowledge. *International Journal of Quality & Reliability Management*, 39(2), 495-520.
- Wang, S., Wang, X., & Zhang, J. (2021). A review of flexible processes and operations. *Production and operations management*, 30(6), 1804-1824.
- Wichansky, A. M. (1976). Human Factors Aspects of Queuing: A Critical Review. *Human Factors*, 18(2), 161-172.
- Wise, S., Duffield, C., Fry, M., & Roche, M. (2020). Clarifying workforce flexibility from a division of labor perspective: a mixed methods study of an emergency department team. *Human resources for health*, 18(1), 17.
- Yousuf, A., Haddad, H., Pakurár, M., Kozlovskiy, S., & Felföldi, J. (2019). The effect of operational flexibility on performance: a field study on small and medium-sized industrial companies in Jordan.
- Zhang, H., Ma, W. M., Zhu, J. J., Wang, L., Guo, Z. J., & Chen, X. T. (2023). How to adjust the expected waiting time to improve patient's satisfaction? *BMC Health Services Research*, 23(1), 455.