UNIVERSITY OF GHANA

COLLEGE OF HEALTH SCIENCES

THE IMPACT OF eCLAIMS ON NATIONAL HEALTH INSURANCE CLAIMS MANAGEMENT IN GHANA: A CASE STUDY OF NATIONAL CATHOLIC HEALTH SERVICE

BY

GODWIN ADZAKPAH

(ID NO. 10395118)

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NOVEMBER 2022

DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this university or elsewhere.

28-08-2024

Candidate's Signature: .... Date: ....

Name: Godwin Adzakpah

Supervisors' Declaration

I hereby declare that the preparation and presentation of the theses was supervised in accordance with the guidelines on supervision of theses laid down by the University of Ghana.

Principal Supervisor's Signature: Date: 28-08-2024

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ABSTRACT

An efficient medical claims billing system is critical to mitigating the challenges associated with claim denials and ensuring the sustainability of providing healthcare services. The rapid growth in the Information and Communication Technology (ICT) sector has necessitated the implementation and use of Health Information Systems (HIS) in several healthcare facilities to improve healthcare delivery. This study assesses the impact of Health Information Systems (HIS) in reducing the rate of error margins of health insurance claims submitted by health facilities to the National Health Insurance Authority in Ghana. The study also seeks to assess the impact of HIS on the timeliness of medical claims submission in the National Catholic Health Service in Ghana. Assessing the HIS efficiency rate would build confidence among healthcare providers and other stakeholders to invest in health information technology for an efficient healthcare delivery system. The current study also assesses HIS efficiency rate based on users' perspectives using two information system success model (ISSM) tools and measures the agreement between the two ISSM tools. The study used longitudinal data on monthly claims adjustments due to errors from paper-based and submitted claims using different HISs from 2010 to 2019. The rate of error margins was estimated for each month. Prais-Winsten Segmented Interrupted Time-Series analysis was used to estimate the impact of HIS by comparing claims data before and after the system implementation for each facility. I employed meta-analysis techniques to generate a pooled impact estimate of HIS on error margins of health insurance claims. The study also employed longitudinal data on the monthly timeliness of medical claims from both paper-based and electronic system using various forms of HIS from 2010 to 2019 was used. Number of days spent in submitting medical claims was deduced for each month. Segmented Interrupted Time-Series analysis-based Prais-Winsten method was used to

assess the effect of HIS by comparing the average number of days spent in submitting claims data before and after the HIS implementation for each facility. Meta-analysis techniques were employed to estimate the pooled effect estimate of HIS on average number of days spent in submitting claims. On the HIS efficiency rate, the study was carried using survey method in 25 National Catholic Health Service (NCHS) hospitals in Ghana. The study adapted two self-administered structured data collection tools based on extended ISSM covering six dimensions and upgraded DeLone and McLean models covering seven dimensions respectively. Descriptive statistics such as means and standard deviations were calculated for continuous variables and percentages for categorical variables. Cronbach's alpha was used to assess the internal validity of study dimensions. The normality of data was assessed using the Shapiro-Wilk test. HIS efficiency rate was calculated for the two models using the weighted mean. The bland-Altman method was used to measure agreement between the two models. The total cost of deductions due to errors from the HIS was significantly lower than the paper-based system (HIS=8.15%, paper-based system=10.13%). HIS contributed to an immediate 1.31 percentage point reduction in the error margins of health insurance claims compared to the paper-based system. The timeliness of claims submission was above 75% in majority of health facilities. The average number of days spent submitting medical claims in HIS has significantly reduced compared to paper-based systems (HIS=35.11 days, paper-based=56.51 days; ($p<0.0001$)). The trend analysis showed that HIS contributed to an immediate 5.84 days reduction in the average number of days spent submitting medical claims compared to the manual system. The outcome of the HIS efficiency rate shows that a total of 1416 users from 25 hospitals across the country took part in the study. The two instruments were validated with a content validity index and content validity ratio above 0.90. The Cronbach's alpha measurement was also above 0.75 for both tools. The overall mean HIS efficiency rate was above 80% showing the high efficiency of the HIS. The Bland-Altman method of measurement revealed that 24 (96%) out of 25 hospitals' mean HIS efficiency rate lies between averages of 75.5% and 87.0%. The regression between the mean difference and the average of the two tools shows that there is no statistically significant proportional bias between the application of the two tools to measure HIS efficiency rate (coefficient=-0.50; 95%CI [-1.14 to 0.14] and p-value=0.1228). The HIS recorded lower denied claims costs than the paper-based claims system. The implementation and use of HIS improved the timeliness of medical claim submission. Scaling up the use of HIS for claims submission will reduce the rate of claim denials, ensure the sustainability of providing healthcare services and will ensure prompt reimbursement by the insurer. The findings from this study emphasize healthcare providers' perspective of HIS efficiency rate in a hospital setting in Ghana. The tools adapted in this research can be used to evaluate hospital information system in any future studies since there was no proportional bias between the two models.

DEDICATION

To my wife, Mavis Puopelle Dakorah Adzakpah, PhD, my daughter Nadine Ewoenam Adzakpah and my son, Michael Elinam Adzakpah.

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LIST OF ABBREVIATION

ACF	–	Autocorrelation Function
AIC	–	Akaike Criterion Information
ANC	–	Antenatal Clinic
AR	–	Autoregressive
ARIMA	–	Autoregressive Integrated Moving Average
ATS	–	Average Time Spent
BIC	–	Bayesian Criterion Information
CDR	–	Claim Denial Rate
CVI	–	Content Validity Index
CVR	–	Content Validity Ratio
DM	–	DeLone and McLean model
DOH	–	Department of Health
EHR	–	Electronic Health Record
GH¢	–	Ghana Cedis
GLS	–	Generalised Least Squares
HIS	–	Hospital Information System
HITECH	–	Health Information Technology for Economic and Clinical Health
ISSM	–	Information System Success Model
ITS	–	Interrupted Time Series
MA	–	Moving Average
MAD	–	Mean Absolute Deviation
MAPE	–	Mean Absolute Percentage Error

MLE	–	Maximum Likelihood Estimation
MSE	–	Mean Squared Error
NCHS	–	National Catholic Health Service
NHIA	–	National Health Insurance Authority
NHIS	–	National Health Insurance Scheme
OLS	–	Ordinary Least Squares
PACF	–	Partial Autocorrelation Function
RMSE	–	Root of Mean Squared Error

CHAPTER ONE

INTRODUCTION

Introduction to this Chapter

This chapter discusses the background to the study, the statement of the problem, the purpose of the study, the objectives guiding the study, the research questions to be answered, the significance of this study and how the chapters have been organized.

1.1 Introduction

Implementation of health insurance schemes is at different stages across the globe, especially in developing countries to give the citizens high access to healthcare (Carrin, Doetinchem, Kirigia, Mathauer, & Musango, 2008; Nsiah-Boateng et al., 2017a; Spaan et al., 2012). World Health Organisation (WHO) describe medical billing errors and healthcare fraud as 'the last great unreduced healthcare cost'. In 2014, WHO estimated that the cost of fraud and incorrect payments in the world's healthcare systems is about 7% of total global health expenditure, or US$487 billion (Gee & Button, 2014). According to Sanborn (2017), health insurance companies reject 14% of healthcare providers' claims, amounting to US$262 billion annually. In addition, the denial of claims puts a cost burden such as cost recovery (i.e. identifying reasons for the denial and errors, correcting the errors and resubmitting them for reimbursement) on healthcare providers (Sanborn, 2017). In 2017 alone, the recovery cost is estimated as high as $120 per health insurance claim in the United States and is considered to be a waste within the US healthcare system (Sanborn, 2017). American Hospital Association (AHA) indicated that an amount of $628 billion worth of hospital care has been rendered without payment by the payers (AHA, 2022).

According to World Bank figures, current health expenditure per capita in Ghana is US$75.28 in 2019 from US$16.6 in 2000 (The World Bank, 2022). Certainly, expenditure on health is never going down and will continue to rise. Studies have shown that economic growth in Ghana has seen a sharp rise, with increasing healthcare expenditure (Saleh, 2012, 2013). According to (Schieber, Cashin, Saleh, & Lavado, 2012), Ghana's spending in the healthcare area grew by 11% between 2001 and 2012. Nsiah-Boateng et al. (2017) estimated that adjusted paper-based claims due to errors in claims cost GHS2.81 million representing 4.9% of total reviewed claims of GHS57.50 million (USD15.09 million). This prevalent problem is a cause of large cash flows and puts much burden on providers and patients. The ability to prevent claim denial before the health insurance claim is submitted to the insurers will increase profits, enhance the revenue cycle positively and support the general well-being of patients. Health insurance claim denials, also known as 'claim denial hereafter' are one of the pivotal contributors to the ever-increasing billing and insurance-related costs (BIR) (Yong, Saunders, & Olsen, 2010). According to Farnen (2022), claim denial has the potential to prevent any healthcare provider from being on track. This widespread canker is not just time-consuming rework but also a delayed or lost revenue and put pressure on scarce resources. One claim denial may not be significant but the cumulative effect can be devastating to healthcare providers (Farnen, 2022).

Many providers would ask, why the occurrence of these denied claims leads to uncompensated care? According to Becker's Health IT (2015), three issues that drive claim denial. The first one is that consumers (patients) and insurers are different categories of entities and only a fraction of patients can pay for the cost of their care from their pocket directly. The bureaucratic nature of claims reimbursement processes encountered by healthcare providers and other administrative reasons results in uncompensated claims (Carroll, 2020). The second issue is that healthcare providers are ethically prevented from turning patients away who could not pay for services. After rendering expensive care to such patients, most providers are not able to recover the full payment (Jacob, 2014). The third is that many patients are not always in the position to know in advance how much the care would cost or are not able to determine the treatment to receive. Having been given a surprise bill by the provider, they would struggle to settle the bill or be unable to do so leaving the care provided to be uncompensated (Kirzinger, Muñana, Wu, & Brodie, 2019).

A critical concern to providers in the healthcare business is uncompensated claims and to the best of our knowledge, studies on hospital information systems (HIS) are limited on this very important subject (Jinhyung & Choi, 2019). Several studies have affirmed the benefits derived from HIS in the area of improved quality of care, decreased mortality among patients, and a reduction in cost of care (Atasoy, 2019; Ayabakan, Bardhan, Zheng, & Kirksey, 2017; Jones, Heaton, Rudin, & Schneider, 2012) and in Ghana (Achampong, 2012), but the effect of HIS on uncompensated care by insurers due to errors remains a very important gap in literature. To examine the important role of HIS such as the electronic claim system in solving the challenge of uncompensated claims, the authors decided to focus on denied claims as one of the major elements of uncompensated claims in the Ghanaian healthcare system. This study intends to assess the impact of electronic claims on error margins of Health Insurance Claims (denied claims) and its causes in the National Catholic Health Service (NCHS) in Ghana. From the earlier explanation, most healthcare consumers in Ghana do not pay for the care received by themselves and healthcare providers file claims on their behalf for reimbursement from the National Health Insurance Scheme in Ghana. This process is very cumbersome and time-consuming but healthcare insurers continue to deny payment to healthcare providers because of medical billing errors and other administrative or technical reasons leading to delayed payment, underpayment and sometimes non-reimbursement (Jacqueline LaPointe, 2020). Grant (2016) suggests that about 80% of medical bills are characterised by errors.

The challenge here is for medical schemes to discern between legitimate and fraudulent claims, which is a mammoth task. Nsiah-Boateng et al. (2017a) posited that an essential part of operating an efficient and viable healthcare financing system is the successful discovery of fraud, errors and abuse. The extent of claims denial experienced by the healthcare sector should therefore be determined to manage this challenge effectively (Thornton, Brinkhuis, Amrit, & Aly, 2015). The next section discusses the research problem of this study.

For this study, eClaims refers to any health insurance claims captured on a storage drive (i.e. CD, pen-drive etc.), real-time online or web-based or through any hospital-based health information management systems. The aim of moving from paper-based claims to electronic-based claims was to reduce human engagement in the claims process and reduce errors that come with claims processing at the healthcare provider level and its review at the National Health Insurance Scheme (NHIS) level. The NHIS has established a Claims Processing Centre (CPC) to process eClaims from health providers throughout the country. All the 25 selected health facilities submit eClaims through; (1) an XML file that converts health insurance claims from the hospital's electronic medical records systems and (2) a web-based electronic system known as eClaim or ClaimIT and submit claims data. This claims information is submitted to NHIS' CPC located in the capital, Accra of Ghana, where the authorities vet the submitted claims electronically. The paper-based claims on the other hand are done through completing manual claims forms by the healthcare providers for each valid subscriber, compiling all the completed forms for a respective period and submit to the NHIS for reimbursement.

1.2 Problem Statement

Billing errors and healthcare fraud have been described by the WHO as 'the last great unreduced healthcare cost'. In 2014, measurable average losses caused by fraud and incorrect payments in the world's healthcare systems were estimated at 7% of total global health expenditure, or US$487 billion (Gee & Button, 2014), and the WHO has identified financial leakage as one of the 10 leading causes of healthcare system waste globally (World Health Organization, 2010). Irrespective of different payment models, challenges exist at the interface of medical billing and medical practice across the globe.

A study conducted by Nortjé and Hoffmann (2014) in South Africa shows that the nature of fraudulent activities encompassed the submission of false claims and irregular coding, resulting in higher amounts being billed, which is a similar pattern reported by Thornton et al. (2015), Debpuur, Dalaba, Chatio, Adjuik, and Akweongo (2015) and Flynn (2015). The study conducted by Thornton et al. (2015) revealed that denied claims occur mostly in the form of claiming for services not rendered (false/phantom claims), up-coding, unbundling of codes, rendering of unnecessary services, using unauthorised service providers, identity fraud, duplicate claims, and the sharing of healthcare benefits with members not belonging to the medical scheme. Debpuur et al. (2015) also revealed that members seeking unnecessary healthcare services abused the national health insurance scheme in Ghana. The study further shows that members of the scheme also shared scheme membership cards with non-members (Debpuur et al., 2015).

In the Ghanaian context, Nsiah-Boateng et al. (2017a) estimated that adjusted paper-based claims due to errors in claims cost GHS2.81 million representing 4.9% of total reviewed claims of GHS57.50 million (USD15.09 m). Most of the recent studies conducted in the area of management of fraud in healthcare mainly investigated how technology can assist in fraud detection (Joudaki et al., 2016; Mansor, 2015; van Capelleveen, Poel, Mueller, Thornton, & van Hillegersberg, 2016; Wakoli, Orto, & Mageto, 2014). A study by Wakoli et al. (2014) on the medical claims of insurance companies in Kenya found that the K-Means clustering model could be used to identify suspicious fraudulent claims. The study by Joudaki et al. (2016), which focused on physician claims in an Iranian private healthcare insurance company, found that data mining techniques such as cluster analysis could be utilised to identify suspected fraudulent claims and providers. van Capelleveen et al. (2016) also found that unsupervised data mining techniques could be used to identify outlier claims and utilise Medicaid data focusing on dentists' healthcare claims for one state in the United States.

According to Jinhyung and Choi (2019), the information systems (IS) literature on hospital information systems (HIS) (eClaims system) has paid little attention to the issue of denied claims or error margins of claim, to the best of my knowledge, although it continues to be a significant policy concern as well as a significant challenge to the healthcare industry. According to studies, a significant amount of the HIS literature shows the wealth of value that HIS brings to the table in terms of reduced costs, improved patient mortality, and improved care quality (Atasoy, 2019; Ayabakan et al., 2017; Jones et al., 2012), but there is still a significant gap in the literature regarding how HIS affects denied claims or error margins of the claim. Although a denied claim is regarded as a major risk, there is limited available scholarly literature on the phenomenon in Ghanaian health insurance schemes. This study aimed to quantify the extent of error margins in Ghanaian health insurance schemes in terms of claims. Moreover, this study explored the impact of the eClaims vis-a-vis the manual claims in the management of the National Health Insurance Scheme in the Ghanaian context. The research questions and objectives that were derived from the problem under investigation in this study, namely error margins in health insurance scheme claims in Ghana, are outlined in the following section.

1.3 Research questions

The main research question to be addressed by this study is; Does the use of the eClaims system by National Catholic Health Service Hospitals significantly reduce health insurance claims errors than paper-based claims?

The specific research questions are as follows:

1. What is the impact of eClaims on error margins of claims submitted by health facilities?
2. What is the estimated and predicted claim denial rate?
3. What are the causes of error margins of claims submitted by health facilities?
4. What is the impact of eClaims on the timeliness of claims submitted by health facilities?
5. What is the efficiency of hospital information system used by health facilities?

1.4 Main Objective

To evaluate the impact of eClaims on National Health Insurance claims and reimbursement in Ghana.

1.4.1 Specific objectives

1. To evaluate the impact of eClaims on error margins of claims (claim denial rate).
2. To estimate and forecast claim denial rate
3. To assess the causes of error margins of claims (claim denial rate).
4. To evaluate the impact of eClaims on the timeliness of claims submission.
5. To assess the efficiency of hospital information systems used by health facilities.

1.5 Justification

In Ghana, as well as in other developing nations, the health sector encounters several obstacles, namely in regards to handling health insurance claims at the healthcare provider level. The implementation of the National Health Insurance Scheme (NHIS) in 2003 was a significant milestone aimed at improving the availability of healthcare services for the whole Ghanaian population (NHIA, 2017). Nevertheless, healthcare providers have been burdened by inefficiencies in claims administration, which have compromised its effectiveness. The use of the eClaims system offers a substantial potential to tackle these difficulties. However, it is crucial to do thorough research to assess the effects of these systems and pinpoint areas that require enhancement. This research is of utmost importance for multiple reasons.

The conventional manual system of claims processing in Ghana has been marked by delays, inaccuracies, and a high prevalence of errors such as filing of duplicate claims, overbilling, and the inclusion of services that were not supplied. A study conducted by Ubindam (2019) found that the manual claims procedure frequently resulted in substantial delays in reimbursements, which had a detrimental effect on healthcare providers' cash flows and their capacity to offer high-quality care. The inefficiencies of the manual approach are also associated with increased administrative expenses and a greater probability of errors, so exacerbating the constraints on the limited resources of the NHIS. Researching the effects of the eClaims system on claims management is essential to ascertain the degree to which these systems have enhanced efficiency and precision. Gaining a comprehensive understanding of how the eClaims system has specifically tackled the limitations of the manual system can offer useful insights for policymakers and healthcare providers, informing their decisions on future investments in technology and process enhancements.

Although the eClaims system can transform health insurance claims handling in Ghana, its execution has encountered difficulties. These factors encompass the unequal implementation of the eClaims system among healthcare professionals, especially in rural regions where there may be restricted availability of technology and infrastructure. Conducting research is necessary to comprehend the obstacles and hindrances to the successful execution of the eClaims system in Ghana. This entails determining the variables that affect the acceptance of Hospital Information Systems (HISs) by healthcare providers, as well as the consequences of these obstacles on the overall efficiency of the Hospital Information Systems. By tackling these obstacles, stakeholders may devise ways to promote the wider implementation of HISs and guarantee that all healthcare providers, irrespective of their scale or location, can reap the advantages of these systems.

Ghana's experiences in adopting electronic claims systems for national health insurance claims management can offer useful insights to other countries grappling with comparable difficulties. Many low- and middle-income countries are struggling with problems related to ineffectiveness, and inadequate data administration in their health insurance programs. This study intends to enhance the worldwide body of knowledge on best practices for health insurance claims administration by researching the impact of the eClaims system in Ghana. This research can also contribute to the creation of recommendations and frameworks for the deployment of eClaims systems in different settings, thereby ensuring that the potential advantages of these systems are achieved on a larger level. The research findings can be a significant resource for policymakers and health system management worldwide as more countries seek to utilise technology to enhance healthcare financing.

There is an obvious necessity for researching the impacts of electronic claims systems on the management of national health insurance claims in Ghana. This research is crucial for tackling inefficiencies in claims processing, increasing transparency and mitigating fraud, strengthening data management and decision-making, identifying the obstacles to eClaims system implementation, and contributing to worldwide knowledge and best practices. This research offers evidence-based insights into the effectiveness of the eClaims system, which can contribute to the ongoing success and sustainability of the NHIS. Ultimately, it aims to provide access to high-quality healthcare for all Ghanaians.

1.6 Operational definition of key terms

Electronic claims (eClaims): It is a detailed electronic invoice that a healthcare provider (such as a hospital) sends to the health insurer to request reimbursement. This invoice shows exactly what services you received. The eClaims also refer to any health insurance claims captured on a real-time online or web-based, or through any hospital-based health information management systems.

Error margins of claims (or Claims Denial Rate): This is the ratio of the amount deducted due to errors in claims to the total amount of claims cost submitted, multiplied by 100%.

Number of days spent submitting claims: This is the sum of days from the beginning of the new month until the date on which the previous month's medical claims were submitted.

Hospital Information System (HIS): It is a comprehensive software solution designed to manage and integrate various aspects of hospital operations (including Patient registration and admission, Clinical data management, Pharmacy management, Laboratory and radiology information systems, Billing and insurance claims processing, etc.) (AHIMA, 2012).

Electronic Claims (eClaims) System: It is a subset of the HIS that helps healthcare providers process health insurance claims electronically and submit them to insurance companies.

eClaims (now CLAIM-it) System – Own by NHIS: It is software that serves as a platform that allows health providers credentialed by the NHIS to generate and submit claims. Claims are submitted electronically by downloading and saving claims on a flash drive (Extensible Markup Language (XML) file) for later submission or submitted directly to NHIS over the Internet (NHIS, 2024).

1.7 Theoretical framework

1.7.1 Adoption and diffusion of innovations

The topic of user acceptance of technology is extensively discussed in adoption literature across numerous fields. The diffusion of innovations theory is one of the models that serve as the foundation for user acceptance research (Rogers, 1995). The conditions that either increase or decrease the likelihood of an innovation being adopted are the primary focus of diffusion research. Rogers (1995) defined diffusion as "the process by which an innovation is communicated among the members of a social system over time through certain channels. "Rogers' Innovation Diffusion Theory states that potential users base their decisions regarding an innovation's adoption or rejection on their preconceived notions about it. He divides the process of diffusion into five stages: knowledge, persuasion, decision, action, and confirmation (Figure 1).

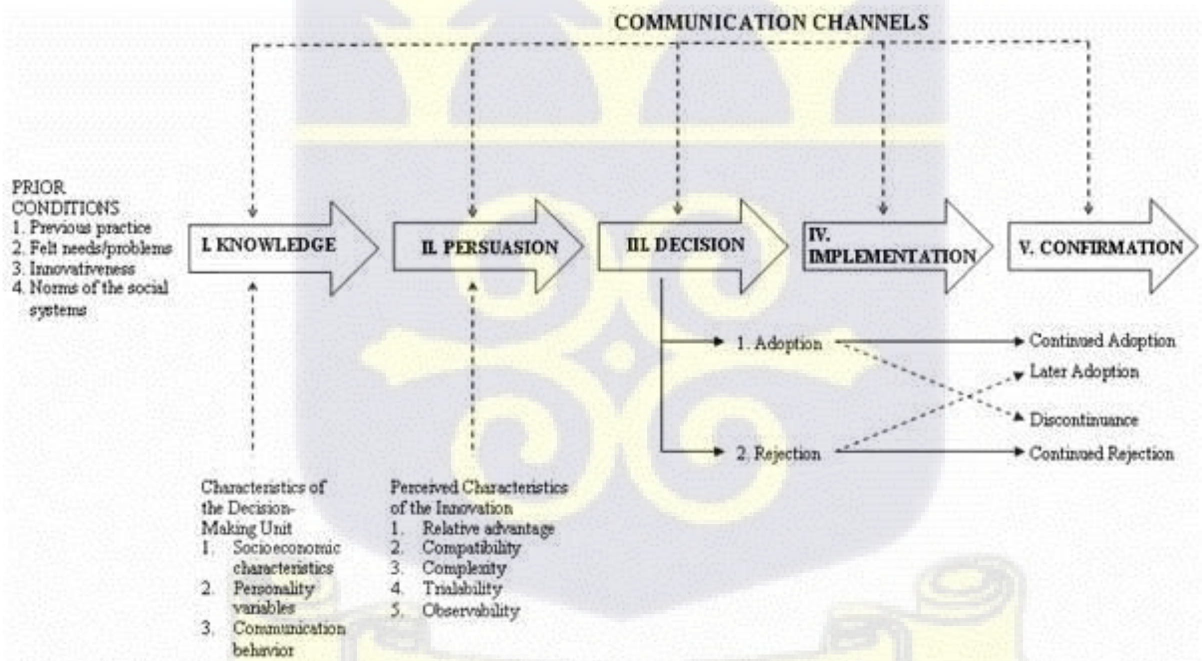

Figure 1: Diffusion of innovation model (Rogers, 1995)

Before a new technology is implemented, several steps are taken. To persuade the technology's users, the implementation must be made clear to them, and they must also be aware of the impact and benefits of the new technology in comparison to the current or pre-implementation situation. Users may decide to use the innovation because of their adoption of the new technology. The adoption decision can be voluntary (made by an individual), collective (made by a group consensus), or authority-based (made by a few or one person for the whole group). According to Rogers (1995), the implementation phase begins after the technology has been adopted—or, more precisely, accepted - where the innovation is introduced to a specific setting and users assess its utility. Diffusion, on the other hand, is not the same as adoption. Diffusion is the process by which an innovation is adopted in a group or collective over time, whereas adoption is an individual process in which many factors influence the decision-making (Rogers, 1995). To illustrate how people have used and accepted technology over the past few decades, several theories have been developed. These models explain how new technology can be successfully implemented and the factors that influence behaviour toward its acceptance.

1.7.1.1 Theory of Reasoned Action (TRA) & Theory of Planned Behaviour (TPB)

The theory of reasoned action (TRA) was first proposed by Fishbein, Ajzen, and Belief (1975) as a means of understanding behaviour and predicting outcomes. It is currently being successfully utilized in a wide range of fields (Figure 6). The main assumption of TRA is that people think about the consequences of their actions before deciding to do something or not do something. Additionally, it holds that a person's intent to act is the most important factor in their behaviour. Attitude toward the behaviour and the subjective norm (what other people think) influence this behavioural intention.

According to Fishbein et al. (1975), the term "attitude toward behaviour" refers to a person's "positive or negative feelings about performing target behaviour." According to Fishbein et al. (1975), the subjective norm is the influence of social pressure to perform or not perform a particular behaviour. The level of commitment an individual is willing to put into performing a particular behaviour is known as behavioural intention and is determined by an individual's attitude and subjective norm. According to Fishbein et al. (1975), behaviour is defined as an individual's actual behaviour.

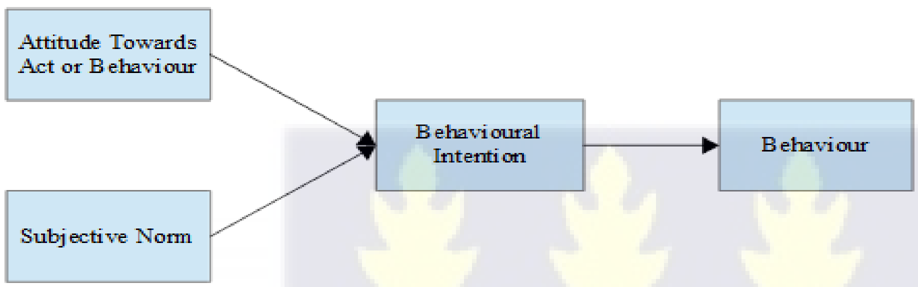

Figure 2: Theory of Reasoned Action Framework (Fishbein et al., 1975)

The fact that the TRA does not account for the influence of social factors on individual behaviour is one of its drawbacks. Intentional behaviour is not always indicative of actual behaviour. Ajzen (1991) modified the TRA by incorporating a third belief dimension known as perceived behavioural control, which influences both intentions to behave and actual behaviour (Figure 2). According to Ajzen (1991), "the perception of an individual for the difficulty of performing a behaviour" is the definition of perceived behavioural control.

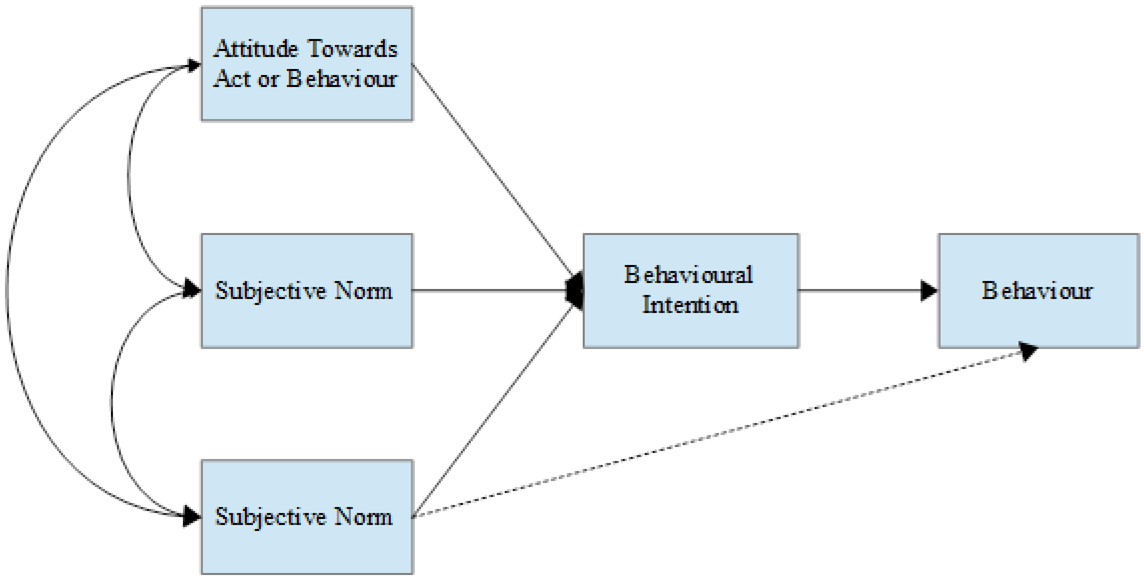

Figure 3: Theory of Planned Behaviour Framework (Ajzen, 1991)

1.7.1.2 Innovation Diffusion Theory (IDT)

Rogers (1995) identified five general characteristics of innovation that influenced the adoption process in his diffusion studies: 1) relative advantage (the degree to which the innovation is regarded as superior to its predecessor), 2) compatibility (the degree to which an innovation is regarded as being consistent with the existing values, requirements, and previous experiences of potential adopters), 3) complexity (the degree to which an innovation is regarded as being difficult to use), 4) observability (the degree to which the results of an innovation are observable to other people), and 5) trialability (the degree to which an innovation may be experimented with before adoption. According to Rogers (1995), an innovation's adoption rate is influenced positively by its relative advantage, compatibility, trialability, observability, and simplicity.

1.7.1.3 Technology Acceptance Model (TAM)

Davis (1989) originally developed the Technology Acceptance Model, which is regarded as the most influential and widely used theory for describing individual acceptance of new information systems (Figure 4). The Theory of Reasoned Action (TRA) has been adapted into TAM specifically to help users accept technology. The model is being used to predict and explain an individual's adoption of new technology.

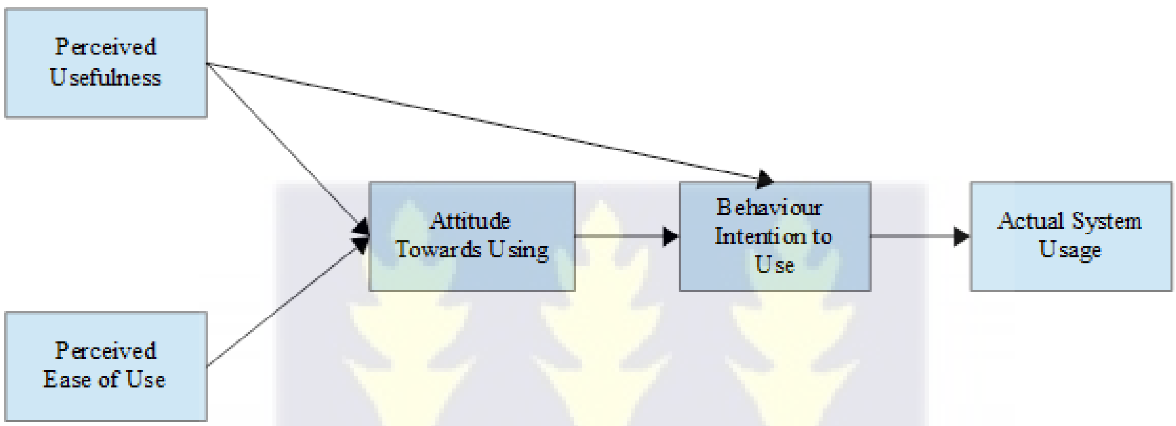

Figure 4: Technology Acceptance Model framework (Davis, 1989)

According to TAM, two behavioural beliefs - perceived usefulness (PU) and perceived ease of use (PEOU)—influence how people feel about using and whether or not they like the behaviour. Similar to TRA, an individual's behaviour toward the intention to use a system eventually influences their attitude, resulting in the system's actual use (Davis, 1989). PEOU refers to the "extent to which a person believes that using the system will be free of effort," while PU is defined as the "extent to which a person believes that using the system will enhance his or her job performance." Additionally, TAM stated that PEOU had a direct impact on PU due to the premise that a system's utility increases with its ease of use.

According to Holden and Karsh (2010), TAM has been utilized extensively in the healthcare setting and predicts a significant portion of the utilization and acceptance of health IT. According to Chau and Hu (2002), research indicates that TAM is superior to TPB in terms of explaining physicians' acceptance of IT. However, individual, organizational, and social factors that clearly influence user acceptance of new technology are not included in TAM.

1.7.1.4 Information System Success Model

A few conceptual frameworks have been created to help inform information system adoption and evaluation. The "Information System (IS) Success Model" developed by DeLone and McLean (1992) (D&M) is perhaps one of the most well-known frameworks for evaluating the numerous complex factors necessary for an effective IT implementation (Figure 9). At first, there were six major measurement dimensions in this framework:

1. Qualitative system: engineering-focused features of the system, such as its usability, system dependability, accessibility, adaptability, and integration;
2. Qualitative information: perception of the timeliness, completeness, reliability, conciseness, and relevance of the information, mostly from the user's point of view (subjective measures);
3. Usage: includes the stakeholder's use, frequency, and duration (this measurement is only valid if system use is not required);
4. Satisfaction of users: is an opinion based on the user's perspective. If a system had to be used, this dimension was added as an alternative measure;
5. Impact on an individual: measures how a system affects user behaviour (such as efficiency, task completion, and decision quality);

6. Impact on the company: impact on organizational metrics like return on investment (ROI) and cost reduction.

There are two ways to look at the model; 1) a logical order from the creation of the system through its use and impact, and 2) from a causal perspective; System use and user satisfaction are influenced by information quality and system quality, both of which are related to the impact on an individual and an organization. According to DeLone and McLean (1992), success ought to be evaluated as a multidimensional construct, and success evaluation ought to be contingent on the purpose of the study and the context of the organization.

The IS Success Model was reviewed by DeLone and McLean, and the authors looked back at how their model was used over the past ten years. According to DeLone and McLean (2003), the authors improved their initial framework in three distinct ways:

1. by combining the two initial system characteristics of system quality and information quality with a third dimension known as "Service quality," which measures the perceived quality of the IT service.
2. using "intention to use" in place of "use" to measure how much users use the system.
3. combining the impact on the individual and the organization into a single variable known as "net benefit." Net benefit has a positive effect on user satisfaction and intention to use.

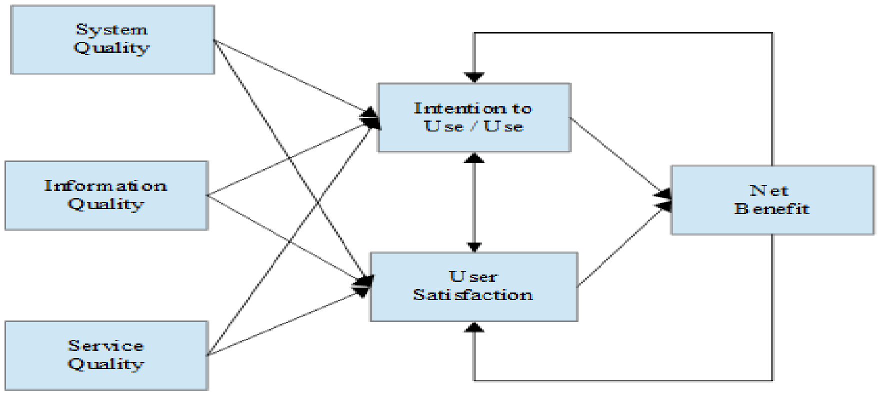

Figure 5: Revised Information System Success Model (DeLone & McLean, 2003)

Numerous healthcare IS evaluation studies have demonstrated that the DeLone & McLean framework works (Figure 5). Van Der Meijden, Tange, Troost, and Hasman (2003) conducted a literature review on the evaluation of patient care information systems from 1991 to 2001. To test the efficacy of the DeLone and McLean framework for management information systems and evaluate the success of such systems, determinations were identified in 2003. The model's six dimensions could be assigned a variety of relevant characteristics. However, some characteristics could not be categorized, primarily in the event of project failure. It was discovered that these factors are connected to organizational aspects, system implementation, and system development.

1.8 Conceptual Framework

This study is a combination of a quasi-experimental design and a cross-sectional study. The study evaluated the impact of hospital information systems (eClaims system) on error margins of claims (claims denial rate). This original study involved the determination of denied claims or error margins of claims across all the study sites involved in the study leading to the estimation and projection of the denial rate for the short-term. The causes of denied claims were also investigated.

The study also evaluated the impact of hospital information systems (eClaims system) on the average time spent submitting claims to the National Health Insurance Scheme for reimbursement. Finally, the efficiency of the hospital information system was also assessed using two established Information System Success Models (ISSM) (i.e. expanded information system success (E-ISSM) and upgraded DeLone and McLean (U-DM) models) from the perspective of healthcare professionals. The applicability of the two ISSM tools was finally determined by assessing the agreement between the two ISSMs using the Bland-Altman method. Figure 6 below shows the conceptual framework used in this study.

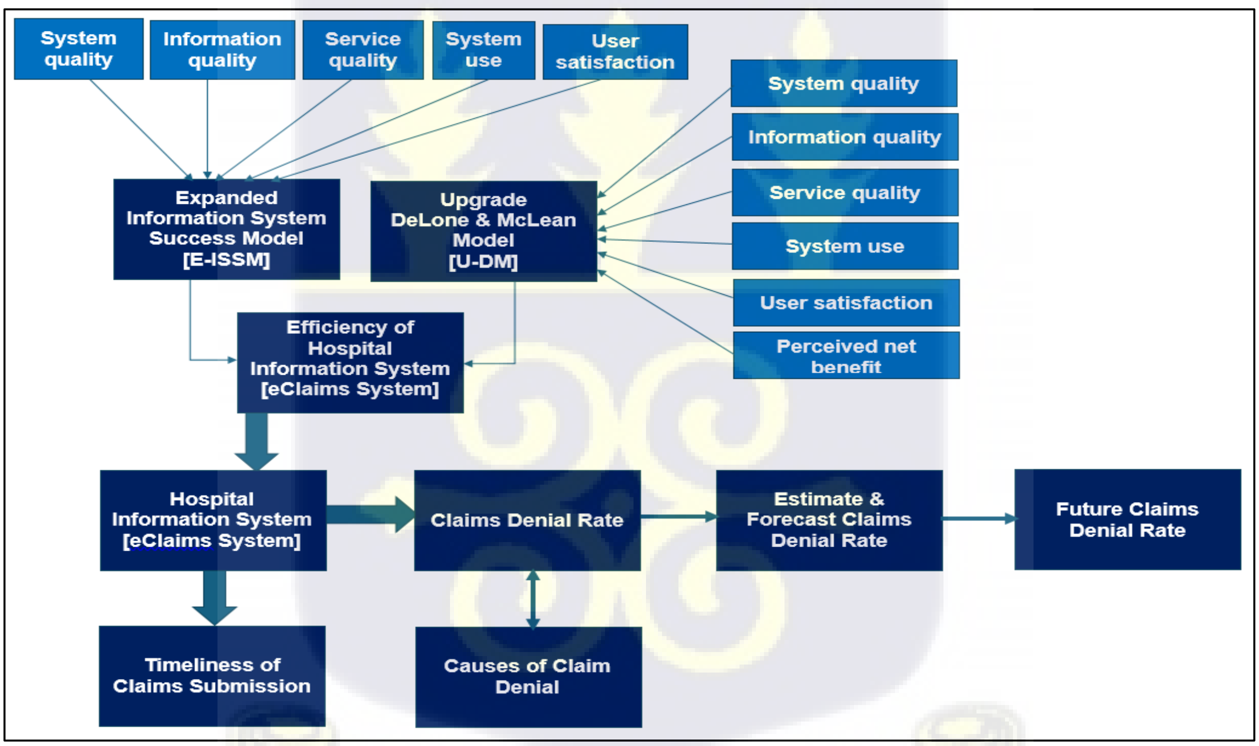

Figure 6: Conceptual framework: Factors influencing claim errors and timeliness of claim submission
Source: Author's concept

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The previous chapter introduced the study. The purpose of this chapter is to review literature pertaining to claim denial, Health Information System and Health Insurance Claim Processing. Clinical Data Characteristics and Processing of Health Insurance Claim. This chapter also reviews the Framework for Understanding the Fundamental Elements Affecting Billing Accuracy, Improvement Strategies for Improving Billing Accuracy, Reasons for denied claims, claim denials and strategies for minimizing errors. The Overview of Ghana's National Health Insurance Scheme and overview of health facility claims processing and submission systems were also reviewed. Information system implementation in healthcare and hospitals, Adoption and diffusion of innovations were also reviewed. The factors that contribute to a successful HIS implementation are also outlined in the chapter.

2.2 Claim denials

In a typical demand and supply environment, customers pay for services they have consumed and suppliers can also refuse to supply in exchange for cash. However, this basic principle may not necessarily apply in the healthcare industry. The healthcare industry in the United States between 2000 and 2017 alone lost 628 billion dollars to uncompensated care (AHA, 2022). In 2018 alone, over 41.3 billion dollars were lost to care without receiving compensation for healthcare services provided after the Affordable Care Act (ACA) was passed (AHA, 2022). According to Blumberg, Buettgens, Holahan, & Pan (2019), any abolishing of ACA is likely to increases issues of health care without compensation to the tune of 52 billion dollars every year. A study conducted by

Bartsch et al. (2020) indicated that this loss excludes non-compensation as a result of the COVID-19 pandemic as well as workers who lost their jobs amid the pandemic could not pay for their hospital bills (Shulkin, 2020).

In Ghana, Nsiah-Boateng et al. (2017) GHS2.81 million representing 4.9% of the total reviewed manual claims of GHS57.50 million (USD15.09 million) were lost to uncompensated health insurance claims.

The issue of uncompensated claims is an important difficulty for healthcare providers, policymakers and other stakeholders in the healthcare industry. Someone must be responsible for the cost of the uncompensated claims; hence, providers come in by increasing the cost of services to everyone (i.e., individual patients, private/government payers and taxpayers) to make up for the lost revenues. The lack of adequate attention to tackling issues of uncompensated care could increase healthcare cost around the world.

One may ask why the issue of uncompensated claims continues to occur. According to Becker's Health IT (2015), uncompensated care can occur from three dimensions. First, consumers of health care (i.e., patients) and health insurance companies (payers) are different entities. Only a handful of patients can pay for health care directly from their pocket (out-of-pocket payment). For this reason, health insurance claims from healthcare providers to health insurance companies undergo some form of excessive bureaucratic means that are likely to result in claim denials due to errors in claims and other administrative reasons (Carroll, 2020). The second dimension is that healthcare providers are prevented from turning away patients simply because they cannot afford care, especially in public health facilities. Having provided health care to such patients who could not pay for services, healthcare providers are not able to retrieve the full cost of the expensive care (S. Jacob, 2014). The third and final dimension is that many patients are not able to forecast the cost of health care or do not fully have control over the kinds of treatment to receive for their illnesses. After having been presented with a surprising medical bill, they find it difficult to settle the bills leaving the cost of health care uncompensated (Kirzinger et al., 2019).

Claim denial is widespread throughout Africa, impacting multiple industries such as healthcare, insurance, and pensions. The significant frequency of claims rejection has been ascribed to several issues, such as administrative inefficiencies, insufficient paperwork, fraudulent activities, and rigorous regulatory prerequisites. Claims denial in the healthcare sector can lead to delayed or denied access to necessary medical services, which worsens health disparities throughout the continent (Schwartz et al., 2022).

Claim denial in the insurance sector is frequently associated with the intricacy of insurance contracts, wherein policyholders may lack a complete comprehension of the terms and conditions, resulting in accidental non-compliance. In addition, insurance companies may utilise stringent claims evaluation protocols to reduce payouts, which can further complicate the claims system (Schwartz et al., 2022). The high frequency of claims denial in Africa can be attributed to the absence of regulatory control and the limited legal options accessible to policyholders.

Ghana, like with a great number of other African nations, is confronted with considerable issues with the denial of claims, notably in the field of health insurance. The National Health Insurance

Scheme (NHIS), which was created to offer cost-effective healthcare to the people of Ghana, has been consistently troubled by problems related to the rejection of claims. Research conducted by Jacob (2018) revealed that a significant proportion of claims made by healthcare providers to the NHIS experience delays or rejections. These issues primarily stem from flaws in paperwork, inaccuracies in coding, and procedural mistakes. The private insurance industry in Ghana encounters comparable difficulties. Insurers frequently deny claims by strictly adhering to policy restrictions, perhaps without sufficient information or explanation to policyholders (Wang, Otoo, & Dsane-Selby, 2017). This has resulted in a loss of trust in the insurance sector as well as widespread dissatisfaction among policyholders worldwide.

A range of measures have been implemented throughout Africa to tackle the issue of claims denial. Electronic claims processing systems have been implemented in the healthcare industry to simplify the submission and review process, hence decreasing the chances of errors that may result in denial (Mwangi, Musembi, Kamau, & Obunga, 2024; Renner-Micah, Effah, & Boateng, 2020). Furthermore, there have been efforts to create training programs for healthcare providers that focus on correct documentation and coding techniques, with the aim of reducing procedural errors (Abekah-Nkrumah, Antwi, Attachey, Janssens, & Rinke de Wit, 2022).

In Ghana, the National Health Insurance Scheme (NHIS) has implemented various measures to decrease the number of claims that are rejected. Notable advancements have been made, such as the implementation of an electronic claims system that enables immediate filing and processing of claims, alongside the creation of a claims review committee to address conflicts between healthcare providers and the NHIS (Jacob, 2018). In addition, there have been initiatives to raise public awareness and educate policyholders on their rights and obligations within insurance agreements. This has resulted in a decrease in the number of claims being rejected owing to a lack of understanding regarding the terms of the policy (Wang et al., 2017). The insurance regulatory system in Ghana has been enhanced to safeguard policyholders. The National Health Insurance Scheme (NHIS) has implemented regulations mandating insurers to furnish explicit and prompt justifications for any rejections of claims and to enable channels for policyholders to challenge such determinations (Jacob, 2018). These policies have enhanced transparency and accountability in the sector, however, there are still obstacles to overcome in their complete implementation.

2.2.1 Claim denials and strategies for minimizing errors

According to recent research on minimizing fraud in the healthcare industry, a variety of methods may be of use in reducing errors. The following subsections will discuss these strategies, which include member verification at the point of service, fraud awareness, stakeholder collaboration, data mining techniques, and personnel with the necessary skills.

2.2.1.1 Member verification at the point of service

Member verification at the point of service can help reduce the risk of illegibility fraud (Debpuur et al., 2015). To make it easier for healthcare providers to determine whether a member in need of care qualifies for the service, the authors also suggested enhancing the quality of the image.

2.2.1.2 Awareness of Fraud

According to Flynn (2015), healthcare insurance members' awareness of fraud may assist in reducing this risk. Members ought to be informed about how healthcare plans function, which is through cross-subsidization of costs (Debpuur et al., 2015).

2.2.1.3 Collaboration among stakeholders

Healthcare funders, both public and private, ought to work together to reduce losses caused by fraud in an effective and efficient manner (Flynn, 2015).

2.2.1.4 Methods for Data Mining

Data mining is the process of applying statistics, mathematics, artificial intelligence, and machine learning to a large amount of data to find patterns and meanings (Abdallah, Maarof, & Zainal, 2016). In healthcare fraud detection, supervised and unsupervised data mining methods dominate (Joudaki et al., 2016). Abdallah et al. (2016) claim that, while the unsupervised approach detects fraud in data that is not classified as fraudulent, supervised data mining uses previously known and determined data that has been marked as fraudulent. As a result, numerous studies have been conducted on the support of systems as a means of reducing healthcare fraud. In the sections that follow, we'll go over the research on how systems can be used to prevent healthcare claim fraud. Since previous studies have only focused on detection.

Furlan and Bajec (2008) looked into how a fraud management system could be used to support all activities targeting fraud. Furlan and Bajec (2008) choice for the unit of analysis was Slovenia.

According to Furlan and Bajec (2008), these authors gathered empirical data by conducting semi-structured interviews with 15 fraud investigators from Slovenia's public compulsory insurance and insurance companies, service providers from a variety of medical fields, and law experts who were familiar with fraud.

Furlan and Bajec (2008) also developed a fraud management system for one of Slovenia's voluntary health insurers using a case study approach. The study's objective was to comprehend the practical difficulties associated with implementing a comprehensive management system that supports all fraud prevention measures. The findings backed up the idea that the fraud management system should be used for more than just healthcare fraud detection. It should also be used to support other activities like deterrence, prevention, investigation, sanction and redress, and monitoring.

In contrast to Furlan and Bajec (2008), a survey by Wakoli et al. (2014) only focused on using system support to catch fraud in Kenya. A representative sample of 15 insurance companies' medical claims data was utilized (Wakoli et al., 2014). Using the Java programming language and the MySQL database, the average amount claimed for each cluster of medical claims was calculated (Wakoli et al., 2014). Following that, the outlier claims that deviated from the norm were identified for further examination. According to Wakoli et al.'s findings, the K-Means clustering model was found to be effective in identifying suspicious fraudulent healthcare claims that warrant further investigation (Wakoli et al., 2014).

The research carried out by Joudaki et al. (2016) aimed to demonstrate how healthcare fraud and claim abuse could be identified through data mining. Joudaki et al. (2016) applied data mining techniques to physicians' out-of-pocket medication claims from private practices. They chose one Iranian health insurance company. The study by Joudaki et al. (2016) found that data mining could aid in healthcare fraud detection. The study's conclusion was that 2.5% of doctors committed prescription fraud on their insured patients.

van Capelleveen et al. (2016) carried out a further academic study on the Medicaid program in the United States, this one focusing specifically on paid dental claims. Unsupervised data mining methods were found to be effective by the authors in identifying these claims' outliers (van Capelleveen et al., 2016). They further discussed the results with two experts in healthcare fraud through semi-structured interviews to validate the findings. van Capelleveen et al. (2016) found that experts confirmed that 71% of the claims that the system had identified as outliers were suspicious of fraud and required additional investigation.

For further investigation, various data mining techniques and irregular patterns can be used to identify healthcare fraud (van Capelleveen et al., 2016; Wakoli et al., 2014). Additionally, fraud could be avoided by using built-in automated system rules to reject known activities, such as duplicate claims and claims from members that cannot be read (Nsiah-Boateng et al., 2017a).

2.2.1.5 Personnel with requisite skills

Personnel with the necessary skills ought to be given the task of devising strategies for fraud management (Flynn, 2015). According to Flynn (2015), the various required skills include, among other things, clinical and statistical expertise. The industry of Ghana's National Health Insurance Scheme is the subject of the following section.

2.3. Health Information System and Health Insurance Claim Processing

2.3.1 The Impact of Hospital Information Systems (HIS) on Claim Errors

The processing of claims in the health sector is multifaceted due to the several thousands of patient diagnoses and conditions and procedural codes and ICD–10 codes as well as the different health insurance payer rules, hospitals and different patient types. It is therefore important to understand claim processing methods with regards to medical data collection, organisation, integration and reconciliation. In this medical data collection and organisation process, errors and mistakes are likely to occur in diverse ways in the area of incorrect diagnoses and procedural codes, medical necessity, mismatched diagnoses and treatment, and incorrect client and provider information. A number of these mistakes can be avoided using appropriate data collection procedures and payer guidelines and requirements.

Studies on the implementation and use of information technology systems have shown to improve the quality of data and also streamline the line of communication within the business organisation process (Barua, Kriebel, & Mukhopadhyay, 1995; Kohli & Grover, 2008; Melville, Kraemer, & Gurbaxani, 2004). Similar outcomes have also been reported in the healthcare industries through the adoption of health information technologies. Studies conducted around health information technologies revealed that hospital information systems (HIS) can enhance interaction among prescribers and patients, improve information sharing and dissemination among health professionals, improve quality of data and data accuracy, and create greater transparency by making sure that patient documentation is legible and complete (Adjerid, Adler-Milstein, & Angst, 2018; Johnson et al., 2011; Mishra, Anderson, Angst, & Agarwal, 2012; Ozdemir, Barron, & Bandyopadhyay, 2011). It is important to add that these systems can ensure conformity by for forcing all users in the system to follow the information system protocol and business rules to provide consistent data collection. The adoption of HIS in-healthcare delivery and the huge volume of medical data collection and processing using HIS can improve the health insurance claim process from the point of data collection to claims submission to health insurance payers. Therefore, the adoption of and use of HIS can play an important role in medical claims documentation and processing of patient encounters. However, the impact of hospital information systems on the error margins of health insurance claims has not received adequate attention in health information system literature. The intension of this study is close this gap by assessing the impact of electronic claim system on claim error margins – claims denial.

2.3.2 Enabling Factors of Hospital Information System Impact on Claim Errors – Claim Denials

Regrettably, stakeholders would naturally expect to see improvement in accuracy and efficiency from HIS not materialising, especially within the healthcare environment where difficult processes concerning procedures and subjective decision-making happen. The adoption and use of HIS demands redesigning workflow processes where codes are well set up in the HIS. This process is normally complicated and sometimes creates disturbances in work processes and workflows. Camilleri and Diebold (2019) for instance, indicated that, restructuring patients' workflow experiences in the implementation of hospital information system comes with reduced efficiency in medical insurance claim processing. The reason is that, redesigning patients' encounters in HIS involves introduction of new services or an improvement in the existing ones. Therefore, healthcare providers are required to put-in more investment in the area of equipment, health professionals and infrastructure (Bazzoli et al., 2007) which intend escalate the cost and the number of cost layers within the HIS for medical claim processing and management.

In addition, the adoption and use of HIS may leads to digitization of medical care procedures that may not necessarily be in line with health insurance payer regulations for medical claim processing. This is because, health care providers may different commitments from health insurance payers and may undertake some procedures and drugs prescriptions which are not covered by the health insurance company policies. According Lason (2022) and Rosato (2019), such exceptions may include undertaking preventive processes, specific surgeries that are elective, multiple processes of the same diagnosis related groupings and prescribing drugs which are not covered by the health insurance policy. One of the important benefits of automating medical claim processing is that it eliminates health insurance payer's discretionary role of disallowing any erroneous health insurance claim. Within the manual claim processing, health insurance claim officers can overlook or pardon any medical claim errors and thereby approving reimbursement to the healthcare providers. So, the digitization of claim processes reduces the tendency of health insurance claim officers to use discretion to disallow or approve health insurance claim. In addition to that, the implementation of HIS allows data entry and capture done automatically and also widens the scope of health information collection within the healthcare organisation. The enormous growth in volume of medical information within health information systems juxtaposed with the manual medical records could make medical claim processing more cumbersome and time-consuming. Therefore, there is a need for a more scientific assessment of electronic claim impact on claim error margins – claim denials than just the theoretical prediction of electronic claim impact on claim error margins.

2.3.3 Barriers to the use of HIS for mitigating claims denial

By implementing enhanced accuracy and efficiency in documentation, coding, and billing systems, Hospital Information Systems (HIS) can significantly decrease claims rejection rates. However, in African and Ghanaian settings, several challenges hinder the effective utilisation of Health Information Systems (HIS) in addressing claims rejection.

Financial Constraints

The greatest obstacle to the adoption and efficient use of Health Information Systems (HIS) is the financial burden linked to procuring, installing, and maintaining these systems. Numerous healthcare establishments, particularly in areas with limited resources, do not have the financial resources to allocate towards modern Health Information System (HIS) technologies. The budgetary constraint influences both the initial system purchase as well as the continuous expenses linked to technical support, training, and software upgrades (Bostan, Johnson, Jaspersen, & Randell, 2024; Green et al., 2015). Many hospitals so still depend on manual approaches, which are more prone to mistakes and result in greater denial of claims.

Lack of Technical Expertise

Successful implementation of a Health Information System (HIS) requires a certain level of technical expertise, both in terms of initial system configuration and ongoing maintenance. Ghana and other African countries have a shortage of healthcare professionals who possess the necessary skills to effectively operate and oversee Health Information Systems (HIS) (Atasoy, 2019; Ayabakan et al., 2017; Jones et al., 2012). Inadequate proficiency in this domain may result in inefficient utilisation of the system, inaccuracies in data input, and challenges in resolving problems, all of which may lead to claim denials owing to erroneous or insufficient information.

Resistance to Change

Healthcare practitioners may encounter opposition while adopting novel technology, such as Health Information Systems (HIS). Resistance may occur because of a lack of knowledge of the technology, concerns about an increased effort, or reservations about the dependability of electronic systems compared to old paper-based methods (Larbi, 2018; Yusif, Hafeez-Baig, & Soar, 2020a). Opposition to adopting and implementing the Health Information System (HIS) may lead to the system being underutilised or used incorrectly, hence reducing the potential benefits of the system in reducing claims rejection.

Inadequate Infrastructure

The effectiveness of Health Information Systems (HIS) relies on having a strong infrastructure, which includes reliable electricity, internet access, and adequate hardware. Infrastructure challenges in specific regions of Africa, including certain parts of Ghana, pose significant barriers to the successful implementation of Health Information Systems (HIS) (Mensah et al., 2023). The presence of frequent power outages, slow internet speeds, and outdated computer systems could hinder the smooth operation of the Health Information System (HIS), leading to delays and inaccuracies in the claims process.

Data Privacy and Security Concerns

Concerns arise regarding the confidentiality and protection of data when utilising Health Information Systems (HIS), particularly in environments with insufficient cybersecurity measures. Healthcare facilities may have reservations about fully implementing Health Information Systems (HIS) due to concerns regarding the security of patient data and unauthorised access to confidential information (Bommareddy, Khan, & Anand, 2022; Mensah et al., 2023). These concerns may result in a limited adoption of HIS functions, which can hinder their effectiveness in reducing claims denial.

Interoperability Issues

An obstacle that hinders the efficient utilisation of Health Information Systems (HIS) is the lack of interoperability among various systems in the healthcare industry. The lack of complete compatibility among Health Information Systems (HIS) used by different hospitals, insurance firms, and government agencies often presents challenges in exchanging and communicating data (Bhartiya & Mehrotra, 2014; Yusif, Hafeez-Baig, & Soar, 2020b). Lack of interoperability can result in inconsistencies in patient records and billing data, leading to higher rates of claims denial.

To fully utilise the capabilities of Hospital Information Systems in reducing claims denial and enhancing healthcare processes, it is imperative to address various obstacles that currently exist. Several challenges need to be overcome, including financial constraints, limited technical expertise, resistance to change, inadequate infrastructure, concerns about data privacy, and interoperability issues. To enhance the efficiency of Health Information Systems (HIS) in minimising claims denial in Africa and Ghana, it is essential to tackle these challenges through targeted investments, capacity building, and regulatory reforms.

2.4. Clinical Data Collection and Processing of Health Insurance Claim

In the traditional setup of patient encounter of an outpatient department, an initial conversation is carried out to collect some medical information which is preceded by an examination (verbal or physical). Physicians diagnose the patient's health condition based on the medical information and the examination carried out and provide a series of procedures to be followed (Bagheri, Ibrahim, & Habil, 2015). Within a typical hospital information system consultation, such information as the patient's demographics, history of medical conditions, current medical conditions, medications (current or past), current diagnosis and procedures are coded and stored in the HIS.

The medical billing process or claim processing is one of the last stages of the hospital consultation process which is heavily dependent on characteristics of the clinical data obtained during the patient encounters. At this level, an integration of all the data relating to the patient is done using a health information system (or a health insurance claim officer in the absence of HIS). An assessment of a medical claim is done by matching the rules and guidelines of the health insurance payer is followed after the patient's data integration, passes the outcome through a validation process and then moves on to submit the claims to the health insurance payer (FitzGerald et al., 2011). This process can be enhanced using a hospital information system from the point of registration/scheduling to processing and submitting the claims.

The application of hospital information system in enhancing health insurance claim processing and submission is dependent on the characteristics of the basic clinical data and how responsive is claim processing to claim errors. In this sense, the effect of hospital information systems are dependent on accuracy of clinical data and its responsiveness to claim errors.

2.4.1 Accuracy of Clinical Data:

According to Weiskopf and Weng (2013), the extent to which medical data is correct, complete and used in clinical and administrative decision-making is dependent on the accuracy of the clinical data. This situation is so because one cannot predict when patients will encounter the care provider or the provider ordering care, the documentation of medical information without a planned schedule suffers from incompleteness, data gaps and errors (Wu, Roy, & Stewart, 2010). Furthermore, respective healthcare providers also write medical diagnoses and conditions differently and may use different diagnostic codes; for example, different stages of cancer-related conditions may be classified differently with varying definitions and may also change over time. In addition, laboratory investigation can come with different measurements and orders with varying corresponding billing codes and are updated frequently within the same healthcare system (Kim et al., 2019). Based on these underlying factors, clinical data is prone to data accuracy issues.

The implementation and use of hospital information system (HIS) has improved medical information capturing. An HIS provides the basis for an easy and accurate way of recording clinical data using templates leading to more accurate data capture. Thus, hospitals with HIS have a more consistent and up-to-date medical information that enhance completion of claim forms with ease and greater accuracy and thereby reducing the chances of claim denials as a results documentation mistakes or incomplete data. According to Bell and Thornton (2011), once accurate data is captured, HIS enables efficient and up-to-date data access and use, which reduces the probability of errors in health insurance claim processing and submission. By extension, HIS reduces the probability of errors in claims processing compared to the manual system thereby reducing claim denials.

Studies have shown that day-to-day tasks and acceptable standards of processes performed by HIS produce few errors (Aujesky et al., 2011; Hoffer Gittell, 2002). Concerning the management of chronic conditions, there are more standardizes processes based on protocols which require less information capture from patients than expected in the management of acute conditions, hence the capabilities of HIS minimizes claim processing errors (Anker, Koehler, & Abraham, 2011; Nolte, Knai, & McKee, 2008; Wakefield et al., 2008). Bavafa, Hitt, and Terwiesch (2018) added that the routine form of chronic disease management requires less information than acute and has common symptoms making it easier for HIS claim processing. The reason is the capturing of chronic conditions in HIS is more specific and hence fewer errors. So, the frequent visit of the patient with chronic conditions or elective cases makes their data more specific and standardized over time. There is continuous update of the medical history, clinical diagnoses and conditions, medications and procedures leaving lesser room for claim errors in the HIS. This shows that the HIS has more effect in reducing the probability of claim errors leading to claim denials.

2.4.2 HIS Responsiveness to Claims Processing Errors:

The use of HIS in the healthcare setting over the years have increased creating more refined patient health information such as their medical histories, prescription information and diagnoses (Adler-

Milstein, Adelman, Tai-Seale, Patel, & Dymek, 2020). The more refined and detailed patient information in addition automation of claim processing can respond to errors in health insurance claim processing for cases that are deemed to be more complicated. Compared to the paper-based system processing of health insurance claims, where claims are validated by health insurance claim officers and back-end medical coders and billers (Jacqueline LaPointe, 2022), HIS has the capabilities of responding to claim errors and can detect claims that contain inaccurate information about patient's transactions. This is because the automated claims processes contain business information rules coded into the HIS that respond to medical claim errors more frequently. Hitherto, these errors could be resolve through discussions and negotiations between healthcare providers and insurance payers within the paper-based system. As discussed earlier, claim officers who process and assess medical claims can use their discretion to disallow or reimburse erroneous health insurance claims. On the other hand, the automated claims process will adhere strictly to the predefined business rules in HIS by denying or rejecting a claim and sending it back to the providers for review and re-processing or otherwise (Jacqueline LaPointe, 2022). So, the assertion that HIS is responsive to health insurance claim errors in claim processing and management and thereby improving the likelihood of denials of claim holds compared to the paper-based system.

Coding relating to diagnostics and procedures plays an important role in claim processing as the justify the condition of injury of patients concerning the characteristics of patients and procedures undertaken (Jacqueline LaPointe, 2022). Diagnoses-related grouping plays patients into similar conditions and costs of patient care. Health insurance reimbursement tariffs seriously rely on such code categories and any inconsistencies and medical claim errors can results in claim denial and payment. The transition from International Classification of Diseases (ICD) version 9 to ICD version 10 in 2014 was one of the major changes in coding that happened to health insurance billing and management. The ICD-10 coding manual contains almost 19 times as many diseases and procedures compared to the ICD-9 coding system (Topaz, Shafran-Topaz, & Bowles, 2013). Though the transition was meant to improve the coding accuracy of diagnoses and procedures, it also increased the depth of conditions codes thus burdening the HIS in processing health insurance claims. Topaz et al. (2013) indicated that improvement in granularity of medical data can worsen errors in clinical data by revealing misleading or incomplete medical data. A study conducted by Minich-Pourshadi (2011) reported that, the transition from ICD-9 to ICD-10 has worsen the rate of errors in claims giving rise to late submission of health insurance claims and also increasing the chances of denial of claims by payers. Therefore, the increasing adoption of HIS can inherently make the HIS more responsive to nonadherence and prone to errors, especially in the wake of ICD-10. The next section discusses the National Health Insurance Scheme ACT 650.

2.4.3 Tools for processing data for insurance claims

All 25 sampled health facilities use the same paper-based and electronic-based systems (Hospital Information System) to process clients' health insurance claims. The client's NHIS card is checked when they enter the facility at the first point of call (the Health Information Unit at the OPD). He or she is processed for cash and carry once the card is invalid or a non-NHIS member. A person with a valid NHIS card is assigned to the NHIS, and the service is provided under the NHIS benefit package. Either manually or electronically, treatment bills are sent to the NHIS for reimbursement. Figure 7 depicts the NHIS Claims processing in healthcare facilities in greater detail. In the next section, information system implementation in healthcare and hospitals is discussed.

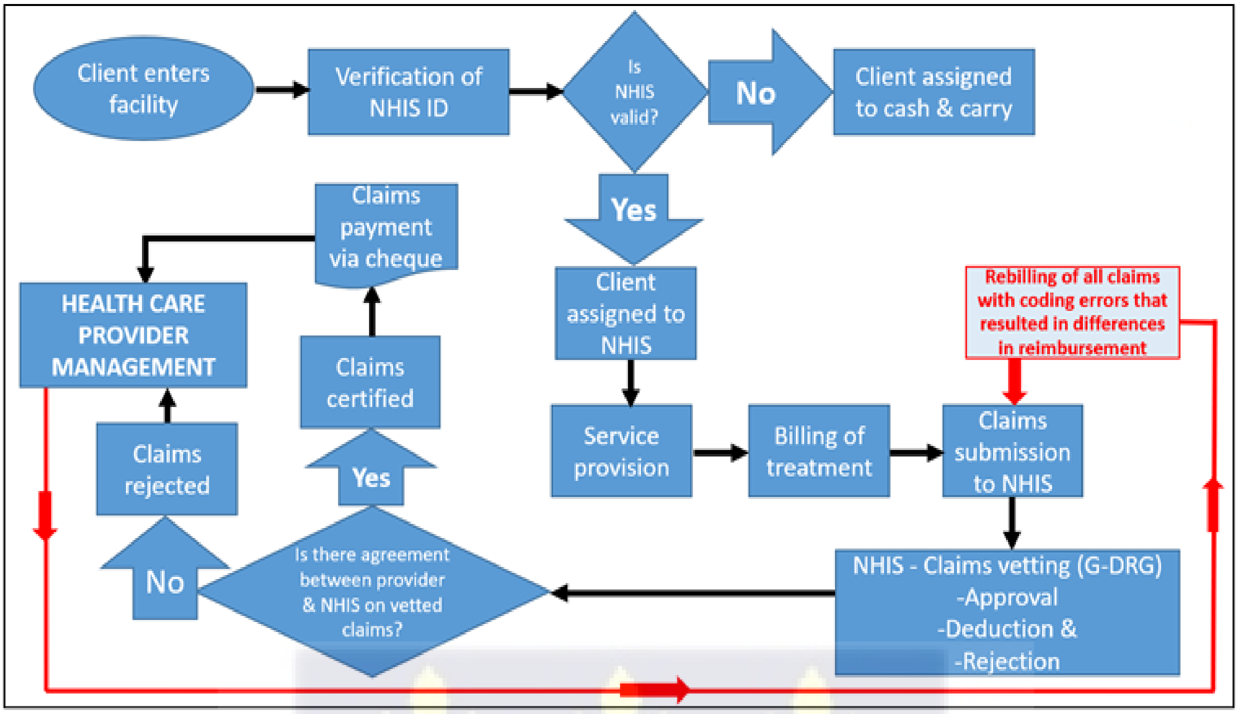

Figure 7: Flowchart on NHIS Claims processing in healthcare facilities
Source: Authors' Analysis

2.4.3.1 Improvement Strategies for Improving Billing Accuracy

Several potential ways to increase the accuracy of evaluation and management (E/M) billing can be seen when the literature review is framed within the framework of Leavitt's components of organizational change. The research analysis helps us figure out which strategies are under the control of physician organizations and how they should put these strategies into action. Figure 7's concept map depicts the various options for physician organizations.

Training and Education: It is well established that physicians require additional education and training in billing and coding procedures. The knowledge of coding rules and guidelines was found to be significantly lacking in physicians, according to numerous studies. Even though some of these studies are quite old, more recent ones (Agrawal, Taitsman, & Cassel, 2013; Howard &

Reddy, 2018; Ng & Lawless, 2001; Sa, Cohen, & Marculescu, 2001). Physicians are not adequately prepared for the regulatory environment governing their reimbursement by medical schools, fellowships, or residency programs. However, the Centres for Medicare and Medicaid (CMS) initiated several initiatives to reduce improper payments. Individual physician education programs (Probe and Educate Reviews) aimed at physicians who perform poorly in billing reviews are one of these initiatives (U.S. Department of Health and Human Services, 2016). Group practices of physicians ought to follow suit. Group practice compliance departments can proactively conduct their own reviews and develop individualized training programs by utilizing the CMS comparative billing reports, which are a billing analysis that enables physicians to compare their billing patterns to those of their peers.

Simplification of E/M Billing Guidelines: There are numerous criticisms of the complexity of management coding guidelines and evaluation guidelines in the literature. Every study shows that the guidelines are too hazy and ambiguous to ensure consistent coding. By combining the evaluation and management guidelines from 1995 and 1997 into a single, comprehensive set, the OIG has even advocated for simplification (Department of Health and Human Services, 2014). The CMS has agreed to simplify some policies, even though they did not accept this recommendation. The number of E/M service levels for office visits will be reduced from five levels to two in 2020. Only the appropriate documentation to support the two coding levels will be required of physicians. Additionally, some of the documentation requirements for E/M services were reduced by the CMS in 2019. The CMS anticipates lowering E/M improper payment rates by simplifying these billing guidelines. However, the current E/M guidelines contain numerous complexities and will continue to be problematic unless they are completely revised.

Technology Adoption: Technology can be a powerful enabler, but it can also be a hindrance if it is not properly implemented, taught, or used in workflows. EMRs have tools that, if used correctly, promise to cut down on billing errors. Additionally, E/M services can benefit from the successes of hospital computer-assisted coding technology as technology develops. However, CIOs must actively advocate for the creation and implementation of these technological solutions to ensure that adoption barriers are quickly removed and a return on investment is achieved.

Physician Attitudes: According to some studies, physician attitudes hinder accurate billing. If physician attitudes are not in line with these improvement initiatives' objectives, none of the suggested strategies will be successful. Physicians who up-code to maximize reimbursement must be identified and dealt with by compliance departments. In a similar vein, internal compliance programs are required to identify physicians who do not try to learn the rules governing billing and coding. According to Fichman (2000), information systems (IS) have the potential to significantly lower healthcare costs and enhance clinical outcomes. However, Yang, Kankanhalli, Ng, and Lim (2015) observed that, in comparison to organizations in other industries like manufacturing, financial services, and transportation, many hospitals and medical practices have yet to realize this potential.

2.5 National Health Insurance Scheme (NHIS ACT 650)

The National Health Insurance Scheme (NHIS) in Ghana was the first to be established in sub-Saharan Africa by the National Health Insurance Act 650 of 2003. It is governed by the National Health Insurance Regulation (Legislative Instrument – L. I. 1809) of 2004. The National Health

Insurance Scheme's goal is to give everyone in Ghana, especially the poor and the vulnerable, financial access to high-quality basic health care services. Cross-subsidization, in which the economically active pay for children, the elderly, and the indigents, is a feature of the National Health Insurance Program (NHI).

The NHIS is funded by a central National Health Insurance Fund (NHIF) that gathers funds from the National Health Insurance Levy (NHIL), a 2.5% tax on certain goods and services, and a 2.5% tax on Social Security and National Insurance Trust (SSNIT) contributions, primarily from formal sector employees (Alhassan, Nketiah-Amponsah, & Arhinful, 2016). In addition, the NHIF generates revenue through premium payments and donations. As per Alhassan and colleagues' research in 2011, employees in the formal sector who contribute to SSNIT are not required to pay premiums. In 2012, over 70% of the funding inflows for the NHIS were acquired from the NIL. The study further indicated that SSNIT contributed 17.4% of the total inflows, whereas premium payments made up 4.5%. The NHIF receives additional income from various sources, such as cash granted by the Parliament of Ghana, grants, donations, voluntary contributions, and interest generated from investments (Alhassan et al., 2016).

2.5.1 Challenges of the National Health Insurance Scheme

The National Health Insurance Scheme (NHIS) established under Act 650 in Ghana was created to ensure that healthcare is accessible and affordable for all Ghanaians. However, over the years, the scheme has encountered various difficulties, particularly in terms of reimbursing healthcare providers. These shortcomings have a serious effect on the sustainability and effectiveness of the scheme.

Funding and Financial Sustainability

One of the major challenges of the NHIS is the ability to secure adequate financial resources. The scheme is mostly funded using a mix of premiums, taxes on goods and services, levies and government allocations. However, the accumulated monies from these sources usually become inadequate to pay for expenses associated with healthcare services provided under the programme by service providers. The inadequate funding has contributed to the healthcare providers encountering delays in receiving reimbursements thereby affecting the quality of healthcare services (Danquah, 2017).

Delayed Reimbursements

The NHIS has encountered difficulties in reimbursing healthcare facilities. The reimbursement process is mostly delayed due to bureaucratic bottlenecks, insufficient evidence, and the requirement for meticulous scrutiny to deter false claims. The delays result in cash flow issues for healthcare facilities, which in turn cause challenges in sustaining operations, procuring supplies, and compensating staff (Danquah, 2017). As a result, numerous healthcare providers may be unwilling to accept the NHIS valid card bearers or impose a copayment charge to take care of the delays.

Fraud and Abuse

Apart from financial and reimbursement difficulties faced by the NHIS, they also encounter fraud and exploitation of the system by healthcare providers and patients, which exerts pressure on its limited resources. Some healthcare providers engage in upcoding or charging for services that were not provided, while other patients take advantage of the system by engaging in provider shopping which is sometimes termed as needless healthcare care. This conduct leads to financial losses and worsens the issues of delayed reimbursement (Alhassan et al., 2016; Kittoe & Asiedu-Addo, 2017).

Inadequate Claims Processing Systems

The claims processing system of the NHIS frequently encounters problems due to its inefficiency and susceptibility to errors. Several healthcare providers often use manual submission of claims, hence increasing the chances of errors and inconsistencies in the submitted claims. Moreover, the absence of a comprehensive computerised claims processing system has posed challenges in optimising the reimbursement process and minimising delays (Nsiah-Boateng et al., 2017a; Sodzi-Tettey, Aikins, Awoonor-Williams, & Agyepong, 2012).

Lack of Provider Compliance and Accountability

Hospitals providing services under the NHIS are mandated to comply with the NHIS Act 650 when submitting claims for reimbursement. However, adhering to the standards is mostly faced with insufficient instructions, ineffective exchange of information, and a dearth of systems to ensure responsibility. The lack of compliance with the requirements contributes to the refusal of claims or delayed processing time, which adds more complexity to the reimbursement process (Asare & Ibrahim, 2017).

Service Coverage and Quality

Although the NHIS has the goal of offering extensive healthcare coverage, there are apprehensions over the sufficiency of the services included and the standard of treatment delivered. Certain crucial treatments and prescriptions are not included in the program, resulting in patients having to pay for them out of their own pockets. In addition, the provision of care at NHIS-participating facilities is occasionally impaired because of financial limitations imposed by delayed payments and inadequate funding (Kipo-Sunyehzi, 2021; Kodom, Owusu, & Kodom, 2019).

Low Premiums and Contribution Evasion

The NHIS is funded by the premiums collected from participants, although these premiums are frequently kept at a low level to ensure that the program is accessible to everyone. Nevertheless, the meagre premiums fail to adequately address the escalating expenses associated with healthcare services, resulting in a financial burden on the scheme. In addition, there is a problem of contribution evasion, where certain individuals and employers neglect to fulfil their obligatory obligations, hence worsening the financial troubles of the system (Alhassan et al., 2016; Fusheini, Marnoch, & Gray, 2017).

Administrative and Operational Challenges

The NHIS encounters numerous administrative and operational obstacles, such as excessive bureaucratic procedures, insufficient coordination among the parties involved, and poor systems for monitoring and evaluating its performance. These issues result in inefficiencies in the administration of the plan, specifically in the handling and repayment of claims (Alhassan et al., 2016; Danquah, 2017; Nsiah-Boateng et al., 2017a).

Substantial progress has been made under the NHIS since its establishment under the ACT 650 in improving access to healthcare in Ghana. Nonetheless, the scheme faces several challenges that can collapse the long-term sustenance and viability. Major issues such as financial issues, delayed payments, fraud, insufficient claims processing systems, and provider compliance should be of concern. To overcome these obstacles and ensure the long-term survival of the plan, issues of an administrative and financial framework of the NHIS, improve the efficiency of claims processing, and strengthen accountability must be strengthened.

2.5.2 Criminal and civil penalties and fines in the Ghanaian NHIS system

The National Health Insurance Act, 2012 (Act 852) enshrined the criminal and civil penalties and fines in Ghana. This is in the fourth section: Adjudication and additional regulations. An Authority officer can be charged with an offense under the act; a member of the National Health Insurance Program who, to submit a claim, conspires with a healthcare provider or another individual; a healthcare provider who submits a claim to the Authority for payment to defraud the National Health Insurance Scheme or attempts to do so; and a person who enrols in the National Health Insurance Scheme despite not being eligible to do so (National Health Insurance Act, 2012).

2.6 Reasons for denied claims

Recent examples of denied claims include Ponzi and pyramid schemes, securities fraud, financial scandals involving corporate accounting, healthcare fraud, insurance fraud involving automobiles, and art forgery fraud (Gong, McAfee, & Williams, 2016). The various forms of reasons for denied claims are the focus of the following discussion.

2.6.1 False claims

False claims, also known as phantom claims, are made to the healthcare funder for services that were not provided (Thornton et al., 2015). According to Pande and Maas (2013), this is the most prevalent form of fraud committed against healthcare funders. When there is an agreement between the service provider and member to defraud the healthcare funder, such claims are sometimes submitted to the provider, who is working with the insured member (Abdullahi & Mansor, 2015). Other times, without the member's knowledge, service providers obtain the member's health insurance information and submit false claims (Flynn, 2015). Service providers may also conspire with one another to submit false claims (Joudaki et al., 2016). Identity fraud can also happen without the member knowing about it, as in syndicate scams where the goal is to use the member's profile to make false claims to the healthcare insurer (Flynn, 2015).

2.6.2 Over-servicing or unnecessary healthcare services

This occurs when a healthcare provider provides a service that is in excess of what is necessary (Abdallah et al., 2016). According to (Flynn, 2015), the provided service is questionable in comparison to the usual practice followed by the service provider's peers and does not improve the patient's clinical outcome. According to van den Heever (2012), members place their faith in the healthcare provider but are unable to ascertain the kind of assistance that is required. According to Rashidian, Joudaki, and Vian (2012), health insurers receive a false diagnosis of a medical condition to justify the service provider's excessive prescriptions and tests. According to Pande and Maas (2013), a doctor in the United States blinded some psychiatric patients by performing unnecessary eye operations on them.

2.6.3 Sharing health benefits with non-members

Members of health insurance who hand out membership cards to non-members seeking medical care (Debpuur et al., 2015) commit fraud of this kind. In contrast to syndicated fraud, health insurance members freely consent to an illegible individual using their membership card.

2.6.4 Claiming an excluded product as a covered benefit

The service provider misrepresents the information on the account to indicate that a covered service or benefit was provided to claim an excluded product (Flynn, 2015). For instance, the author discovered that in Australia, prostitutes were misrepresenting a claim to the health insurer as massage therapy, which is a covered benefit, and providing sexual services, which are excluded benefits.

2.6.5 Coding errors

Coding errors as stated by Abdallah et al. (2016) posit that, up-coding, code padding, and unbundling of codes are all examples of coding irregularities. Rashidian et al. (2012) defined up-coding as the practice of billing a patient for a more expensive service than was provided. According to Bauder, Khoshgoftaar, and Seliya (2017), up-coding fraud can occur when a healthcare provider submits a claim to the funder claiming that the consultation lasted 30 minutes when the patient was only seen for 10 minutes. According to Thornton, Mueller, Schoutsen, and Van Hillegersberg (2013), code padding is the fraudulent billing of additional codes for services provided, whereas unbundling of codes is the charging of multiple individual codes to obtain a greater monetary benefit than charging for a single inclusive code.

2.6.6 Waiving of members' deductibles

This occurs when service providers fraudulently waive co-payments at the point of service, which are imposed by health insurers to reduce costs (Thornton et al., 2015). Due to the insured's agreement with the insurer, this practice will increase demand for these providers' services.

2.6.7 Unreadable service providers

In this regard, non-medical professionals provide members with healthcare services and file claims with the health insurance company (Legotlo, 2017; Pande & Maas, 2013). In the public sector of South Africa, the outsourcing of healthcare for psychiatric patients resulted in 91 deaths, highlighting the danger posed by unregistered providers of healthcare (Makgoba, 2017).

2.6.8 Double billing

Duplicate claims are situations in which a service provider bills the funder twice for the same service (Abdallah et al., 2016; Thornton et al., 2013). Nsiah-Boateng et al. (2017a) in their study of the Ghanaian healthcare insurance industry, providers were submitting duplicate claims unacceptably.

2.6.9 Self-referrals and Kickbacks

Providers may refer patients to other service providers for services that are not necessary to increase service utilization (Abdallah et al., 2016). The healthcare professional who refers patients for further treatment occasionally receives kickbacks (commission) or has financial stakes in the company (Thornton et al., 2015). False claims, providing clinically unnecessary healthcare services, coding errors, double billing, waiving members' deductibles, kickbacks, self-referrals, and claiming for excluded products or services are all examples of healthcare fraud. Additionally, members of a healthcare insurance plan share their benefits with members who cannot read them, defrauding funders of healthcare. Even though they are not qualified healthcare professionals, unqualified individuals also defraud healthcare insurers by providing healthcare services. The member's health may be harmed by unjustified healthcare services (Pande & Maas, 2013). Additionally, fraudulent claims consume funds intended for healthcare provision (Nsiah-Boateng et al., 2017a). The management of fraud risk is the topic of the following section.

2.7 Overview of Ghana’s National Health Insurance Scheme

National health insurance schemes (NHIS) are crucial in enhancing healthcare accessibility in low- and middle-income countries (LMICs), specifically in Sub-Saharan Africa. The National Health Insurance Scheme (NHIS) was founded in 2003 in Ghana to offer financial security and enhance the availability of healthcare services for the populace.

An Act of Parliament (ACT 650, Amended Act 852) was passed in 2003 that made Ghana the first nation in sub-Saharan Africa to implement NHIS (National Health Insurance Act, 2012). Full implementation began in 2004. Every Ghanaian is required to enrol in a health insurance plan by the NHIS amended Act 852 (2012) (National Health Insurance Act, 2012). However, the relatively large informal sector in Ghana and the NHIA's limited administrative capacity prevent this constitutional provision from being effectively implemented.

The National Health Insurance System (NHIS) is financed by a central National Health Insurance Fund (NHIF), which is funded by a 2.5% tax on selected goods and services called the National

Health Insurance Levy (NHIL). 2.5% of contributions to the Social Security and National Insurance Trust (SSNIT), most of which come from workers in the formal sector; payment of premiums as well as donations. Premium payments are not required for those who are employed in the formal sector and contribute to SSNIT. In 2012, the NIL accounted for more than 70% of the NHIS's financial inflows; 4.5 percent from premium payments and 17.4 percent from SSNIT contributions. The Ghanaian parliament's allocated funds, grants, donations, gifts/voluntary contributions, and investment interest are additional sources of funding for the NHIF. According to (Agyepong & Adjei, 2008), several health financing mechanisms, including the Out-of-pocket Payment (OOP), were unable to guarantee financial accessibility and universal health coverage for the population, making the introduction of the NHIS necessary (Arhinful, 2003).

The NHIS does not attempt to treat all diseases that insured members experience. The NHIS benefits list, on the other hand, covers many common diseases like diarrhoea, malaria, and infections of the upper respiratory tract. In a similar vein, members who are covered by NHIS are entitled to treatment for medical emergencies such as traffic accidents. Additionally, pregnant women are exempt from paying NHIS premiums under the free NHIS for pregnant women policy. The National Health Insurance Scheme (NHIS) does not cover relatively uncommon diseases like cancer.

Overall, more than 60% of the NHIS's active members fall into the premium exemption category (those under the age of 18 and those over 70), indigents and pregnant women (Alhassan et al., 2016). Due to the large number of NHIS members who receive premium exemption without co-payment (subscribers sharing the cost of health care with insurance providers for specified conditions) and the rising cost of medical logistics/supplies and health service delivery, critics of the Ghanaian NHIS claim that the program is overly generous and financially unsustainable (Alhassan et al., 2016).

The National Health Insurance Authority (NHIA) was established as part of the National Health Insurance Act of 2003 (Act 650) and became operational in 2004 to begin providing universal health coverage in Ghana (Duku, Asenso-Boadi, Nketiah-Amponsah, & Arhinful, 2016). It took the place of the 1980s' cash-and-carry drug policy and fees for health services, which required Ghanaians to pay for all health care out of their own pockets. The NHIS was created to cover more than 95% of Ghana's disease burden at its inception. The only exceptions were cancer treatment (except breast and cervical cancer), organ transplants, cosmetic surgery, and a few others on the exclusion list (Ankrah et al., 2019). According to Nathaniel Otoo (2016), in December 2014, approximately 29 million outpatient visits were recorded, or about three outpatient visits per enrolee annually. The active subscriber base was 10.5 million, or 39% of the total population. The percentage of active members varied greatly by region; When compared to the Ashanti region, which is Ghana's most densely populated region and has the smallest population, the Upper West region had the lowest active membership (4%). According to Dixon, Tenkorang, and Luginaah (2011), a significant factor in NHIS subscription was socioeconomic status (SES); Compared to Ghanaians with lower SES, those with higher SES are more likely to subscribe. Urban living and higher educational attainment are additional determinants (Dixon et al., 2011). Social Security and National Insurance Trust (SSNIT) contributors and pensioners, people under the age of 18, people over the age of 70, pregnant women, indigents (the core poor), people with mental health conditions, categories of disabled people designated by the Minister responsible for Social

Welfare, and beneficiaries of the Livelihood Empowerment Against Poverty Programme (LEAP) are exempt from paying premiums to remove these obstacles and expand coverage to Ghanaians with lower SES, lower educational status, and those who Diverse sources provide the NHIS with operating funds. These include 74% from a national health insurance levy of 2.5 percentage points on goods and services, 20% from worker contributions of 2.5 percentage points to SSNIT, 3% from non-actuarially determined premium payments by informal sector scheme registrants, 2% from interest on investments, and 1% from other sources (Tariff Operation Manual, 2015).

2.8 The Impact of eClaims System on National Health Insurance Claims Management in Sub-Saharan Africa

Electronic Claims Systems (eClaims system) have emerged as an essential improvement in the administration of National Health Insurance Schemes (NHIS) worldwide, specifically in low- and middle-income countries (LMICs) in Sub-Saharan Africa. These solutions offer enhanced efficiency, precision, and openness in claims handling, tackling the difficulties associated with manual, paper-based systems. This review provides a thorough analysis of the existing information about the effects of Electronic Claims Systems (eClaims system) on the administration of claims in the National Health Insurance Scheme (NHIS). It specifically focuses on the experiences of Low- and Middle-Income Countries (LMICs) in Sub-Saharan Africa, with a particular emphasis on Ghana.

The primary objective of National Health Insurance Schemes in Sub-Saharan Africa is to offer economic security and enhance the availability of healthcare services. Nevertheless, these programs have historically encountered obstacles such as delayed claims processing, fraudulent activities, administrative inefficiencies, and insufficient payment mechanisms. Ghana, Rwanda, Tanzania, and Kenya have implemented the eClaims system to address these difficulties, achieving different levels of success.

Efficiency and Timeliness of Claims Processing

An extensively proven advantage of the eClaims system in Sub-Saharan Africa is the notable enhancement in the effectiveness and promptness of claims processing. A study conducted in Ghana by Jacob, (2018) revealed that the adoption of Electronic Claims Systems (eClaims system) significantly decreased the time required for claims processing, reducing it from several months to a few weeks. This improvement resulted in faster payments for healthcare providers. Similarly, the implementation of the Health Management Information System (HMIS) in Rwanda, which incorporates electronic claims processing, has significantly reduced the time taken to reimburse healthcare providers (Barakabitze, Aloyce, Rashidi, & Shao, 2023). The evidence indicates that eClaims system facilitates the administrative process by decreasing the time needed for submitting, verifying, and reimbursing claims. Enhancing efficiency is vital for the sustainability of NHIS since it boosts provider satisfaction and guarantees uninterrupted service delivery.

Accuracy and Fraud Reduction

The use of the eClaims system is essential in enhancing the precision of claims processing and minimising the incidence of errors. Manual systems are susceptible to errors and tampering, resulting in substantial financial losses. The built-in automated validation procedures in the eClaims system minimise the probability of errors and facilitate the identification of fraudulent claims. The deployment of the Electronic Claims System (eClaims system) in Ghana resulted in a decrease in fraudulent activities, as indicated by the National Health Insurance Scheme (NHIS) (Owusu-Oware, Effah, & Boateng, 2018). The system's capacity to digitally monitor and examine claims enables enhanced supervision and responsibility. A study conducted in Tanzania found that the implementation of the NHIF's electronic claims system has effectively detected and prevented fraudulent claims (Barakabitze et al., 2023).

Cost Implications

Although the initial installation of the eClaims system necessitates a major investment in infrastructure, training, and technology, the long-term cost savings are tremendous. Research conducted in multiple Sub-Saharan African nations demonstrates that the decrease in administrative expenses, along with the savings resulting from less fraudulent activities, is more than the initial costs. Rwanda's decision to invest in the Health Administration Information System (HMIS), which incorporates Electronic Claims Submission (eClaims system), has been supported by the potential long-term advantages of enhanced claims administration and decreased operational expenses (Nshimyiryo et al., 2020). The 2020 report from the National Health Insurance Authority (NHIA) in Ghana emphasised the favourable financial effects of the Electronic Claims System (eClaims system), acknowledging its role in enhancing the long-term financial viability of the plan.

Challenges in Implementation

Although there are well-documented advantages, the adoption of the eClaims system in Sub-Saharan Africa has encountered numerous obstacles. The digital gap continues to be a substantial obstacle, especially in rural regions where there is little availability of dependable internet and technology. In Ghana, the adoption of the Electronic Clinical System (eClaims system) has been a significant challenge for healthcare providers in distant locations (Abekah-Nkrumah et al., 2022). The presence of resistance to change among healthcare practitioners and NHIS staff has been identified as a significant barrier. The shift from manual to electronic systems necessitates both technical training and a culture transformation that embraces digital technologies. Furthermore, there are widespread worries regarding the security and privacy of data, especially in situations where the infrastructure for cyber-security is not well-established.

Impact on Healthcare Delivery

Further investigation is needed to understand the wider influence of the eClaims system on the delivery of healthcare. Although data is supporting the improvement of claims processing and reduction of fraud with the eClaims system, its direct influence on patient outcomes and the quality of healthcare services remains uncertain. According to research, expedited reimbursements in healthcare facilities may enhance resource availability, perhaps resulting in improved service delivery (NHIS, 2024). Nevertheless, further investigation is necessary to establish a definitive correlation between the deployment of the eClaims system and healthcare results.

Comparative Analysis with Other LMICs

Comparative analyses conducted on several Sub-Saharan African nations indicate that the effectiveness of eClaims system implementation is impacted by multiple aspects, including the dedication of the government, the strength of the current healthcare infrastructure, and the degree of digital literacy among healthcare workers. Rwanda has had notable success in adopting Electronic Health Record (EHR) systems, thanks to robust government backing and a well-developed Health Management Information System (HMIS) architecture (Nshimyiryo et al., 2020). Conversely, nations with less developed infrastructure and little government assistance have encountered more substantial obstacles in the implementation of the eClaims system. The available research indicates that electronic claims systems have a predominantly favourable effect on the handling of national health insurance claims in Sub-Saharan Africa. This influence is primarily seen in terms of improved efficiency, accuracy, and reduction of fraudulent activities. Ghana, Rwanda, and Tanzania exemplify the advantages of the eClaims system, despite the difficulties associated with infrastructure, reluctance to adapt, and data security.

Nevertheless, the available evidence is still insufficient, especially when it comes to understanding the overall effects of the eClaims system on healthcare provision and claims denial rate in Ghana. Subsequent studies should prioritise these domains, along with developing tactics to surmount the obstacles encountered while adopting the eClaims system in settings with limited resources. The successful implementation of Electronic Clinical Systems (eClaims system) in certain nations provides important insights for other Low- and Middle-Income nations (LMICs) in the same region who are contemplating similar advancements.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The preceding chapter has reviewed the literature pertaining to fraud and related issues, public health evaluation approaches and the application of interrupted time series designs in evaluation of public health interventions and meta-analysis. This chapter is written in two parts based on secondary and primary data. This chapter describes the research methodology used in the study. The study population, research design, instrument for data collection, target population, sample size determination, sample size and sampling technique, data sources, data management and analysis, and data validity are presented. A description of the data analysis and statistical techniques utilized in the study is also provided. Finally, this chapter highlights the ethical considerations and procedures that were considered. The study is aimed at among others investigating the effect of eClaims on health insurance management in National Catholic Health Facilities in Ghana.

3.2 The study site/area

3.2.1 National Catholic Health Service

The National Catholic Health Service (NCHS) is a private not-for-profit healthcare provider, owned by the Catholic Church in Ghana (NCHS, 2022). The institutional health facilities (i.e. hospitals and clinics) of the NCHS began in the early 1950s at a time when there was an urgent need to provide such facilities for rural dwellers who had virtually no access to modern orthodox health care and often requested them (NCHS, 2022). Expatriate missionary professional staff supported by local auxiliary workers introduced and manned these institutions at the time (NCHS, 2022). Thus, all the hospitals of the NCHS started as little clinics and primary health care facilities.

By the 1960s services were expanded and/or introduced to include Mobile Clinic services, Natural Family Planning services, Primary Health Care services, Diocesan Pharmacies and Rehabilitative services (NCHS, 2022). Maternal and Child Health care was also intensified and further improved. Its official structure as the Catholic Health Service began in 1964 when the Ghana Catholic Bishops Conference set up the Department of Health (now "Directorate of Health") of the National Catholic Secretariat. The then Department's mandate was to (NCHS, 2022):

i. ensure that Catholic health care services reach remote and rural areas of Ghana where people than without basic health service; and
ii. ensure that then existing Catholic Health Facilities were effectively supported in management.

The Conference also set up a National Catholic Medical Advisory Board to advise the Department. By 1973 a full-time Executive Secretary, (Rev. Sr. Ancilla Fox, SSL) was appointed to coordinate the work of the Catholic Hospitals in Ghana (NCHS, 2022).

In 1977, the first Policy of the church health service was developed and adopted in a document entitled "The Church's Role in Health Care". This Policy led to changes that brought about increased cooperation and coordination of the institutions, which had hitherto worked almost independently of each other. Further to the proposed changes, a National Catholic Health Council was inaugurated in May 1977 to replace the National Catholic Medical Advisory Board (NCHS, 2022). By this time, the Catholic Health Service comprised 26 hospitals, 30 clinics, 3 Nursing Training Colleges and 3 midwifery Training colleges (NCHS, 2022). The Department also had four units apart from the Executive Secretary's office namely:

- Coordinating Units for Hospitals and Clinics
- Primary Health Care Unit
- Natural Family Planning and Family Life Education Unit and
- Catholic Drug Centre

The Ministry of Health granted official permission for the Church to start Primary Health Care in 1980 (NCHS, 2022). Before this, the Hospitals and Clinics were already involved in home-based care and intense outreaches to villages around their locations, each one providing basic care in what was most needed by each community served (NCHS, 2022). The Catholic Drug Centre (now Catholic Medicines Centre) was also established under the management of the Department in 1981. Minimal user fees had always been charged for accessing services by Church institutions to cover the cost of medicines, other inputs as well as salaries of staff. Development partners and some missionaries supported the funding of budgets of the institutions (NCHS, 2022). The Department had the following development partners who supported various aspects of the work of the Catholic Hospitals from the early 1970s to the 1980s: CEBEMO (Holland); MEMISA (Holland); BEGECA (Germany); MISEREOR (Germany); CARITAS (Italy); HELP THE AGED (UK); CAFOD (England); AUSTRALIAN CATHOLIC RELIEF (Australia); TROCAIRE (Ireland); and KNIGHTS OF MALTA (Malta).

The 1977 Policy was reviewed and replaced with another "The Policy of the Catholic Church on the Role and Functions of the Church in Health Care Delivery System in Ghana" (NCHS, 2022). It was adopted in July 1993 to guide the way forward for the Service. This document recognized that more Ghanaian professional staff were now in the employ of the Church Health Service; the cost of services had become prohibitive; more government support was being accessed under a special arrangement between the Church and government; and more resources were still required. By this time, there was better collaboration among the institutions but a greater need for stronger cooperation and coordination of the Church's health service with better well-defined approaches and goals was required (NCHS, 2022).

In response to the rising cost of care, and in their quest to remove the financial access barrier, some facilities started their mutual health insurance schemes in the Brong-Ahafo region, where Catholic institutions are the predominant caregivers (NCHS, 2022). The notable one is the Nkoranza Scheme which was launched in 1992 with remarkable success. The fact of its establishment in a rural and semi-urban setting with remarkable results encouraged the government to introduce the National Health Insurance Scheme having modified the design of these schemes (NCHS, 2022).

The Service reviewed the 1993 Policy in 2003 which received approval from the Ghana Catholic Bishops Conference and effectively created the National Catholic Health Service with the mandate to coordinate Catholic health care provision in Ghana (NCHS, 2022). The Policy had 7 thematic goals which have been the bedrock for planning services at all levels of the service since as follows: Identity; Management; Human Resources for Health; Service Delivery; Drugs and Therapeutics; HIV/AIDs; Health Financing; and Health Research (NCHS, 2022).

3.2.2 National Catholic Health Facilities

The NCHS has a total of 144 health facilities across the length and breadth of Ghana (NCHS, 2022a). Out of the 144 health facilities, 47 are hospitals, 82 are clinics, 10 are health training institutions and 5 are specialised institutions (NCHS, 2022a). All the health facilities are accredited National Health Insurance Scheme facilities providing the Ghanaian people healthcare. These health facilities account for an annual outpatient attendance of 3.2million, 349,000 admissions and 76,000 deliveries (NCHS, 2022a). This study focused on 25 hospitals that have provided healthcare services to NHIS clients since 2010 and have automated their claims processes along the line to bring efficiency in claims transactions and clinical outcomes using various electronic medical records.

3.4 Research Method

Research design is referred to as the blueprint for fulfilling research objectives and answering questions where it aids the researcher in the allocation of limited resources by posing crucial choices in the methodology (Kelliher, 2005). Other definitions are that research design is an activity- and time-based plan and a guide for selecting sources and types of information to obtain answers to research questions (Blumberg, Cooper, & Schindler, 2014). Research design `deals with a logical problem and not a logistical problem' (Yin, 2008).

Though it can be complicated to select an appropriate research design, Cooper, Schindler, and Sun (2006) are of the view that by creating a research design which uses a combination of methodologies, researchers can achieve greater insight than if they were to follow methods which used frequency or methods which have been mentioned the most in media. It is therefore erroneous to equate a particular research design with either quantitative or qualitative methods. Yin (1993), a respected authority on case study design, has stressed the irrelevance of the quantitative and qualitative distinction for case studies.

To conduct this study, however, a quantitative method (quasi-experimental and cross-sectional studies) was used. There are inherent advantages to the quantitative research method. The quantitative method chosen in this research work is a survey method in which data was collected at one point in time. This involved self-completing questionnaires. To Crossley and Vulliamy (2013), survey research can provide information that is generalizable to larger groups, although the information that can be collected is typically limited to information that the respondents are prepared and able to provide.

3.5 Secondary data

3.5.1 Sub-study Design

The study employed a quasi-experimental design by assessing retrospective health insurance data before and after the introduction of the Hospital Information System (HIS) for the management of both transactions and clinical data within the selected hospitals in the National Catholic Health Service (NCHS). A quasi-experimental study design is a research methodology that is designed to assess interventions or treatments without the use of random assignment (Cook & Campbell, 2007). Quasi-experiments differ from actual experiments in that they do not involve the random assignment of individuals to distinct groups, such as treatment and control (Trochim, Donnelly, & Arora, 2016; Trochim, 2020). Instead, non-random assignment is used, which can introduce possible biases. Nevertheless, they remain significant in evaluating causal connections, particularly in circumstances when randomisation is impractical or unethical (Cook, 1979; Cook & Campbell, 2007). Some of the advantages include being more feasible to execute in practical situations where randomisation is either not possible or unethical, and more generalisable results may be obtained in real-world settings than those obtained from rigidly controlled experiments (Eliopoulos et al., 2004). Another advantage is that the method is applicable when random assignment is not feasible due to ethical constraints (Cook & Campbell, 2007). Disadvantages include; There is a higher likelihood of bias because of the non-random assignment, which makes it more difficult to demonstrate a cause-and-effect relationship (Cook, 1979). Controlling for all confounding variables is difficult without randomisation, which could potentially distort the results (Trochim et al., 2016). The outcomes may be influenced by the differences between groups, which can result in inaccurate conclusions (Eliopoulos et al., 2004).

The NCHS is one of the faith-based not-for-profit healthcare providers under the auspices of the Department of Health of the National Catholic Secretariat in Ghana. The study was conducted across the three ecological zones in 25 NCHS facilities with accreditation that have offered health services in Ghana since 2010 and have used HIS to automate their claims processes along the line to bring efficiency in claims management and clinical outcomes using various Hospital Information System (HIS) (Figure 8).

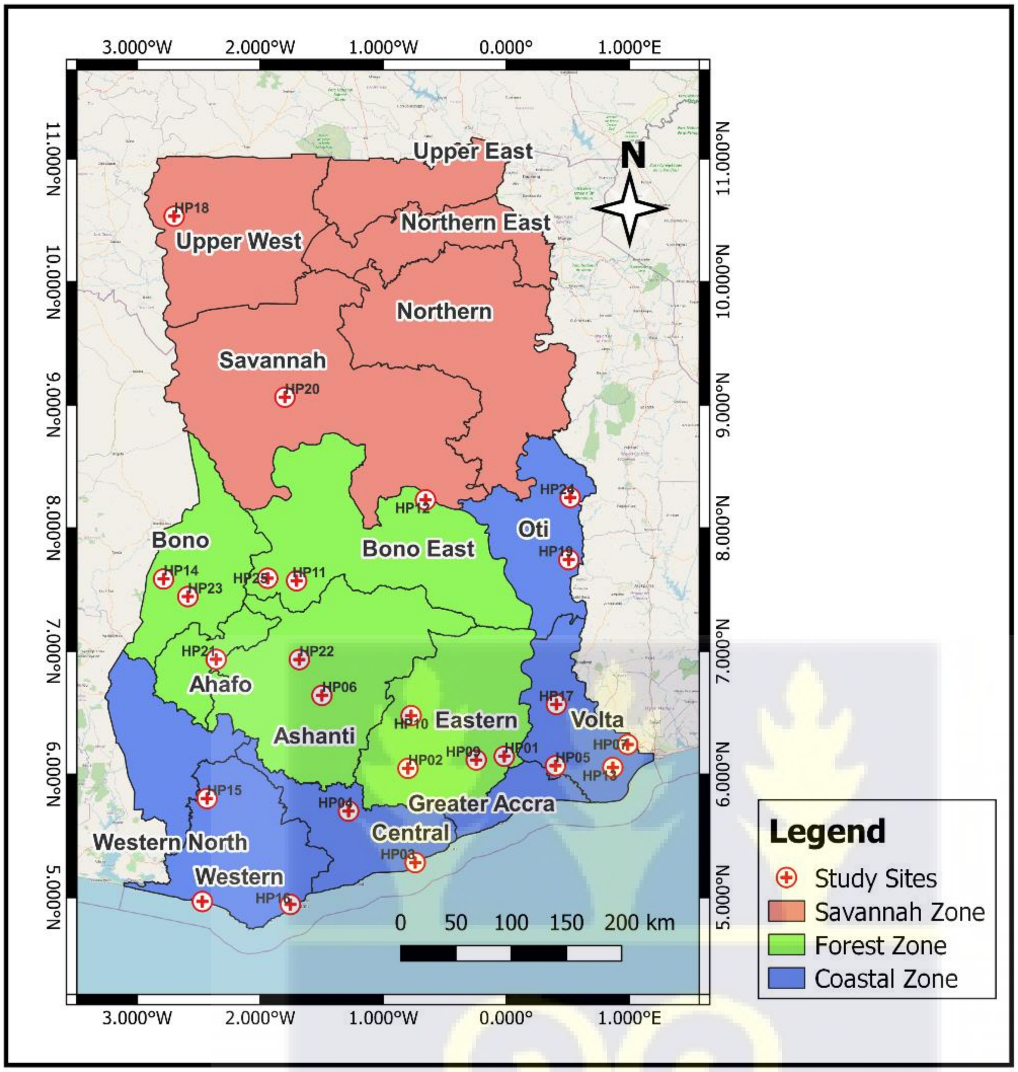

Figure 8: Selected health facilities across the three ecological zones of Ghana
Source: Authors' analysis

3.5.1.1 Intervention

For this study, electronic claims (eClaims) refer to any health insurance claims captured on a storage drive (i.e. CD, pen-drive, etc.), real-time online or web-based, or through any hospital-based health information management systems. The aim of moving from paper-based claims to electronic-based claims was to reduce human engagement in the claims process and reduce errors that come with claims processing at the healthcare provider level and its review at the National Health Insurance Scheme (NHIS) level. The NHIS has established a Claims Processing Centre

(CPC) to process electronic claims from health providers throughout the country. All the 25 selected health facilities submit electronic claims through; (1) an XML file that converts health insurance claims from the hospital's electronic medical records systems and (2) a web-based electronic system that submits claims data. This claims information is submitted to NHIS' CPC located in the capital, Accra of Ghana, where the authorities vet the submitted electronic claims. The paper-based claims, on the other hand, are done through completing manual claims forms by the healthcare providers for each valid subscriber, compiling all the completed forms for a respective period, and submit to the NHIS for reimbursement.

3.5.3 Claim processes in health facilities

Processing of clients' health insurance claims for both paper and electronic-based systems is the same for all the 25 health facilities sampled. When a client enters the facility at the first point of call (Health Information Unit at the OPD), his or her NHIS card is verified. Once the card is invalid, he/she is processed for cash and carry. A valid NHIS card bearer is assigned to the NHIS and provision of service based on the NHIS benefit package is rendered. Billing of treatment is done manually or electronically and submitted to the NHIS for reimbursement. Details of the NHIS Claims processing in healthcare facilities can be found in Figure 7.

3.5.4 Study Population

The study population included hospitals accredited by the National Health Insurance Authority submitting claims (paper and electronic) to the NHIS. These comprised of 25 hospitals. The study population also involved permanent healthcare professionals working in these hospitals.

3.5.5 Sample Size and Sampling Technique

All providers who have been accredited and submitted claims (paper and electronic) to the national health insurance scheme from January 2010 to December 2019 were included in the study. The claims submitted after December 2019 by providers were excluded from the study due to several months of outstanding reimbursement (over 10 months of arrears starting from January 2020) owed by the National Health Insurance Authority to all the study sites included in the study at the time of the study.

3.5.5 The Outcome of Interest

The outcome of interest is the rate of error margins of health insurance claims. This is defined as the ratio of the amount deducted due to errors in claims to the total amount of claims cost submitted, multiplied by 100%.

Concerning the impact of eClaims on the Average Number of Days Spent submitting health insurance claims to the NHIS, the primary outcome of interest is the Average Number of Days Spent submitting health insurance claims to the NHIS. The average number of days spent submitting claims data was determined for each health facility. The average Number of Days Spent in submitting claims is defined as the sum of days beginning the new month until the date on which previous month medical claims were submitted divided by total number of months. These analyses were conducted for each health facility and the results are presented in tables.

3.5.6 Data Collection

An Excel data collection template was developed to collect monthly data from January 2010 to December 2019. Data was obtained on the following indicators: the month of health insurance claims, the date upon which claims were submitted, the total amount of claims cost, the amount of claims cost reimbursed and reasons for deductions. Dates for the introduction of electronic systems to improve medical claims management and submission were also obtained. Names and types of software were also collected. Below is the summary of different periods where the HIS was implemented at the various health facilities (Table 1).

Table 1: HIS implementation period for each health facility

Hospital Code	Region	Date of HIS implementation
HP01	Eastern	April 2014
HP02	Eastern	January 2014
HP03	Central	January 2019
HP04	Central	January 2012
HP05	Volta	October, 2013
HP06	Ashanti	March 2018
HP07	Volta	March 2018
HP08	Western	January 2014
HP09	Eastern	April 2012
HP10	Eastern	January 2014
HP11	Bono East	January 2014
HP12	Bono East	June 2013
HP13	Volta	January 2014
HP14	Bono	January 2014
HP15	Western	June 2019
HP16	Western	May 2019
HP17	Volta	January 2019
HP18	Upper West	January 2018
HP19	Oti	January 2014
HP20	Savannah	January 2014
HP21	Ahafo	June 2019
HP22	Ashanti	January 2014
HP23	Bono	January 2012
HP24	Oti	January 2013
HP25	Bono East	January 2015

Source: Fieldwork, 2022

3.5.7 Inclusions and exclusions criteria

All claims (paper and electronic) submitted from January 2010 to December 2019 were examined for the study. Health facilities not using electronic medical records systems were excluded from the study since the study needed data from pre-and post-eClaims systems for the study. All claims (paper and electronic) submitted after December 2019 by providers were also excluded from the study.

3.6 Primary data

3.6.1 Sub-study design

The study used a census approach where every end-user of the HIS was recruited for the study. The study involved 1416 healthcare professionals who are users of the electronic hospital information system in 25 National Catholic Health Service (NCHS) hospitals. The Implementation of the electronic hospital information systems are at different stages for clinical and transitionary processes.

3.6.2 Instrument and data collection

This study used a structured survey questionnaire based on the upgraded DeLone and McLean model (DeLone & McLean, 2003) and extended ISSM (Otieno, Toyama, Asonuma, Kanai-Pak, & Naitoh, 2008) to obtain data from health professionals on their perceived HIS efficiency. The questionnaires were distributed and self-completed anonymously by only users of the HIS in the 25 respective health facilities within the NCHS. Targeted users include physicians, nurses, dispensary staff, medical laboratory staff, accounts and health insurance claims officers and health information management officers. A data collection officer was assigned to each hospital for the collection of the completed questionnaires. A day's training was provided to all the data collection officers based on the objective of the study. Data was collected for a period of two and half months starting from April 2022. The questionnaire comprises two parts; section 1 is on respondent characteristics and section 2 covers HIS evaluation measures on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) (see Table 2). The study was approved by the ethical committee of NCHS.

The data collection tools have five interconnected thematic areas for the extended ISSM (E-ISSM) model (i.e. system quality, Information quality, service quality, system use and user satisfaction) and six dimensions for the upgraded DeLone and McLean (U-DM) model (i.e. system quality, Information quality, service quality, system use, user satisfaction and potential net benefit) of information system evaluation measures. Demographic information of respondents was also collected. The information systems dimensions have been defined based on the literature below;

Hospital Information System Quality has three dimensions namely; “system quality”, “information quality” and “service quality” which together affect system use and “user satisfaction”. System quality can be termed as patient care activities and processes done using computer-based system. In other words, the HIS capabilities are required to offer healthcare services to patients. The net effect is that the interrelated workflow of HISs would lead to improved patient care (Ammenwerth, Iller, & Mahler, 2006; Urbach & Müller, 2012).

“Information quality” refers to the value and worth of output emanating from HISs by the users (Urbach & Müller, 2012). Users would be much happier to use the HISs for patient related activities at any time when the output is complete, current, secure and easy to comprehend.

“Service quality” can be defined as the ability of the HIS managers to troubleshoot HISs and users’ requests due to downtime (Urbach & Müller, 2012). The objective of the service quality is to measure the support system provided by HIS managers since poor user support can lead to inadequate trust and low motivation to use the HIS.

“System use” is defined as the level at which users are using the HIS to provide healthcare services. The extent or frequency of use by the users is used as measurement yardstick.

“User satisfaction” is referred to as how users felt that the HIS was key to enhancing the quality and effectiveness of the service delivery offered to patients (DeLone & McLean, 2003; Urbach & Müller, 2012).

“Potential net benefits” refers to the overall benefits (negative or positive) that stakeholders of the organization obtain from the total use of the HIS. This is measured by evaluating the organizational or individual impact (Urbach & Müller, 2012). For this study, individual impact was assessed since primary users were the focused of the study.

Table 2: Study construct and measures of assessment

Construct	Construct Definition	No. of items		Scale
		E- ISSM	U-DM	
System quality	HISs capabilities required to offer healthcare services to patients (Ammenwerth et al., 2006; Urbach & Müller, 2012).	16	4	5 – Point Likert
Information quality	The value and worth of output emanating from HISs by the users (Urbach & Müller, 2012).	22	4	5 – Point Likert
Service quality	The ability of the HISs managers to troubleshoot HISs and users' requests due to downtime (Urbach & Müller, 2012).	6	4	5 – Point Likert
System use	The level at which users are using the HIS to provide healthcare services	3	4	5 – Point Likert
User satisfaction	How users felt that the HIS was key to enhancing the quality and effectiveness of the service delivery offered to patients (DeLone & McLean, 2003; Urbach & Müller, 2012).	4	3	5 – Point Likert
Potential net benefits	Overall benefits (negative or positive) that stakeholders of the organization obtain from the total use of the HIS (Urbach & Müller, 2012).	N/A	5	5 – Point Likert

E-ISSM – extended Information System Success Model (Otieno et al., 2008); U-DM – upgraded DeLone and McLean model (DeLone & McLean, 2003); NA – Not applicable

3.6.3 Participants

Targeted healthcare professionals were selected from six departments comprising; physicians, nurses, dispensary officers, medical laboratory officers, health insurance claims/account officers and health information officers. The respondents were permanent staff who had worked in the hospital for at least six months with HIS experience before the study. In all, a total of 1416 healthcare professionals from 25 selected NCHS hospitals were selected for the study. The distribution of responses can be found in Table 3.

Table 3: Distribution of respondents by health facility and department

Hosp code	Nurses		Physicians		Dispensary		Medical Laboratory		Accounts/ Claims		Health Information		Total	
	ND	NR (%)	ND	NR (%)	ND	NR (%)	ND	NR (%)	ND	NR (%)	ND	NR (%)	ND	NR (%)
HP01	75	63 (84)	6	4 (67)	9	9 (100)	7	7 (100)	8	8 (100)	6	6 (100)	111	97 (87)
HP02	90	77 (86)	15	13 (87)	7	7 (100)	11	11 (100)	11	11 (100)	6	6 (100)	140	125 (89)
HP03	31	21 (68)	11	9 (83)	5	5 (92)	7	7 (94)	3	3 (100)	8	6 (75)	66	51 (77)
HP04	53	40 (75)	10	8 (80)	9	9 (100)	12	10 (83)	11	11 (100)	12	9 (75)	107	87 (81)
HP05	60	48 (80)	10	6 (60)	3	2 (59)	7	7 (94)	6	6 (100)	5	5 (100)	92	74 (80)
HP06									5	4 (80)			5	4 (80)
HP07									12	10 (83)			12	10 (83)
HP08	51	37 (73)	8	5 (63)	6	6 (100)	5	5 (100)	3	3 (100)	5	5 (100)	78	61 (78)
HP09	55	48 (87)	9	6 (67)	6	6 (100)	20	17 (85)	5	5 (100)	6	6 (100)	101	88 (87)
HP10	44	30 (68)	12	8 (67)	10	10 (100)	10	9 (90)	15	13 (87)	15	12 (80)	106	82 (77)
HP11	32	27 (84)	5	5 (100)	6	6 (100)	8	8 (100)	8	7 (88)	5	5 (100)	64	58 (91)
HP12	30	23 (77)	4	4 (100)	5	5 (100)	6	6 (100)	10	9 (90)	12	10 (83)	67	57 (85)
HP13	45	37 (82)	7	6 (86)	5	5 (100)	7	7 (100)	6	6 (100)	4	4 (100)	74	65 (88)
HP14	40	26 (65)	6	6 (100)	6	6 (100)	6	6 (100)	4	4 (100)	6	6 (100)	68	54 (79)
HP15									8	5 (63)			8	5 (63)
HP16	58	35 (60)	3	3 (91)			2	2 (100)	2	2 (100)	2	2 (100)	67	44 (65)
HP17	35	22 (63)	4	4 (100)	4	4 (100)	7	7 (100)	9	9 (100)	3	3 (100)	62	49 (79)
HP18									10	7 (70)			10	7 (70)
HP19	57	36 (64)	6	4 (62)	2	2 (100)	4	4 (100)	5	5 (100)	5	5 (100)	79	56 (71)
HP20	35	25 (71)	6	4 (67)	2	2 (100)	5	5 (100)	8	6 (75)	4	4 (100)	60	46 (77)
HP21									8	5 (63)			8	5 (63)
HP22	60	49 (82)	15	11 (73)	10	9 (90)	10	6 (60)	15	10 (67)	10	9 (90)	120	94 (78)
HP23	45	36 (80)	6	6 (100)	7	7 (100)	7	7 (100)	7	7 (100)	10	8 (80)	82	71 (87)
HP24	40	32 (80)	4	4 (100)	6	6 (100)	5	5 (100)	6	4 (67)	5	5 (100)	66	56 (85)
HP25	40	36 (90)	10	6 (60)	10	8 (80)	5	4 (80)	10	8 (80)	10	8 (80)	85	70 (82)
Total	976	748 (77)	158	122 (77)	119	114 (96)	152	140 (92)	195	168 (86)	139	124 (89)	1738	1416 (81)

Hosp code – Hospital code; ND – Number distributed; NR – Number returned
Source: Fieldwork, 2022

3.7 Data management and statistical analysis

3.7.1 Sub-analysis [To assess the impact of eClaims on error margins of claims (claim denial rate)]

Secondary data focused on the Rate of error margins of claims from the 25 Catholic Health facilities was used. Rate of error margins of the claims is defined as the ratio of amount of deducted due to errors in claims to the total amount of claims cost submitted, multiplied by 100%. This calculation was conducted for each health facility and the results are presented in tables. Also, the number of days spent in submitting claims data was determined. The number of days spent in submitting claims is defined as sum of days beginning the new month until the date on which previous month health insurance claims was submitted. This analysis was conducted for each health facility and the results are presented in tables. The unit of analysis was monthly submissions made by each health facility to the National Health Insurance Scheme.

Monthly paper-based and electronic health insurance claims data submitted by health facilities was accessed from their health insurance claims register. The data was exported and converted into STATA Version 15 for analysis. Descriptive statistics (such as frequencies, means and standard deviations) were used to describe the data. To achieve a test of normality, the Shapiro-Wilk and Bartlett tests were used to assess the symmetry of all continuous data. Two paired samples t-test was also performed to test for differences in Rate of error margins of the claims between the pre-eClaims and post-eClaims.

3.7.1.1 Segmented Interrupted Time-series (ITS) Analysis

Segmented Interrupted time-series (ITS) analysis was used. A time series is a continuous sequence of observations on a population, taken repeatedly (normally at equal intervals) over time (Bernal, Cummins, & Gasparrini, 2017). In an ITS study, a time series of a particular outcome of interest is used to establish an underlying trend, which is 'interrupted' by an intervention at a known point in time (Bernal et al., 2017). A 120-month data (January 2010 to December 2019) for pre and post-eClaims submitted by health facilities (Zhang, Wagner, Soumerai, & Ross-Degnan, 2009) was analysed. This type of analysis is commonly used to analyse the effects of interventions in a situation where a control group is difficult or impossible to find (Campbell, Reeves, Kontopantelis, Sibbald, & Roland, 2009; Singer, Willett, & Willett, 2003). In this model, the variation within the data was partitioned into three components to provide independent tests for the

1) Slope before the introduction of eClaims (using paper-based),
2) Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual)
3) Difference between pre-eClaims and post-eClaims slopes (sustained impact)

In the model estimation, each outcome variable's growth over time will be linear before and after the eClaims implementation. Three predictors were included in the linear regression model: MONTH, pre-eClaims, and post-eClaims. MONTH was coded as sequential numbers so that 1 represents January 2010 and 120 represents December 2019. eClaims was set at a dummy variable as 0 before the eClaims go-live date (for each health facility) and 1 after that. Post-eClaims was created to measure months of eClaims using experiences after the go-live date. The score of post-eClaims will be 0 for all months before the post-eClaims period and incremented by 1 in each month afterwards. MONTH was used to estimate the outcome variable's slope in scores in the pre-eClaims period (test 1). eClaims was used to calculate the level change for the post-eClaims period (test 2). Post-eClaims was used to estimate the difference in slope from the pre-eClaims to the post-eClaims period.

In this study, an interrupted time series analysis was used to ascertain the impact of eClaims (intervention) on the rate of error margins of claims. In interrupted time series, measurements are made periodically from the dependent variable before and after the intervention. Interrupted time series design does not require the control group to create a causal relationship between the intervention and the outcome. It is the strongest type of quasi-experimental study to assess the short-term and long-term effects of one or more interventions (Rashidian et al., 2013; Wagner, Soumerai, Zhang, & Ross-Degnan, 2002). The assumption is that the interventions of eClaims have more effects on reducing margins of error in electronic claims as compared to the manual health insurance claims completed by healthcare facilities to the National Health Insurance Authority (NHIA).

In time series, changes in the dependent variable of the intervention are divided into 2 general categories: changes in level and changes in slope. A change in the level indicates a quick or short-term change (in the first month after the intervention) and the change in slope (monthly trend) represents a long-term change in the dependent variable (Bernal et al., 2017; Linden, 2015). Figure 9 shows the Segmented Interrupted Time Series (SITS) analysis framework for the study.

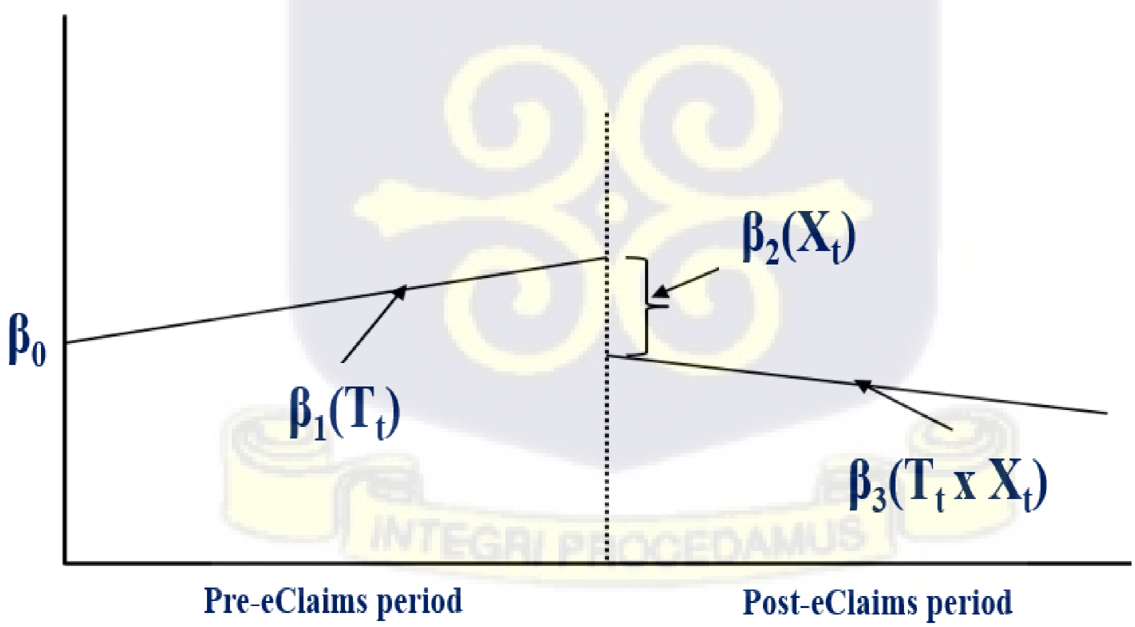

Figure 9: Segmented Interrupted Time Series (SITS) analysis framework for Objective 1 and 4
Adapted from (Bernal et al., 2017; Linden, 2015)
Source: Author's analysis

The regression model I used to estimate the effect of eClaims on the rate of error margins of claims at the NHIA is as follows (Equation 1):

$Y_t = \beta_0 + \beta_1 \times Time_t + \beta_2 \times Intervention_t + \beta_3 \times$ Time after intervention $+ \varepsilon_t$ ------ (Eq 1)

Where;

- Y_t is the rate of error margins of claims in month t;
- Time represents time in months at time t from the start of the observation period;
- Intervention is a dummy (indicator) variable representing the intervention (the pre-eClaims period is 0, otherwise is 1), which was implemented at various months in the series;
- Time after intervention is counting the number of months after the implementation of eClaims at time t;
- β_0 represents the intercept or starting level of the rate of error margins of claims;
- β_1 is the slope of the rate of error margins of claims until the implementation of eClaims.
- β_2 represents the changes in the level of rate of error margins of claims in the period immediately following the implementation of eClaims (compared to the counterfactual);
- β_3 represents the difference between pre-and-post-eClaims slopes of the rate of error margins of claims; and
- ε represents error at time t

The same concept was applied for regression model II to estimate the effect of eClaims on average number of days spent in submitting health insurance claims to the NHIA designated as (Equation 2):

$Y_t = \beta_0 + \beta_1 \times Time_t + \beta_2 \times Intervention_t + \beta_3 \times \text{Time after intervention} + \varepsilon_t$ ------ (Eq 2)

Where;

- Y_t is average number of days spent in submitting health insurance claims to the NHIA in month t;
- Time represents time in months at time t from the start of the observation period;
- Intervention is a dummy (indicator) variable representing the intervention (the pre-eClaims period is 0, otherwise is 1), which was implemented at various months in the series;
- Time after intervention is counting the number of months after the implementation of eClaims at time t;
- β_0 represents the intercept or starting level of the average number of days spent in submitting health insurance claims to the NHIA;
- β_1 is the slope of the average number of days spent in submitting health insurance claims to the NHIA until the implementation of eClaims.
- β_2 represents the changes in the level of the average number of days spent submitting health insurance claims to the NHIA in the period immediately following the implementation of eClaims (compared to the counterfactual);
- β_3 represents the difference between pre-and-post-eClaims slopes of the average number of days spent in submitting health insurance claims to the NHIA; and
- ε represents error at time t.

In the context of Interrupted Time Series Analysis (ITSA), a counterfactual denotes the estimated scenario of what could have transpired to the outcome variable in the absence of the intervention or event under investigation. The counterfactual serves as a hypothetical continuation of the pre-intervention trend (in the case of this study; claims rejection rate in the manual system) into the post-intervention period (i.e. claims rejection rate in the eClaims system). It acts as a comparison point to assess the impact of the intervention (Bernal et al., 2017).

Developing a counterfactual requires a thorough examination of the data before the intervention to identify a pattern, which can then be used to forecast what might have occurred if the intervention had not been implemented. Through the comparison of observed outcomes after the intervention with a hypothetical scenario, researchers can estimate the impact of the intervention (Linden, 2015). The observed post-intervention data compared to the counterfactual provides valuable insights into the impact of the intervention (Wagner et al., 2002).

3.7.1.2 Autocorrelation

A second assumption of standard regression models is that observations are independent. This assumption is often violated in time series data because consecutive observations tend to be more similar to one another than those that are further apart, a phenomenon known as autocorrelation. Fortunately, in many epidemiological data, autocorrelation is largely explained by other variables, in particular seasonality; therefore, after controlling for these factors, residual autocorrelation is rarely a problem. Nevertheless, autocorrelation should always be assessed by examining the plot of residuals and the partial autocorrelation function and, where data are normally distributed, conducting tests such as the Breusch-Godfrey test (Bhaskaran, Gasparrini, Hajat, Smeeth, & Armstrong, 2013; Godfrey, 1996). Where residual autocorrelation remains, this should be adjusted for using methods such as Prais regression or autoregressive integrated moving average (ARIMA), described in more detail elsewhere (Nelson, 1998; Prais & Winsten, 1954). For time series data, the Durbin–Watson statistic is the most common measure used to evaluate the presence of autocorrelation in the data (Sen & Srivastava, 1997). In this study, Prais-Winsten (PW), a generalised least squares method, which provides an extension of OLS where the assumption of independence across observations is relaxed was used to adjust for autocorrelation assuming first-order autocorrelation (lag-1) (Prais & Winsten, 1954; Press, 2017). This method was chosen because it has commonly been used in practice (Hudson, Fielding, & Ramsay, 2019; Jandoc, Burden, Mamdani, Lévesque, & Cadarette, 2015) or because it has been shown (through numerical simulation) to have improved confidence interval coverage relative to the methods commonly used in practice (Turner, Forbes, Karahalios, Taljaard, & McKenzie, 2021).

3.7.1.3 Determining effect size using Random Effect Meta-Analysis

To reveal the effectiveness of electronic claims on error margins of claims and average number of days it takes to submit claims, meta-analysis was employed to calculated Cohen's effect size. Based on Borenstein, Hedges, Higgins, and Rothstein (2021) recommendation, the effect size for each health facility was first determined. As the Q-statistic is used for multiple significance testing across several means, it was used to determine heterogeneity among the sampled study properties. Borenstein et al. (2021) indicated that the Q-statistic and p-value could be used for testing the null hypothesis but should not be used to estimate the true variance. For example, the significantly low p-value ($p < 0.001$) does not indicate greater heterogeneity than the p-value of ($p < 0.049$); however, the statistically significant p-value ($p < 0.05$) indicates that heterogeneity exists (Lipsey & Wilson, 2001). In addition to the Q-statistic and p-value, the I-square statistic can also be used to show that the variation is not due to chance but rather indicates the heterogeneity of the sample; such heterogeneity exists only with high I-square values; a low I-square statistic is represented by a value of 25%, 50% represents a medium I-square statistic, whereas a high I-square statistic is represented by 75% (Deeks, Higgins, & Altman, 2011; Higgins, Thompson, Deeks, & Altman, 2003). Finally, 95% confidence intervals (CI) were calculated, based on procedures suggested by Lipsey and Wilson (2001), to test the statistical trustworthiness of the individual and averaged effect sizes. Confidence intervals are a good indicator of the trustworthiness of the effect sizes; if the confidence intervals include zero, it means that the true effect size is zero, and thus not trustworthy. For all scenarios considered, the results (estimates of slopes and intercepts). *P*-value<0.05 was considered statistically significant. STATA 15 software was used for the analysis.

3.7.2 Sub-analysis [To estimate and forecast claim denial rate]

3.7.2.1 Time Series Models

Time series analysis has been utilized in numerous engineering, economic, and medical fields. A significant subject that can assist decision-makers in developing future policies and plans to address various human issues is monitoring the responses of a phenomenon over time and anticipating future responses. Both statistical and machine-learning or artificial intelligence methods have been used for predicting time series issues have been recorded in literature. It is common practice to evaluate this kind of data and estimate future reactions about time using statistically based techniques like ARIMA. Three processes are combined in the ARIMA model: specifically, the Autoregressive (AR) process, the Combination (I) process (by taking the distinction), and the Moving-Normal (Mama) process. In the statistical literature, these processes are referred to as the primary univariate time series models. They are widely used in a variety of applications.

3.7.2.2 Autoregressive (AR) Model

According to Abraham and Ledolter (1983), an AR model predicts future behaviour based on past behaviour. When there is some correlation between the values in a time series and the values that come before and after them, it is used for forecasting. The name autoregressive comes from the fact that you only use data from the past to model the behaviour—auto–means "self" in Greek. The method is essentially a linear regression of the current series' data against one or more previous values from the same series. In the statistical literature, the AR model is referred to as the main univariate time series model. It is utilized frequently in numerous applications. An autoregressive model known as an AR (p) model employs specific lagged values of y_t as predictor variables. Lags occur when one period's outcomes influence subsequent periods. The equation (1) defines the AR (p) model.

$$\mathbf{y_t} = c + \boldsymbol{\alpha}_1\mathbf{y_{t\text{-}1}} + \boldsymbol{\alpha}_2\mathbf{y_{t\text{-}2}} + \cdots + \boldsymbol{\alpha}_p\mathbf{y_{t\text{-}p}} + \boldsymbol{\varepsilon}_t, \mathbf{t} = \mathbf{1}, \mathbf{2}, ., \boldsymbol{T}, \qquad (\mathbf{1})$$

Where $\boldsymbol{\varepsilon}_t$ is a white noise, a sequence of independently and identically distributed (iid) random variables with $E(\boldsymbol{\varepsilon}_t) = \mathbf{0}$ and $var(\boldsymbol{\varepsilon}_t) = \boldsymbol{\sigma}^2$; $i.e.$ $\boldsymbol{\varepsilon}_t \sim \boldsymbol{iidN}\ (\mathbf{0}, \sigma^2)$.

$\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2 \ldots, \boldsymbol{\alpha}_p$: The coefficients of the model, representing the influence of each lagged value on the current value.

3.7.2.3 Moving-Average (MA) model

According to Abraham and Ledolter (1983), a moving average (MA) model uses past forecast errors in a regression model rather than past values of the forecast variable. The moving average model of order q is referred to by the notation MA(q):

$$\mathbf{y_t} = c - \boldsymbol{\epsilon}_t - \boldsymbol{\theta}\boldsymbol{\epsilon}_{t\text{-}1} - \boldsymbol{\theta}_2\boldsymbol{\varepsilon}_{t\text{-}2} - \cdots - \boldsymbol{\theta}_q\boldsymbol{\varepsilon}_{t\text{-}q} \qquad (\mathbf{2})$$

3.7.2.4 Autoregressive moving-average model

A model-based time series fitting model known as an Autoregressive Moving-Average (ARMA) provides a concise description of a (weakly stationary) stochastic process in terms of two polynomials—one for the auto-regression and the other for the moving-average (Abraham & Ledolter, 1983). An ARMA (p, q) can be written by combining the AR(p) and MA(q) models:

$$\mathbf{y_t} = c + \boldsymbol{\alpha}_1\mathbf{y}_{\text{t-1}} + \boldsymbol{\alpha}_2\mathbf{y}_{\text{t-2}} + \cdots + \boldsymbol{\alpha}_\mathbf{p}\mathbf{y}_{\text{t-p}} + \boldsymbol{\varepsilon}_\mathbf{t} - \boldsymbol{\theta}\boldsymbol{\epsilon}_{\text{t-1}} - \boldsymbol{\theta}_2\boldsymbol{\varepsilon}_{\text{t-2}} - \cdots - \boldsymbol{\theta}_\mathbf{q}\boldsymbol{\varepsilon}_{\text{t-q}} \tag{3}$$

3.7.2.5 ARIMA Model

ARIMA, which stands for "Autoregressive Integrated Moving Average," is a class of models that can be used to predict future values by "explaining" a given time series based on its previous values, also known as its lags and lagged prediction errors. Any "non-seasonal" time series can be modelled with ARIMA models, which are not random white noise. According to (Abraham & Ledolter, 1983) an ARIMA model is one in which the AR and MA terms are combined with at least a one-time series difference to make it stationary. For instance, the ARIMA (p, 1, q) model is defined by the equation if y_t is a non-stationary series. In this case, we will take a first difference of y_t to make Δy_t stationary as expressed in the ARIMA (p, 1, q) model below:

$$\Delta\mathbf{y_t} = c + \boldsymbol{\alpha}_1\Delta\mathbf{y}_{\text{t-1}} + \boldsymbol{\alpha}_2\Delta\mathbf{y}_{\text{t-2}} + \cdots + \boldsymbol{\alpha}_\mathbf{p}\Delta\mathbf{y}_{\text{t-p}} + \boldsymbol{\varepsilon}_\mathbf{t} - \boldsymbol{\theta}\boldsymbol{\epsilon}_{\text{t-1}} - \boldsymbol{\theta}_2\boldsymbol{\varepsilon}_{\text{t-2}} - \cdots - \boldsymbol{\theta}_\mathbf{q}\boldsymbol{\varepsilon}_{\text{t-q}} \tag{4}$$

Where $\Delta\mathbf{y_t} = \mathbf{y_t} - \mathbf{y}_{\text{t-1}}$. But if p = q = 0 in equation (4), then the model becomes a random walk model which is classified as ARIMA (0, 1, 0).

3.7.2.6 Box-Jenkins method

A mathematical model developed by Box, Jenkins, and Reinsel (1970) to forecast data ranges using time series inputs is the Box-Jenkins and Reinsel model. According to Brockwell and Davis

(2002), the Box-Jenkins model can forecast using a variety of time series data types. Results are determined by comparing the differences between data points in the method. Using autorepression, moving averages, and seasonal differencing, the method enables the model to generate forecasts by identifying trends. Figure 10 shows the four iterative stages of modelling according to this approach. The four stages of modelling in the Box-Jenkins iterative approach (Abonazel & Abd-Elftah, 2019) are as follows:

Step 1 (Model-identification): this is the stage where we figure out the model's order (p, d, and q) to capture the data's most important dynamic features. Typically, graphical methods (plotting the series, the Autocorrelation function (ACF), partial autocorrelation function (PACF), etc. are used as a result.

The process of verifying the stationarity of the time-series data is called "model identification". The Augmented Dickey-Fuller (ADF) test, graph/time plot assessment, and plotting of the autocorrelation function correlogram (ACF) and partial autocorrelation function (PACF) are the most common methods used in model identification.

The series' stationary was tested with the ADF. The value of the test statistic determines the ADF criterion (Challa, Malepati, & Kolusu, 2018). The null hypothesis is rejected and the alternate hypothesis is accepted if the test statistic value is less than the critical value (CV); otherwise, the situation is reversed. The alternative hypothesis asserts stationarity in the series under consideration, whereas the null hypothesis asserts its absence.

Step 2 (Model estimate and selection): using step 1 to estimate the parameters of various models before selecting a first model (using information criteria). Maximum Likelihood Estimation (MLE) and non-linear least-squares estimation are the most common estimation methods.

Step 3 (Model checking): determining whether the estimated and provided models are adequate. Particularly, residual diagnostics are used in this respect. The mean and variance of the residuals ought to remain constant over time and be independent of one another; showing the residuals' ACF and PACF can help uncover misspecification. We'll have to go back to step one and try again if the estimate isn't good enough. In addition, to determine which model is best suited to the data, the estimated model ought to be compared with various ARIMA models. The three most frequently used criteria in model selection are mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Mean Absolute Deviation (MAD).

Step 4 (Forecasting): we can use the chosen ARIMA model for forecasting if it meets the requirements of a stationary univariate process.

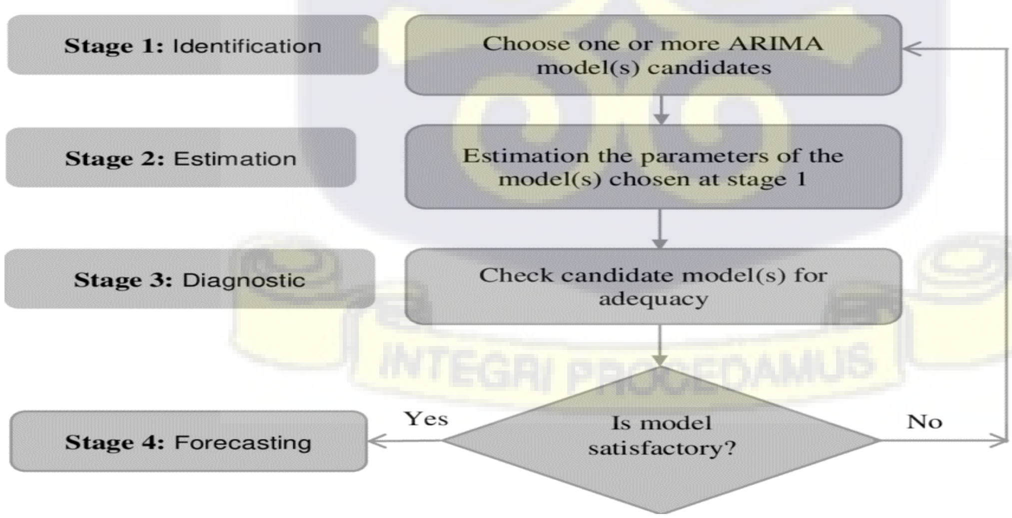

Figure 10: The stages of the Box-Jenkins method (Abonazel & Abd-Elftah, 2019)

3.7.3 Sub-analysis [To assess the efficiency of hospital information systems used by health facilities]

Descriptive statistics such as means and standard deviations were calculated for continuous variables whilst frequencies and percentages were determined for health professionals' demographic variables. All negative responses were reversed before undertaking analysis for study constructs. The normality of data was assessed using the Shapiro-Wilk test (González-Estrada & Cosmes, 2019). HIS efficiency rate was determined using the weighted average method. HIS efficiency rate reference to the healthcare professional's perspective was calculated for respective measures followed by the total dimensions of questionnaires for respective tools (E-ISSM and U-DM) for all respondents. The overall mean HIS efficiency rate was determined and categorized as follows; High – 75%<=HIS Efficiency rate; Moderate – 50%<=HIS Efficiency rate<75%, low – 25%<=HIS Efficiency rate<50% and very low - HIS Efficiency rate<25% (Z. Ebnehoseini, Jangi, Tara, & Tabesh, 2021; Zahra. Ebnehoseini, Tabesh, Deldar, Mostafavi, & Tara, 2019). HIS Efficiency rate was determined as follows;

- First, the maximum HIS efficiency rate of assessment measures, dimensions and overall dimensions for each user = number of questions × 5 (maximum score for every question on a 1–5-point Likert scale).
- Secondly, the calculated HIS efficiency rate of assessment measures, dimensions and overall dimensions for each user = sum of the obtained score for each question on a 1–5-point Likert scale by each user.
- Finally, HIS efficiency Rate = [the obtained HIS efficiency rate of assessment measures, dimensions and overall dimensions for each user/Maximum HIS efficiency rate of assessment measures, dimensions and overall dimensions for each user] × 100

HIS efficiency rate was validated to check internal validity using the Spearman rank correlation coefficient. It was hypothesized that HIS efficiency rate will be positively significantly correlated to its dimensions (system quality, information quality, service quality, system use, user satisfaction and potential net benefits).

Bland and Altman's measures of agreement were applied to determine the level of agreement between E-ISSM and U-DM models. The unit of analysis was the hospital. Stata 15 was used for the analysis. P-value <0.05 was considered statistically significant.

3.7.3.1 Reliability and Validity of Study Construct

Both instruments; U-DM model (DeLone & McLean, 2003) and E-ISSM model (Otieno et al., 2008) were adapted. The overall Cronbach's alpha was 0.79 and 0.89 respectively indicating high reliability. Individual Cronbach's alpha for various dimensions in the study were also determined. Content Validity Index (CVI) and Content Validity Ratio (CVR) for both tools were also determined. Details of the reliability and validity test are shown in Table 4.

Table 4: Descriptive statistics, Scale and Item reliability test

Dimensions	Number of Items	Cronbach's Alpha Coefficient	Content Validity Index	Content Validity Ratio	Health Professionals (n=1416)		
					Mean	SD	Mean Values under 95% CI
E-ISSM model	51	0.79	96.1	94.1			
System Quality	16	0.89			3.99	0.67	[3.96 - 4.03]
Information Quality	22	0.88			3.93	0.59	[3.89 - 3.96]
Service Quality	6	0.85			4.23	0.79	[4.19 - 4.28]
System use	3	0.86			4.27	0.94	[4.21 - 4.32]
User satisfaction	4	0.79			3.93	0.88	[3.88 - 3.98]
U-DM model	24	0.89	100.0	95.8			
System Quality	4	0.80			4.23	0.90	[4.18 - 4.28]
Information Quality	4	0.80			4.17	0.82	[4.12 - 4.21]
Service Quality	4	0.76			3.96	0.90	[3.91 - 4.01]
System use	4	0.66			4.05	0.81	[4.00 - 4.10]
User satisfaction	3	0.79			4.12	0.94	[4.07 - 4.17]
Perceived net benefits	5	0.80			4.02	0.82	[3.97 - 4.07]

Expanded Information System Success Model (E-ISSM) (Otieno et al., 2008) and Upgraded DeLone and McLean (U-DM) model (DeLone & McLean, 2003) tools were adapted for study.
CI - Confidence Interval; SD – Standard deviation
Source: Fieldwork, 2022

3.8 Ethical and Safety Considerations

Ethical approval with reference number NCS/DOH/B2/2021/01 was obtained from the National Catholic Health Service (NCHS) to use their facilities for this study. All identifiable personal information of respondents was not solicited to ensure anonymity respondents. We also observed COVID-19 protocols (i.e. social distancing, wearing a face mask, washing of hands with soap under running water, and use of hand sanitiser) during the data collection process.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results and the discussion on the results. The sections present the results of the five main objectives of the study. The chapter covers the impact evaluation of the eClaims system on the error margins of claims (claim denial rate), the estimation and projection of the claim denial rate, and the causes of the claim denial rate. Other objectives include the impact evaluation of the eClaims system on the average time spent submitting claims to the NHIS for reimbursement and the assessment of the HIS for-service provision from the healthcare professionals' perspectives.

4.2 To assess the impact of eClaims on error margins of claims

4.2.1 Summary of Health Insurance Data from Health Facilities

25 health facilities submitted a total cost GH¢622.8million to the National Health Insurance Scheme for reimbursement from January 2010 to December 2019 (Table 5). The total amount deducted due to errors represents GH¢46.6million for the period under consideration representing 7.48%. The largest cost of claims submissions came from the Eastern region, costing GH¢121.00million (19.43%) (Table 5). The total cost of claims submitted using the electronic systems was GH¢383.4million (61.6%) compared GH¢239.7million (38.4%) from the paper-based system (Table 5). The total cost of deductions due to errors from the electronic systems was GH¢22.9million (49.1%) compared to GH¢23.8million (50.9%) from the paper-based system (Table 5). Error margins of claims from the paper-based systems were 9.9% compared to 6.0%

from the electronic systems. The high error margin of claims was observed in the Volta region (19.16%) whilst the lowest was recorded in the Ashanti region (0.84%) (Table 5).

Table 5: Summary of Health Insurance Data from Health Facilities in the 11 Selected Regions in Ghana from Jan 2010 to Dec 2019

Regions	Number of Health Facilities	Number of claims submissions n (%)	Total Amount of Claims submitted [million GH₵ (%)] Pre-eClaims (paper-based system)	Post-eClaims (electronic-based system)	Total	Total Amount Deducted due to Errors [GH₵ (%)] Pre-eClaims (paper-based system)	Post-eClaims (electronic-based system)	Total	Claims Error Margin (%)
Ashanti	2	240 (8.0)	9.68 (4.04)	38.00 (9.91)	47.70 (7.66)	209,496.20 (0.88)	183,668.40 (0.80)	393,164.60 (0.8)	0.82
Bono East	3	360 (12.0)	37.80 (15.77)	70.30 (18.34)	108.00 (17.34)	1,979,473.00 (8.33)	4,240,309.00 (18.55)	6,219,782.00 (13.4)	5.76
Central	2	240 (8.0)	16.90 (7.05)	35.10 (9.16)	51.90 (8.33)	2,095,532.00 (8.82)	2,215,890.00 (9.69)	4,311,421.00 (9.3)	8.31
Eastern	4	480 (16.0)	30.10 (12.56)	91.00 (23.74)	121.00 (19.43)	1,606,317.00 (6.76)	4,988,283.00 (21.82)	6,594,600.00 (14.2)	5.45
Volta	4	480 (16.0)	38.20 (15.94)	40.10 (10.46)	78.30 (12.57)	8,189,402.00 (34.47)	6,849,335.00 (29.96)	15,000,000.00 (32.2)	19.16
Western	3	360 (12.0)	32.80 (13.69)	20.10 (5.24)	52.90 (8.49)	6,536,967.00 (27.52)	1,177,475.00 (5.15)	7,714,442.00 (16.6)	14.58
Bono	2	240 (8.0)	14.90 (6.22)	50.40 (13.15)	65.30 (10.48)	894,447.70 (3.76)	485,842.20 (2.13)	1,380,290.00 (3.0)	2.11
Savannah	1	120 (4.0)	6.00 (2.50)	12.00 (3.13)	18.00 (2.89)	671,503.60 (2.83)	1,542,633.00 (6.75)	2,214,136.00 (4.8)	12.30
Oti	2	240 (8.0)	9.48 (3.96)	19.30 (5.03)	28.80 (4.62)	666,547.40 (2.81)	954,870.30 (4.18)	1,621,418.00 (3.5)	5.63
Ahafo	1	120 (4.0)	26.00 (10.85)	1.84 (0.48)	27.90 (4.48)	392,336.70 (1.65)	80,956.31 (0.35)	473,293.00 (1.0)	1.70
Upper West	1	120 (4.0)	17.80 (7.43)	5.26 (1.37)	23.00 (3.69)	515,173.10 (2.17)	139,634.40 (0.61)	654,807.50 (1.4)	2.85
Total	25	3000 (100.0)	239.66 (100.00)	383.39 (100.00)	622.80 (100.0)	23,757,195.70 (100.00)	22,858,896.61 (100.00)	46,577,354.10 (100.0)	7.48

Data are presented as numbers and percentages.
Source: Fieldwork, 2022

4.2.2 Differences between Pre-eClaims and Post-eClaims Mean Error Margin of Claims

The paired t-test for two independent samples revealed that average error margins of claims in the pre-eClaims (paper-based systems) were statistically significantly higher than the post-eClaims (electronic systems) (p<0.0001) (Table 6). Regional analysis also showed that average error margins of claims was statistically significantly higher for paper-based system compared to electronic system in Ashanti, Bono East, Central, Volta, Western, Bono, and Oti regions respectively (Table 6). Only the Ahafo region showed that average error margins of claims were statistically significantly higher for electronic systems compared to paper-based systems (Table 6). However, there was no statistically significant differences in the average error margins of claims between paper-based and electronic systems for Eastern, Savannah and Upper West regions (Table 6).

Table 6: Differences between Pre-eClaims and Post-eClaims Mean Error Margin of Claims from Health Facilities in the 11 Selected Regions in Ghana

	Mean Error Margin (%)				
	Pre-eClaims (paper-based system)		Post-eClaims (electronic-based system)		*P*-value
Regions	Mean (se)	[95% CI]	Mean (se)	[95% CI]	
Ashanti	10.25 (1.24)	[7.79 - 12.70]	2.92 (0.54)	[1.84 - 4.00]	<0.0001**
Bono East	6.07 (0.99)	[4.11 - 8.04]	3.87 (0.51)	[2.87 - 4.47]	0.0295*
Central	12.34 (0.66)	[11.02 - 13.65]	7.57 (0.50)	[6.59 - 8.56]	<0.0001**
Eastern	6.15 (0.83)	[4.50 - 7.79]	5.54 (0.31)	[4.93 - 6.16]	0.4109
Volta	16.35 (0.90)	[14.57 - 18.12]	13.58 (0.92)	[11.76 - 15.40]	0.0370*
Western	14.46 (0.78)	[12.92 - 16.00]	5.87 (0.72)	[4.43 - 7.31]	<0.0001**
Bono	6.47 (0.43)	[5.61 - 7.33]	0.92 (0.08)	[0.75 - 1.08]	<0.0001**
Savannah	11.84 (2.21)	[7.39 - 16.30]	12.34 (1.01)	[10.32 - 14.36]	0.8198
Oti	7.44 (0.49)	[6.47 - 8.42]	5.09 (0.40)	[4.30 - 5.87]	0.0003*
Ahafo	1.63 (0.28)	[1.07 - 2.18]	4.43 (0.74)	[2.62 - 6.24]	0.0155*
Upper West	2.81 (0.38)	[2.06 - 3.56]	2.57 (0.58)	[1.37 - 3.76]	0.7663
Overall	10.13 (0.32)	[9.50 - 10.75]	8.15 (0.20)	[7.77 - 8.54]	<0.0001**

Note: Student's ttest was used to test differences between Pre-eClaims and Post-eClaims Mean Error Margin; *p<0.05 and **p<0.0001 are considered statistically significant; CI – Confidence Interval; se – Standard Error
Source: Fieldwork, 2022

4.2.3 Estimates for the Introduction of eClaims Effects and 95% Confidence Intervals Obtained Using Single-Group Interrupted Time Series Analysis

The segmented regression for the outcome variable of percentage error margins of health insurance claims in health facilities revealed that the baseline percentage error margins of claims in these individual health facilities range from 0.39% to 50.97% (Figure 11). The lowest baseline percentage error margins of claims were observed at HP22 whilst the highest was recorded by HP05 (Figure 11). However, 17 health facilities observed a reduction in monthly changes in percentage error margins of health insurance claims before the introduction of eClaims. These reductions range from 0.01% to 0.59%. Furthermore, these reductions were however statistically significant in 8 health facilities namely; HP01, HP05, HP11, HP12, HP14, HP17, HP20 and HP24 (Table 5). However, 6 health facilities observed increases ranging from 0.01% to 0.07% in percentage error margins of health insurance claims in monthly changes in percentage error margins of health insurance claims before the introduction of eClaims (Table 8). Only two health facilities experienced no monthly changes in percentage error margins of health insurance claims before the introduction of eClaims (Table 7). In the first month after the introduction of eClaims, 15 health facilities observed a reduction ranging from 0.38% to 20.43% in percentage error margins of health insurance claims. Furthermore, these reductions were however statistically significant in 7 health facilities (i.e. HP03, HP08, HP10, HP13, HP14, HP22 and HP23) (Table 5). The highest statistically significant reduction in percentage error margins of health insurance claims in the first month after the introduction of eClaims was observed at HP08 (Table 7). Finally, the analysis further revealed that 8 health facilities observed a reduction in percentage error margins of health insurance claims in the difference between pre-eClaims and post-eClaims slopes period (i.e. HP21, HP03, HP07, HP04, HP08, HP05, HP09 and HP22) (Table 7). These reductions in percentage error margins of health insurance claims in the difference between pre-eClaims and post-eClaims slopes period were statistically significant only in HP03 and HP21 respectively (Table 7).

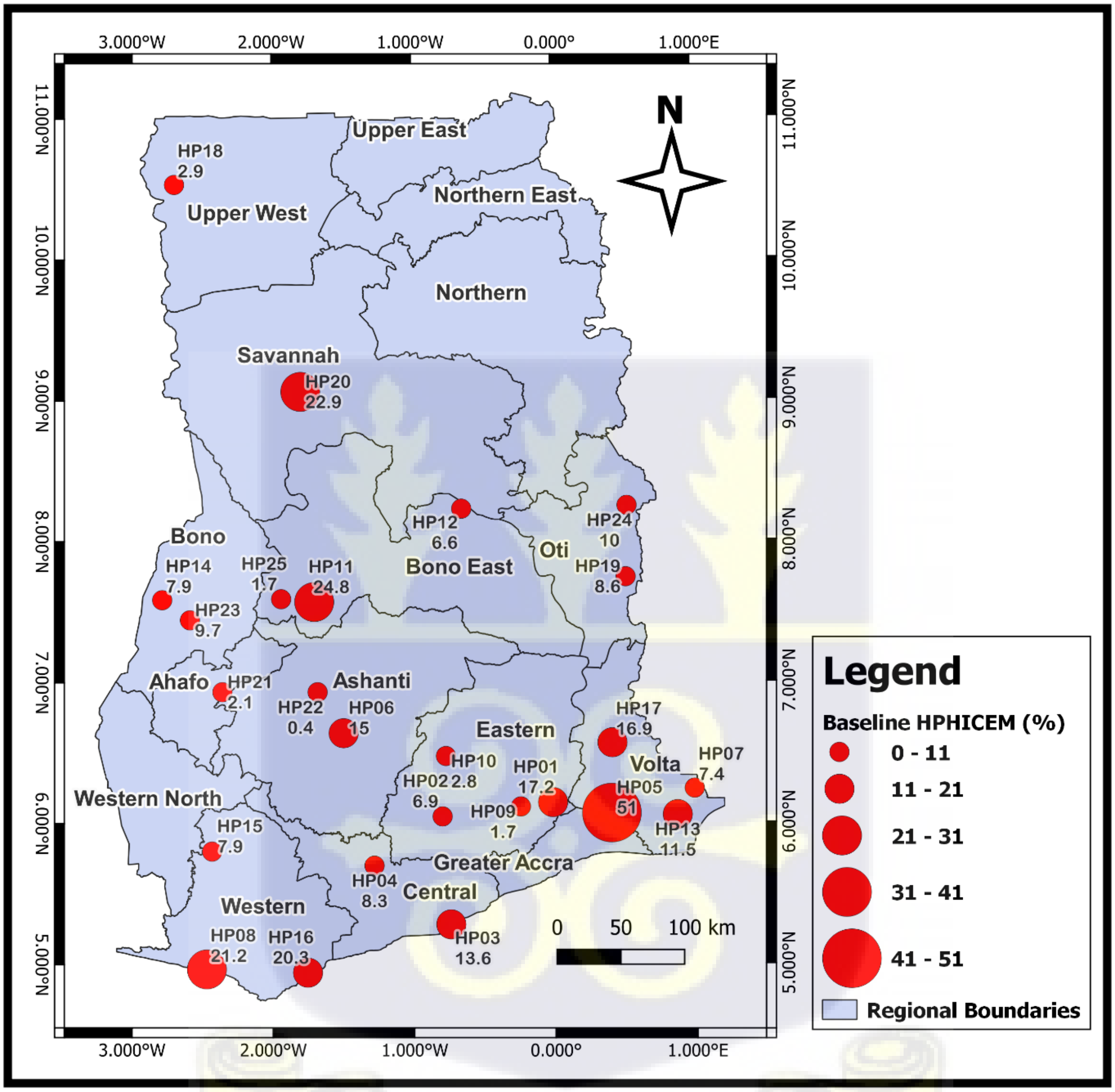

Figure 11: Regional Map of Ghana showing health provider baseline health insurance claims error margins (%) in the 25 NCHS hospitals in Ghana
HPHICEM - Health Provider Baseline Health Insurance Claims Error Margins
Source: Authors' analysis

Table 7: Estimates for the Introduction of eClaims Effects and 95% Confidence Intervals Obtained Using Single-Group Interrupted Time Series Analysis

		Intercept (Baseline level)	Slope prior to intervention					Change in level in the period immediately following intervention initiation (compared with counterfactual)					Difference between preintervention and postintervention slopes				
						[95% CI]					[95% CI]					[95% CI]	
Hospital Code	Region	β_0	β_1	Robust SE	*P*-value	LCI	UCI	β_2	Robust SE	*P*-value	LCI	UCI	β_3	Robust SE	*P*-value	LCI	UCI
HP01	Eastern	17.250	-0.248	0.083	0.003*	-0.412	-0.084	6.272	3.070	0.043*	0.191	12.354	0.257	0.097	0.009*	0.065	0.450
HP02	Eastern	6.929	-0.090	0.130	0.492	-0.348	0.168	3.396	3.297	0.305	-3.135	9.927	0.136	0.136	0.317	-0.132	0.405
HP03	Central	13.643	-0.007	0.026	0.785	-0.058	0.044	-7.878	2.572	0.003*	-12.973	-2.783	-0.484	0.224	0.033*	-0.928	-0.040
HP04	Central	8.277	-0.009	0.154	0.954	-0.314	0.296	3.181	2.368	0.182	-1.508	7.871	-0.055	0.161	0.735	-0.373	0.264
HP05	Volta	50.970	-0.253	0.093	0.008*	-0.438	-0.068	-3.761	3.328	0.261	-10.353	2.831	-0.028	0.129	0.829	-0.284	0.228
HP06	Ashanti	15.029	-0.007	0.057	0.897	-0.120	0.106	-6.595	4.120	0.112	-14.756	1.566	0.347	0.169	0.043*	0.011	0.682
HP07	Volta	7.410	0.002	0.024	0.931	-0.045	0.049	5.342	4.982	0.286	-4.525	15.209	-0.085	0.155	0.585	-0.391	0.222
HP08	Western	21.190	0.071	0.121	0.555	-0.168	0.311	-20.430	3.320	<0.001**	-27.006	-13.854	-0.033	0.130	0.801	-0.290	0.224
HP09	Eastern	1.684	0.038	0.060	0.526	-0.080	0.156	-0.547	1.116	0.625	-2.758	1.663	-0.026	0.067	0.701	-0.158	0.106
HP10	Eastern	2.837	0.013	0.042	0.752	-0.070	0.096	-4.583	1.658	0.007*	-7.867	-1.299	0.082	0.043	0.060	-0.004	0.168
HP11	Bono East	24.755	-0.586	0.202	0.004*	-0.985	-0.187	3.026	2.924	0.303	-2.766	8.817	0.630	0.202	0.002*	0.230	1.031
HP12	Bono East	6.630	-0.141	0.051	0.007*	-0.242	-0.040	-0.440	0.828	0.596	-2.080	1.199	0.135	0.052	0.010*	0.033	0.237
HP13	Volta	11.497	-0.084	0.062	0.179	-0.206	0.039	-6.714	1.804	<0.001**	-10.288	-3.141	0.165	0.065	0.013*	0.036	0.294
HP14	Bono	7.873	-0.113	0.037	0.003*	-0.186	-0.040	-2.222	0.967	0.023*	-4.137	-0.306	0.120	0.040	0.003*	0.041	0.198
HP15	Western	7.947	0.006	0.027	0.820	-0.047	0.059	-5.166	3.870	0.184	-12.831	2.499	0.015	0.930	0.987	-1.826	1.856
HP16	Western	20.306	-0.056	0.037	0.138	-0.130	0.018	-6.888	3.886	0.079	-14.586	0.809	0.581	0.560	0.302	-0.529	1.691
HP17	Volta	16.867	-0.062	0.021	0.004*	-0.104	-0.020	1.574	1.852	0.397	-2.094	5.242	0.239	0.188	0.205	-0.133	0.611
HP18	Upper West	2.883	-0.002	0.012	0.864	-0.026	0.021	-0.380	1.425	0.790	-3.203	2.442	0.032	0.048	0.503	-0.063	0.128
HP19	Oti	8.580	-0.034	0.056	0.547	-0.146	0.078	-1.825	2.180	0.404	-6.144	2.493	0.086	0.076	0.263	-0.065	0.236
HP20	Savannah	22.900	-0.471	0.107	<0.001**	-0.682	-0.259	10.608	3.224	0.001*	4.224	16.993	0.511	0.122	<0.001**	0.268	0.753
HP21	Ahafo	2.123	-0.009	0.013	0.477	-0.034	0.016	4.933	1.118	<0.001**	2.719	7.147	-0.534	0.232	0.023*	-0.993	-0.074
HP22	Ashanti	0.395	0.037	0.027	0.177	-0.017	0.090	-2.309	0.913	0.013*	-4.118	-0.500	-0.020	0.032	0.526	-0.083	0.043
HP23	Bono	9.670	-0.062	0.094	0.510	-0.248	0.124	-6.522	1.119	<0.001**	-8.737	-4.306	0.054	0.094	0.568	-0.133	0.240
HP24	Oti	9.951	-0.158	0.069	0.025*	-0.295	-0.020	2.549	1.449	0.081	-0.322	5.419	0.076	0.071	0.287	-0.064	0.216
HP25	Bono East	1.669	0.066	0.090	0.464	-0.113	0.245	1.347	3.124	0.667	-4.840	7.535	0.084	0.166	0.611	-0.243	0.412

*$p<0.05$ and **$p<0.001$ are considered statistically significant
L/UCI – Lower/Upper Confidence Internal; SE – Standard Error
Source: Field work, 2022

4.2.4 Meta-analysis pooling of aggregate data on Mean Error Margin of Claims using the Random Effects

The pooled effect analysis of percentage error margins of claims in all 25 health facilities has been presented in Table 8. The segmented regression for the outcome variable of percentage error margins of health insurance claims in health facilities revealed that the baseline percentage error margins of claims in these health facilities were 11.48% (Table 8). However, monthly changes in percentage error margins of health insurance claims before the introduction of eClaims reduced by 0.04% with a confidence interval of [-0.07 - -0.02] and was statistically significant (Table 8). In the first month after the introduction of eClaims, a further reduction of 1.31% was observed in percentage error margins of health insurance claims but was not statistically significant (p=0.1513; and CI= [-3.09 - 0.48]) (Table 8). The difference between pre-eClaims and post-eClaims slopes observed an increase of 0.09% error margins of health insurance claims and was statistically significant (p=0.0028; and CI= [-3.09 - 0.48]) (Table 8)—additionally, figures 12 to 14 show forest plots for the various slopes. Figures 12 to 14 revealed that there is substantial variability within the study sites and heterogeneity across the study sites. In the analysis involving the 25 health facilities, the between study sites heterogeneity was moderate, $I^2 \geq 50\%$, the pooled meta-analysis produced the most precise estimate where the length of the confidence intervals for the estimate is significantly smaller (Table 8). However, it was observed that where there was substantial within study sites variability and high between-study-sites heterogeneity, $I^2 \geq 75\%$, the pooled estimate goes with a wider confidence interval which was not significant (Table 8).

Table 8: Meta-analysis pooling of aggregate data on Mean Error Margin of Claims using the Random Effects

Trends	N	Overall Effect Size	Standard Error of Effect Size	[95% CI]	*P*-value	Homogeneity Tests: Cochran's Q Value	df (Q)	P-value	I-squared (%)
Intercept (Baseline level)	25	11.48	1.56	[8.43 - 14.53]	<0.0001***	761.57	24	<0.001**	96.8
Slope prior to the introduction of eClaims	25	-0.04	0.01	[-0.07 - -0.02]	0.0019*	73.06	24	<0.001**	67.2
Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual)	25	-1.31	0.91	[-3.09 - 0.48]	0.1513	151.13	24	<0.001**	84.1
Difference between pre-eClaims and post-eClaims slopes	25	0.09	0.03	[0.03 - 0.14]	0.0028*	59.51	24	<0.001**	59.7

*p<0.05, **p<0.001 and ***p<0.0001 are considered statistically significant

I^2 = Proportion of total variation in effect estimate due to between-study heterogeneity (based on Q)

df - Degrees of freedom

N - Number of Hospitals

Field work, 2022

4.2.4.1 Assessing the immediate impact of HIS (eClaims) implementation on error margins of health insurance claims

The pooled effect estimates of the impact of eClaims on the percentage error margins of claims in all 25 health facilities have been presented in Figure 12. In the first month after the introduction of eClaims, the facilities saw a reduction of about 1.31% in percentage error margins of health insurance claims. The majority 60% (15 out of 25) of health facilities observed a reduction in percentage error margins of health insurance claims in the first month after the introduction of eClaims (see Figure 12).

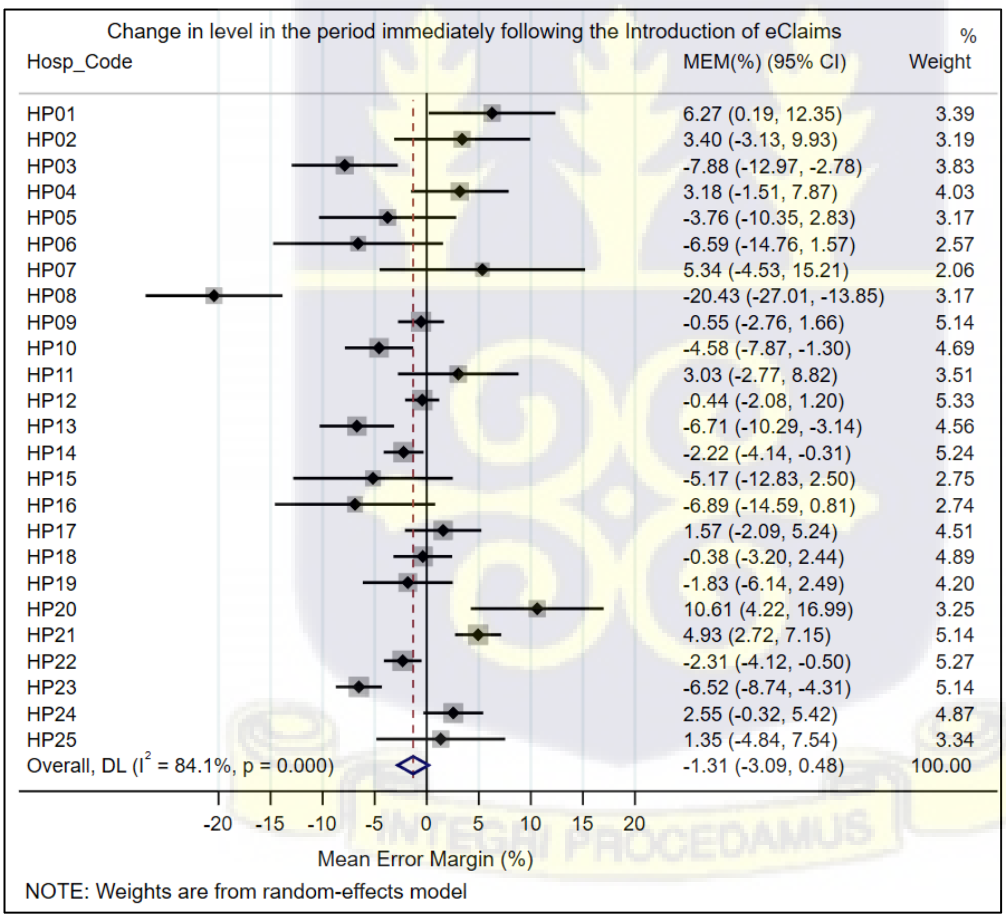

Figure 12: Forest plot for Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual); MEM – Mean Error Margin; Hosp_Code – Hospital Code
Fieldwork, 2022

4.2.4.2 Assessing the sustained impact of HIS (eClaims) implementation on error margins of health insurance claims

Except for a few health facilities that realized the sustained reduction in the error margins of health insurance claims due to the implementation of eClaims, most of the health facilities have not experienced a reduction in the error margins of claims submitted to the insurance authority even after the introduction of the eClaims and in even in some cases, the mean error margin has increased. Only 32% (8 out of 25) of health facilities observed a reduction in percentage error margins of health insurance claims in the difference between the pre-eClaims and post-eClaims slopes. The overall sustained effect of eClaims was minimal (Figure 13).

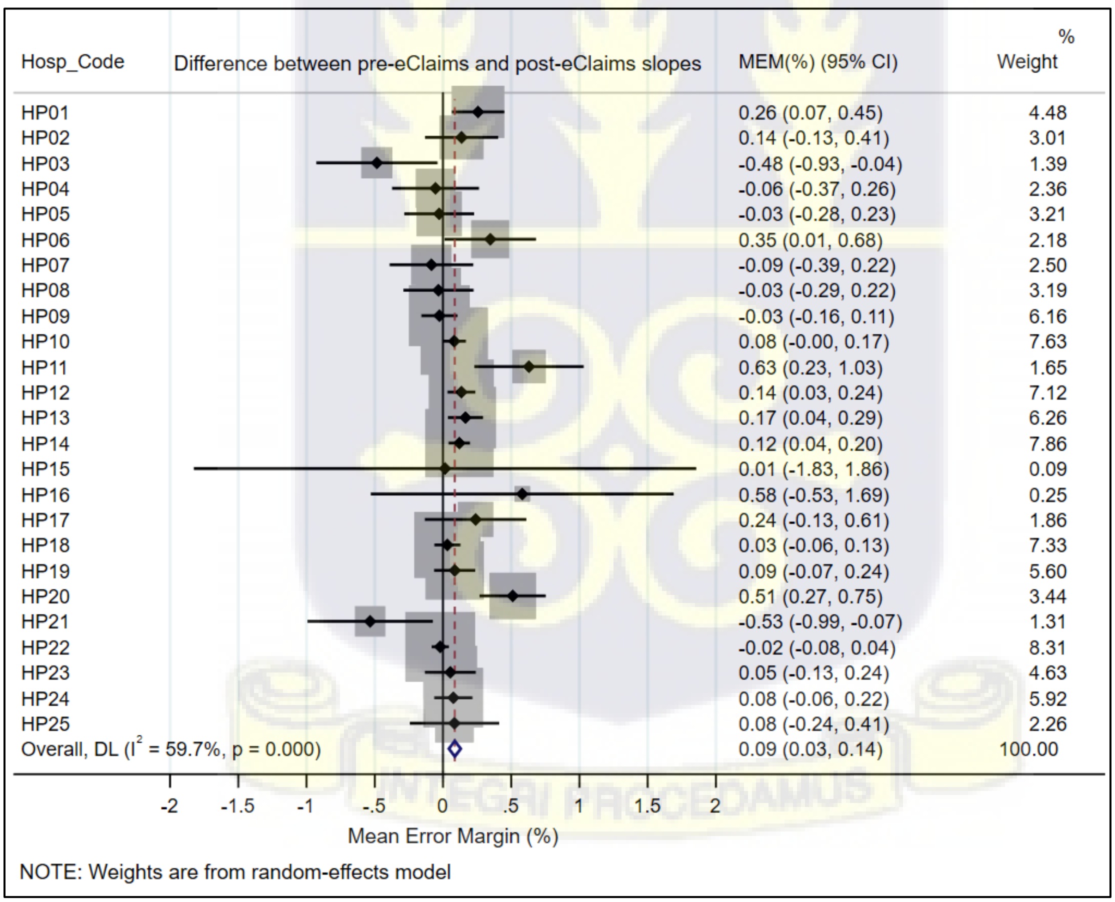

Figure 13: Forest plot for Difference between pre-eClaims and post-eClaims slopes
MEM – Mean Error Margin; Hosp_Code – Hospital Code
Fieldwork, 2022

4.2.5 Meta-analysis pooling of aggregate data on Mean Error Margin of Claims using the Random Effects stratified by Ecological zones

The pooled effect percentage error margins of claims in the 25 health facilities using the Random Effects stratified by Ecological zones have been presented in (Table 9). The segmented regression for the outcome variable of percentage error margins of claims in health facilities was statistically significantly high in Forest (effect size=6.87; p<0.0001 and 95%CI= [3.95 - 9.79]) and Coastal (effect size=15.87; p=<0.0001 and 95%CI= [10.37 - 21.35]) zones in Ghana (Table 9). The Savannah zone recorded insignificant percentage error margins of claims (effect size=12.46; p=0.0058 and 95%CI= [-7.14 - 32.06]). The segmented regression for the outcome variable of percentage error margins of claims in health facilities revealed that the monthly changes in percentage error margins of claims before the introduction of eClaims reduced by 0.04% to 0.22% across the three ecological zones (Table 9). The highest reduction in percentage error margins of claims was observed in Savannah zone (effect size=-0.22; p=0.3383 and 95%CI= [-0.68 - 0.23]) whilst the lowest was observed in Forest (effect size=-0.04; p=0.0767 and 95%CI= [-0.09 - 0.01]) and Coastal (effect size=-0.04; p=0.0243 and 95%CI= [-0.07 - -0.01]) zones respectively (Table 9). The analysis involving the 25 health facilities across the regions observed that there was low ($I^2 \geq 25\%$) to high ($I^2 \geq 75\%$) within study sites variability and between study sites heterogeneity for the three ecological zones (Table 9).

Table 9: Meta-analysis pooling of aggregate data on Mean Error Margin of Claims using Random Effects stratified by Ecological zones

Ecological Zones	Trends	N	Overall Effect Size	Standard Error of Effect Size	[95% CI]	*P*-value	Homogeneity Tests: Cochran's Q Value	df (Q)	P-value	I-squared (%)
Savannah	Intercept (Baseline level)	2	12.46	10.00	[-7.14 - 32.06]	0.2127	21.88	1	<0.0001**	95.40
	Slope prior to the introduction of eClaims	2	-0.22	0.23	[-0.68 - 0.23]	0.3383	18.66	1	<0.0001**	94.60
	Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual)	2	4.73	5.48	[-6.02 - 15.47]	0.3885	9.52	1	0.0020*	89.50
	Difference between pre-eClaims and post-eClaims slopes	2	0.26	0.24	[-0.21 - 0.73]	0.2806	12.98	1	<0.0001**	92.30
Forest	Intercept (Baseline level)	12	6.87	1.49	[3.95 - 9.79]	<0.0001**	148.28	11	<0.0001**	92.60
	Slope prior to the introduction of eClaims	12	-0.04	0.03	[-0.09 - 0.01]	0.0767	34.9	11	<0.0001**	68.50
	Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual)	12	-0.62	1.09	[-2.76 - 1.52]	0.5719	71.48	11	<0.0001**	84.60
	Difference between pre-eClaims and post-eClaims slopes	12	0.09	0.04	[0.02 - 0.17]	0.0150	33.67	11	<0.0001**	67.30

Coastal	Intercept (Baseline level)	11	15.86	2.80	[10.37 - 21.35]	<0.0001**	313.54	10	<0.0001**	96.80
	Slope prior to the introduction of eClaims	11	-0.04	0.02	[-0.07 - -0.01]	0.0243*	17.4	10	0.0660	42.50
	Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual)	11	-3.54	1.94	[-7.35 - 0.26]	0.0676	64.54	10	<0.0001**	84.50
	Difference between pre-eClaims and post-eClaims slopes	11	0.05	0.04	[-0.03 - 0.14]	0.2076	12.48	10	0.2540	19.80

*p<0.05 and **p<0.0001 are considered statistically significant
I^2 = Proportion of total variation in effect estimate due to between-study heterogeneity (based on Q)
df - Degrees of freedom
N - Number of Hospitals
Fieldwork, 2022

4.2.5.1 Assessing the immediate impact of HIS (eClaims) implementation on error margins of health insurance claims stratified by Ecological zones

The pooled effect analysis of percentage error margins of claims for Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual) in all the 25 health facilities stratified by Ecological zones have been presented in Table 9 and Figure 14. The segmented regression for the outcome variable of percentage error margins of health insurance claims in health facilities revealed that Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual) reduced by 0.62% with 95%CI [-2.76 - 1.52] and 3.54% with 95%CI [-7.35 - 0.26] in the Forest and Coastal zones respectively in Ghana (Table 9). These reductions in percentage error margins of health insurance claims were not statistically significant (Table 9). The highest reduction was recorded in Coastal zones whilst the lowest was observed in Forest zone (Figure 14). However, the Savannah zone saw an increase of 4.73% with 95%CI [-6.02 - 15.47] in percentage error margins of health insurance claims and was statistically not significant (Table 9). It is also observed that more than 50% of health facilities in each ecological zone saw a reduction in percentage error margins of health insurance claims in Change in level in the period immediately following the introduction of eClaims (compared with counterfactual). In the analysis involving the 25 health facilities across the three ecological zones, the between-study sites heterogeneity was high, $I^2 \geq 75\%$ for all the ecological zones (Table 9 and Figure 14).

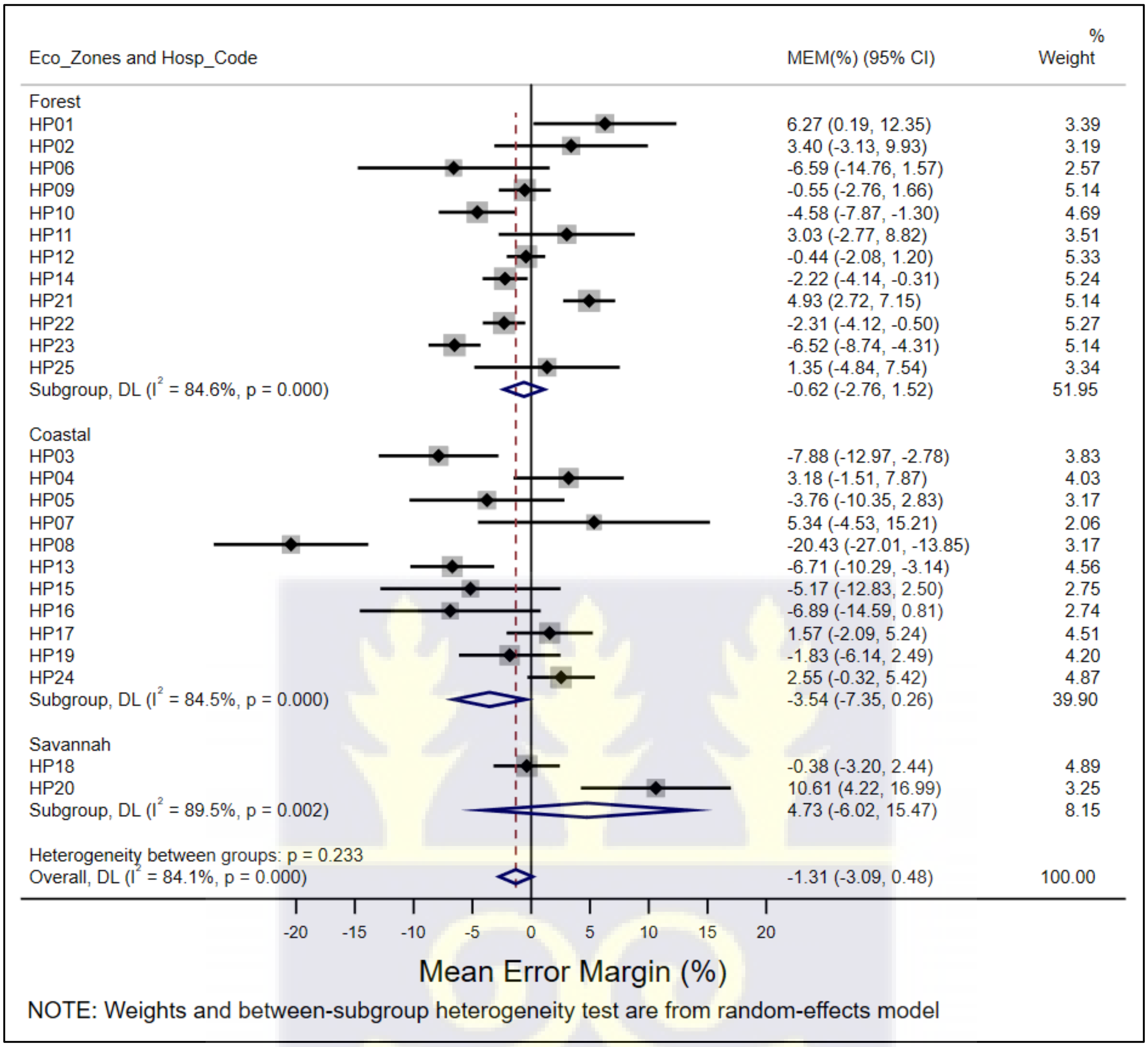

Figure 14: Forest plot for Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual) stratified by Ecological zones
MEM – Mean Error Margin; Eco_zone – Ecological zones; Hosp_code – Hospital code
Fieldwork, 2022

4.2.5.2 Assessing the sustained impact of HIS (eClaims) implementation on error margins of health insurance claims stratified by Ecological zones

The pooled effect analysis of percentage error margins of claims for the Difference between pre-eClaims and post-eClaims slopes in all the 25 health facilities stratified by ecological zones have been presented in Figure 15. The segmented regression for the outcome variable of percentage error margins of health insurance claims in health facilities revealed that Difference between pre-eClaims and post-eClaims slopes increased by 0.05% to 0.26% across the 3 ecological zones in Ghana (i.e. Savannah, Forest and Coastal) with highest statistically significant increase in the forest zone (effect size=0.09%; p= 0.0149; 95%CI= [0.02 - 0.17]) (Table 10). The highest increase was observed in the Savannah zone (effect size=0.26%; 95%CI [-0.21 - 0.73]) (Table 9). Only a few health facilities in Forest (25% out of 12) and Coastal (20% out of 25) zones were able to sustain the impact of eClaims implementation on error margins of health insurance claims (Figure 15). The analysis involving the 25 health facilities across the ecological zones, the between study sites heterogeneity range from low, $I^2 \geq 25\%$ to high, $I^2 \geq 75\%$ (Figure 15). High within-study-sites variability and between-study-sites heterogeneity ($I^2 \geq 75\%$) were observed in the Savannah zone (Figure 15). It was observed that there was moderate study site variability and between-study site heterogeneity ($I^2 \geq 50\%$) for the Forest zone (Figure 15). Low within-study-sites variability and between-study-sites heterogeneity ($I^2 \geq 25\%$) were observed for the Coastal zone (Figure 15).

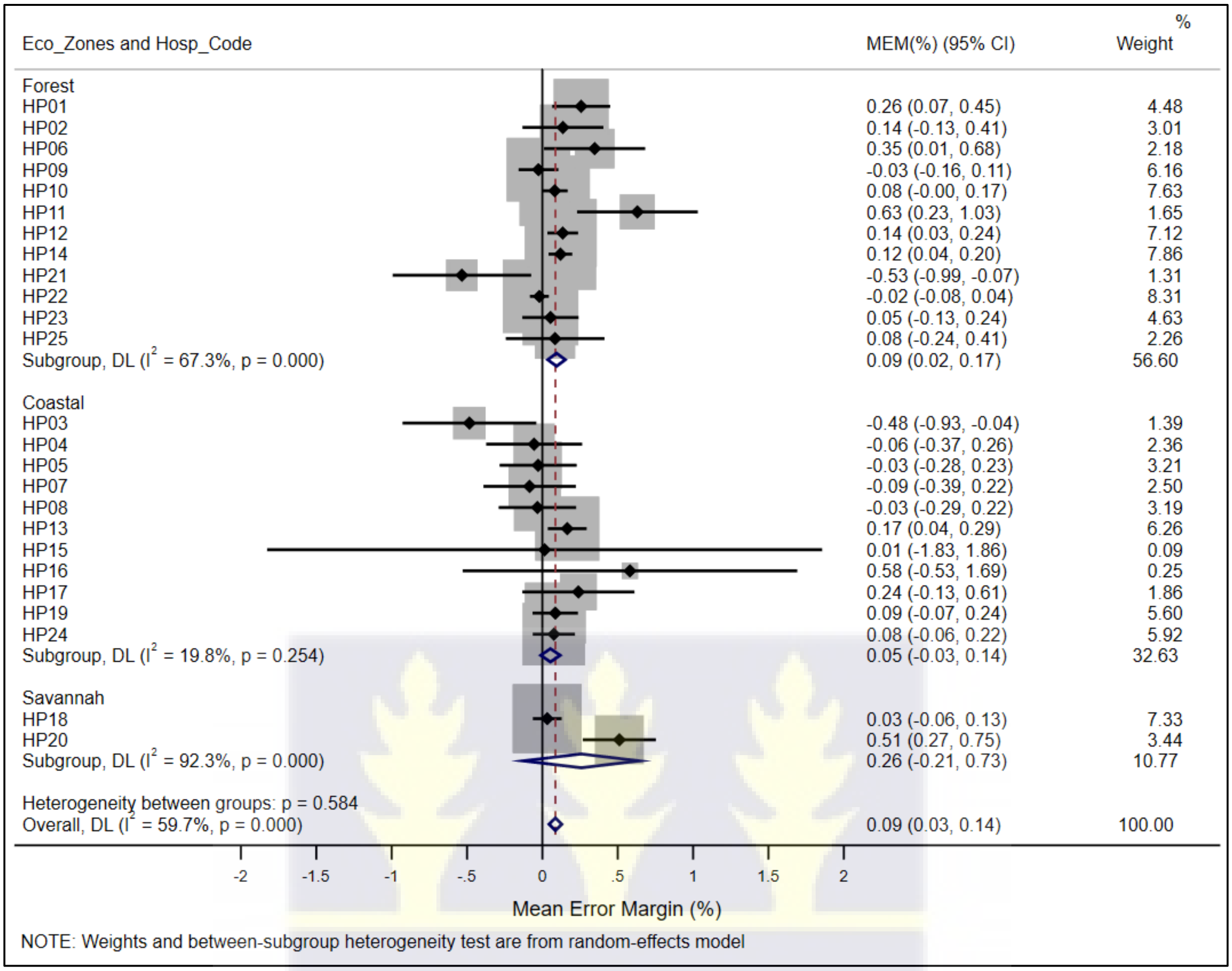

Figure 15: Forest plot for Difference between pre-eClaims and post-eClaims slopes stratified by Ecological zones
MEM – Mean Error Margin; Eco_zone – Ecological zones; Hosp_code – Hospital code
Source: Fieldwork, 2022

4.3 To estimate and forecast claim denial rate

4.3.1 Descriptive Statistics

As shown in Table 10, the mean claim denial rate (CDR) is 7.79% and ±2.52 standard deviation. The large difference between the maximum (16.8%) and the minimum (4.0%) confirms the sudden rise of CDR in Ghana. The CDR series has a long right tail and is non-symmetric, as evidenced by the positive skewness of 1.13. According to Maravall, Pavón, and Cañete (2016), kurtosis should be less than or equal to 5 for normally distributed variables in series with 111 to 160 observations.

In this study, kurtosis was found to be 4.23 for 120 observations. As a result, the CDR series has a normal distribution.

Table 10: Summary statistics of health insurance claim denial rate (%) from 25 NCHS hospitals in Ghana

Variable	N	Mean	Std. Dev.	Median	Min	Max	Skewness	Kurtosis
CDR	120	7.79	2.52	7.28	4.00	16.80	1.13	4.23

CDR - Claim Denial Rate (%); Std. Dev. – Standard Deviation
Source: Fieldwork, 2022

4.3.2 Data Preparation

Before implementing additional methods, the claim denial rate data were successfully validated and verified using the Anderson-Darling normality test (see Figure 16 below).

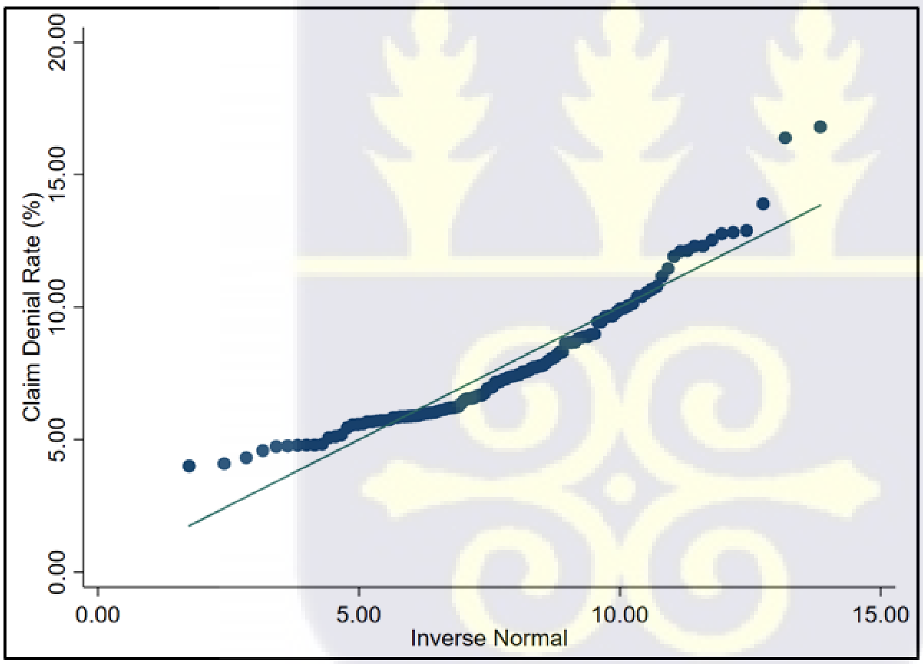

Figure 16: Probability Plot of Claim Denial Rate (%)
Source: Fieldwork, 2022

The Box-Jenkins method was used to model and forecast the claim denial rate (%) from January 2010 to December 2019. The time series plot of the claim denial rate (%) is illustrated in Figure 17.

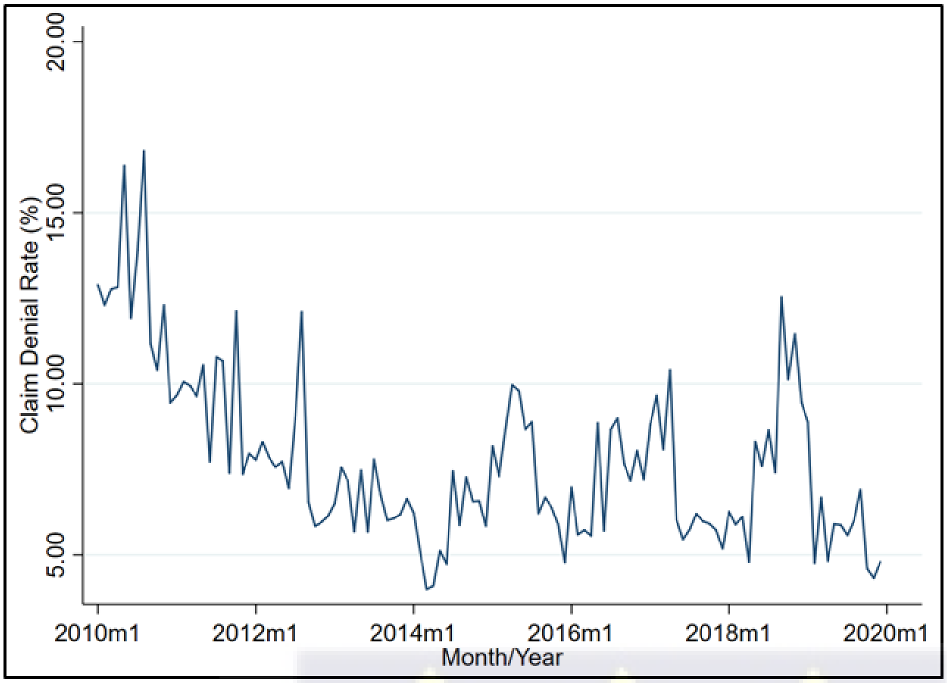

Figure 17: Time Series Plot of Claim Denial Rate (%)
Source: Fieldwork, 2022

4.3.3 Model Identification

The ADF test's results are shown in Table 11. The result indicates that the test statistic value of -5.299 is lower than the CV value of -3.447 and that there is no unit root since *p*-value = 0.0001 < 0.05 and it is significant. This indicates that the CDR is stationary at a 5% significance level. Hence, the null hypothesis is rejected (Challa et al., 2018).

Table 11: Augmented Dickey-Fuller (ADF) Test

Series	Test Statistic	*P*-value	5 % Critical Value (CV)	Analysis	Stationarity
CDR	-5.299	< 0.0001*	-3.447	Test Statistic < 5% CV	Stationary

Statistically significant at p-value<0.0001*
Source: Fieldwork, 2022

Model estimation using the default least squares method precedes the identification phase. The ideal model is chosen from the estimated combinations of various p and q for AR, MA, and d for the integrated seasonality respectively. Subsequently, the rule for the determination of the most proper blend of ARIMA (p,d,q) depends on parsimonious considerations, such as highest number of significant coefficients, lowest Akaike Criterion Information (AIC), lowest Bayesian Criterion Information (BIC) and highest adjusted R^2 (Balli & Elsamadisy, 2012). The presence of seasonality is another important factor that affects time series (Junior, Salomon, & de Oliveira Pamplona, 2014). The results of the first four lags of the CDR, as depicted in Figure 18, show that the autocorrelation coefficient exceeds the limits of statistical significance, which in this time series is seasonality. Additionally, a slow decay is observed, corroborating seasonality data.

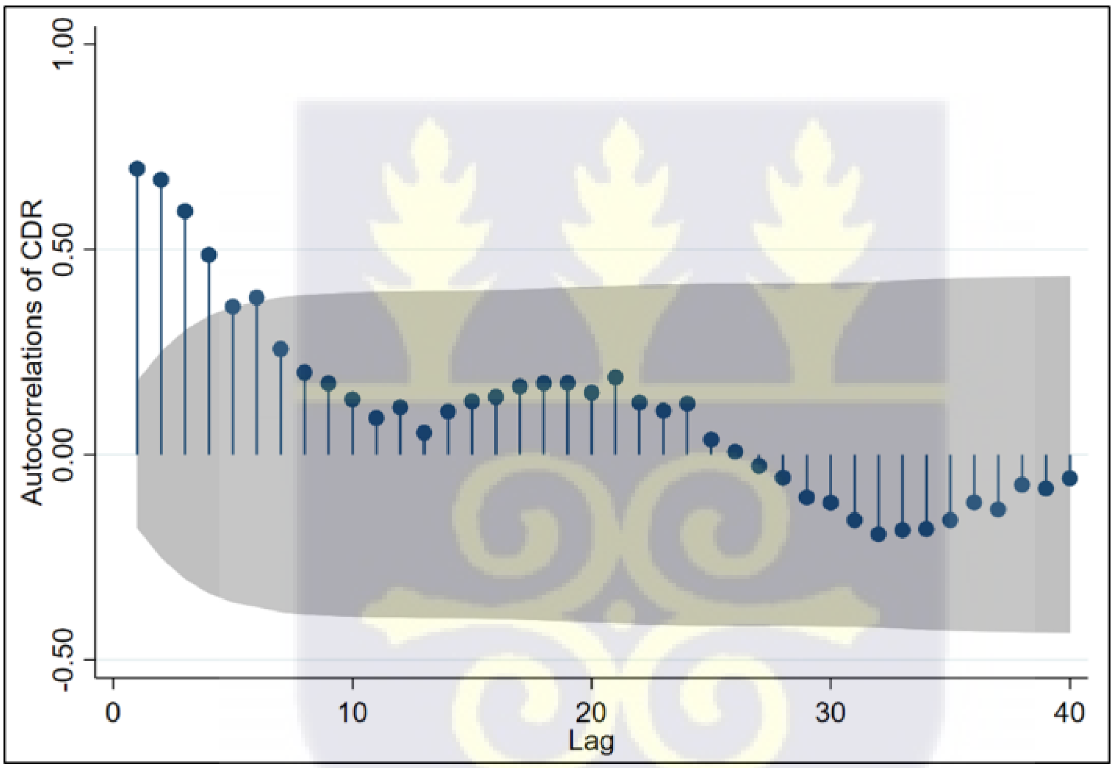

Figure 18: Autocorrelation Function for Claim Denial Rate (%) (with 5% significance limits for the autocorrelations)
CDR - Claim Denial Rate (%)
Source: Fieldwork, 2022

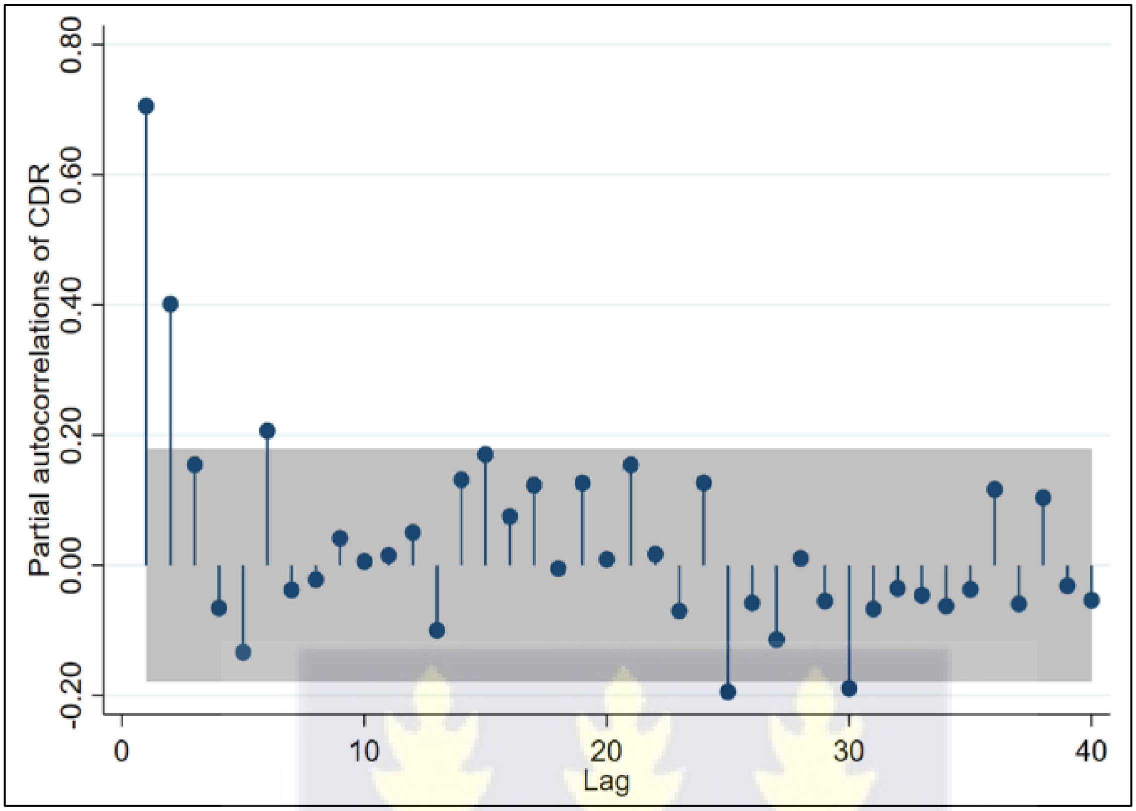

Figure 19: Partial Autocorrelation Function for Claim Denial Rate (%) (with 5% significance limits for the partial autocorrelations)
CDR - Claim Denial Rate (%)
Source: Fieldwork, 2022

4.3.4 Stability Test

According to Nyoni and Nathaniel (2018), the stability test looks at the inverse roots of the AR/MA polynomial(s), which should be within the unit circle. Since the unit circle contains the corresponding inverse roots of the characteristic polynomial, figure 6 indicates that the ARMA (1, 0, 1) model is stable (figure 20). The fact that the corresponding inverse roots of the characteristic polynomials are located within the unit circle demonstrates that the ARMA (2, 0, 1) model is stable (figure 21). The fact that the corresponding inverse roots of the characteristic polynomials are located within the unit circle demonstrates that the ARMA (3, 0, 1) model is stable (figure 22).

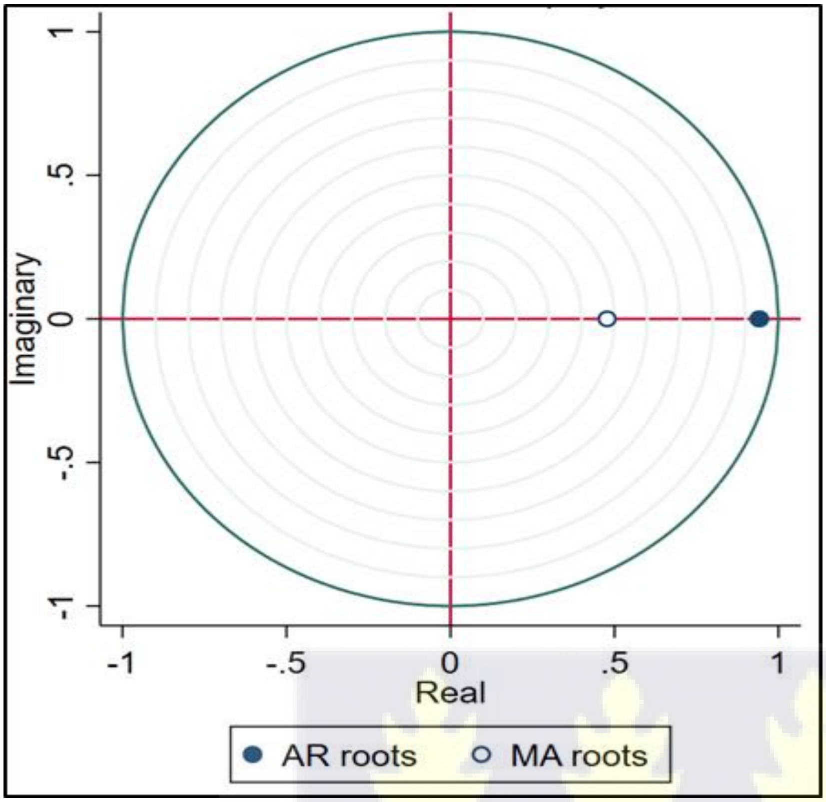

Figure 20: Inverse root of ARMA (1, 0, 1) Polynomials Stability Test
Source: Fieldwork, 2022

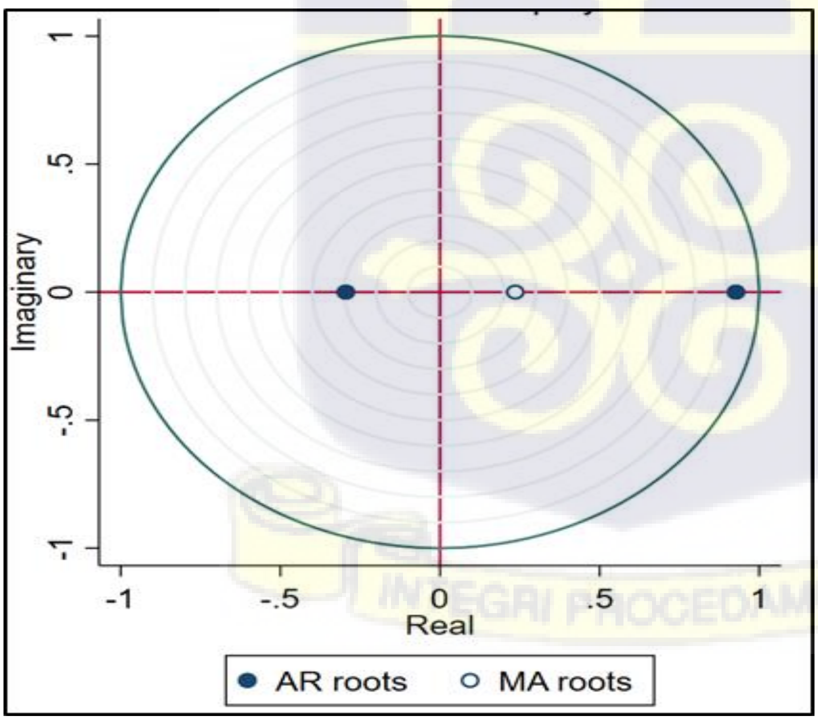

Figure 21: Inverse root of ARMA (2, 0, 1) Polynomials Stability Test
Source: Fieldwork, 2022

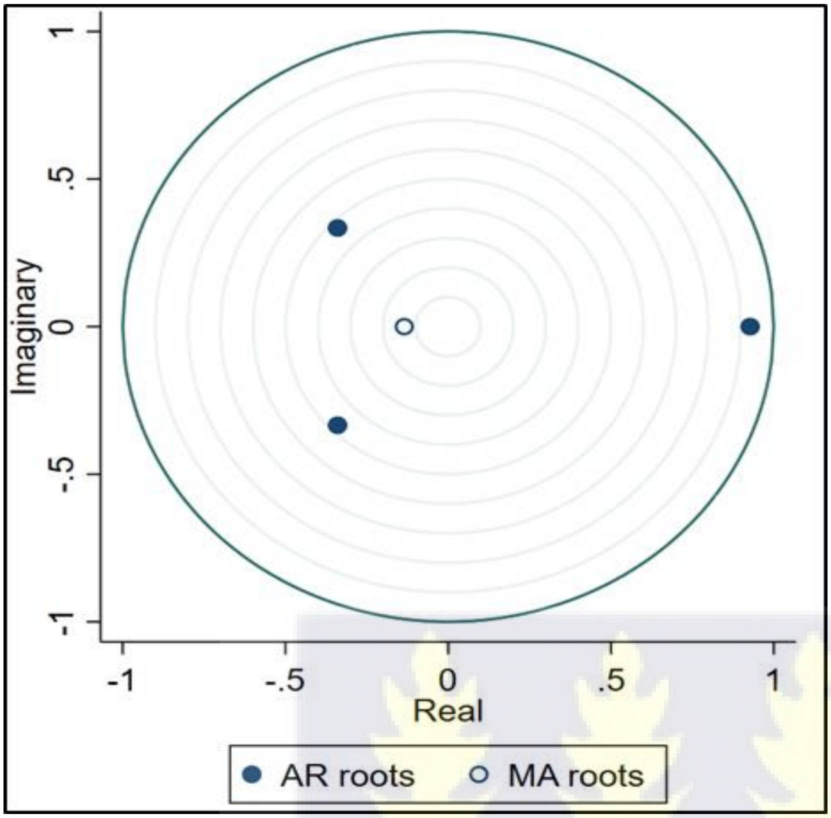

Figure 22: Inverse root of ARMA (3, 0, 1) Polynomials Stability Test
Source: Fieldwork, 2022

4.3.5 Model Parameters Estimation

Based on the estimates in Table 12, the ARIMA (1,0,1) model outperforms the other models, namely ARIMA (2,0,1) and ARIMA (3,0,1), in terms of fit. The ARIMA (1,0,1) model had the highest significant coefficients and the second-largest adjusted R^2 value among the estimates because of its possession. AIC estimates, on the other hand, indicate that ARIMA (2,0,1) is the most desirable model, followed by ARIMA (1,0,1), with ARIMA (3,0,1) having the highest AIC value. As a result, the ARIMA (1,0,1) model is considered the best model with the highest in-sample performance among the three estimates.

Table 12: Model selection criteria

Criteria	Model A ARIMA (1,0,1)	Model B ARIMA (2,0,1)	Model C ARIMA (3,0,1)	Best Model
Most Significant Coefficient (C, AR, MA)	3/3	2/4	1/5	A
SigmaSQ	1.6151	1.5965	1.5888	C
Log-likelihood	-228.4243	-227.0455	-226.4828	A
AIC	464.8485	464.091	464.9656	B
BIC	475.9985	478.0284	481.6906	A
Durbin Watson (DW) statistic	2.0889	1.9673	1.9406	A
RMSE	0.2226	0.1173	0.1173	
MAPE	0.0571	0.1314	0.0404	
Theil's U	0.0466	0.1109	0.0173	
Best Model				A

Compare Akaike Criterion Information (AIC), lowest Bayesian Criterion Information (BIC) (**Smaller is better**); Maximum likelihood (**Bigger is better**); and SigmaSQ - an estimate of the error variance (**Smaller is better**). MAPE – Mean Absolute Percentage Error; RMSE – Root of Mean Squared Error; AR – Autoregressive; MA – Moving Average
Source: Fieldwork, 2022

4.3.6 Model Specification

The following models have been specified following the model estimation shown in Table 12:

ARIMA (1,0,1) Model

$$CDR_t = c + \beta_1 CDR_{t-1} + \alpha_1 \varepsilon_{t-1} + \varepsilon_t \text{ --------------- } (1)$$

where c is the model constant

ARIMA (2,0,1) Model

$$CDR_t = c + \beta_2 CDR_{t-2} + \alpha_2 \mu_{t-2} + \alpha_1 \mu_{t-1} + \mu_t \text{ ------------ } (2)$$

ARIMA (3,0,1) Model

$$CDRt = c + \beta_3 CDR_{t-3} + \alpha_3 \varepsilon_{t-3} + \alpha_1 \varepsilon_{t-1} + \varepsilon_t \text{ --------------- } (3)$$

The model-proving phase follows the estimation phase. This procedure is necessary to ensure that all series information is captured. As a result, the stage involves plotting the correlogram of the ACF and PACF residuals. The ideal model's lag structure should be within the standard error limits'

95% confidence interval. Therefore, a correlogram of the residuals was plotted against the lag lengths to assess the fitness of the ideal model. The residual correlogram's 20 lags and associated statistical values are depicted in Figure 23.

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial Autocor]
1	0.6969	0.7055	59.754	0.0000		
2	0.6702	0.4013	115.48	0.0000		
3	0.5931	0.1544	159.5	0.0000		
4	0.4869	-0.0659	189.42	0.0000		
5	0.3605	-0.1339	205.96	0.0000		
6	0.3827	0.2065	224.76	0.0000		
7	0.2575	-0.0382	233.35	0.0000		
8	0.2003	-0.0223	238.6	0.0000		
9	0.1735	0.0414	242.57	0.0000		
10	0.1348	0.0057	244.99	0.0000		
11	0.0890	0.0149	246.05	0.0000		
12	0.1150	0.0503	247.84	0.0000		
13	0.0532	-0.1001	248.23	0.0000		
14	0.1051	0.1312	249.76	0.0000		
15	0.1298	0.1701	252.11	0.0000		
16	0.1403	0.0747	254.88	0.0000		
17	0.1662	0.1229	258.81	0.0000		
18	0.1739	-0.0052	263.14	0.0000		
19	0.1745	0.1262	267.56	0.0000		
20	0.1510	0.0088	270.9	0.0000		

Figure 23: Residuals Correlogram of ARIMA (1, 0, 1)
Source: Fieldwork, 2022

In the ACF and PACF, the dotted lines represent the standard error (SE) limits. If both are below the SE limits, ACF and PACF do not differ statistically from non-existent at the 5% significance level (Challa et al., 2018). Because the correlogram is flat, the spikes indicate that there is no SE sign. The absence of autocorrelation is demonstrated in Table 13 by the Durbin Watson (DW) statistic (DW) value of 2.0889, which is very close to the threshold value of 2 (Uyanto, 2020). Therefore, the model is ideal for the forecasts.

4.3.7 Forecasting

According to the projections in Table 13, the CDR will be 5.35% in February 2020. This indicates that the CDR in Ghana will decrease from 8.0% in January 2010 to approximately 5.35% by

February 2020. The use of electronic medical records may have contributed to the CDR's declining trend (Nsiah-Boateng et al., 2017a).

Table 13: ARIMA (1,0,1) forecasted results of monthly claim denial rate (%)

	Claim Denial Rate (%)	
Month	Actual	Forecasted
Jan-10	12.89	8.00
Feb-10	12.30	11.80
Mar-10	12.78	11.84
Apr-10	12.83	12.06
May-10	16.39	12.18
Jun-10	11.92	13.89
Jul-10	13.90	12.63
Aug-10	16.80	12.95
Sep-10	11.17	14.45
Oct-10	10.40	12.55
Nov-10	12.30	11.28
Dec-10	9.44	11.56
Jan-11	9.66	10.37
Feb-11	10.06	9.90
Mar-11	9.94	9.86
Apr-11	9.63	9.79
May-11	10.55	9.61
Jun-11	7.73	9.95
Jul-11	10.78	8.81
Aug-11	10.67	9.68
Sep-11	7.39	10.04
Oct-11	12.13	8.69
Nov-11	7.36	10.24
Dec-11	7.96	8.77
Jan-12	7.78	8.35
Feb-12	8.30	8.06
Mar-12	7.85	8.17
Apr-12	7.56	8.01
May-12	7.73	7.80
Jun-12	6.95	7.78
Jul-12	8.98	7.41
Aug-12	12.11	8.17
Sep-12	6.54	9.99
Oct-12	5.83	8.27
Nov-12	5.95	7.12
Dec-12	6.13	6.63

Source: Fieldwork, 2022

Table 13: ARIMA (1,0,1) forecasted results of monthly claim denial rate (%) … continued

	Claim Denial Rate (%)	
Month	Actual	Forecasted
Jan-13	6.50	6.48
Feb-13	7.55	6.58
Mar-13	7.16	7.11
Apr-13	5.68	7.19
May-13	7.47	6.53
Jun-13	5.67	7.05
Jul-13	7.79	6.47
Aug-13	6.74	7.17
Sep-13	6.01	7.02
Oct-13	6.07	6.61
Nov-13	6.18	6.44
Dec-13	6.63	6.41
Jan-14	6.23	6.61
Feb-14	5.08	6.51
Mar-14	4.00	5.93
Apr-14	4.09	5.16
May-14	5.11	4.83
Jun-14	4.74	5.15
Jul-14	7.44	5.12
Aug-14	5.87	6.37
Sep-14	7.26	6.23
Oct-14	6.55	6.81
Nov-14	6.57	6.76
Dec-14	5.84	6.75
Jan-15	8.17	6.40
Feb-15	7.29	7.31
Mar-15	8.68	7.34
Apr-15	9.97	8.00
May-15	9.80	8.91
Jun-15	8.66	9.27
Jul-15	8.88	8.92
Aug-15	6.21	8.85
Sep-15	6.67	7.57
Oct-15	6.39	7.18
Nov-15	5.89	6.86
Dec-15	4.78	6.48

Source: Fieldwork, 2022

Table 13: ARIMA (1,0,1) forecasted results of monthly claim denial rate (%) … continued

Month	Claim Denial Rate (%)	
	Actual	Forecasted
Jan-16	6.98	5.78
Feb-16	5.59	6.46
Mar-16	5.72	6.15
Apr-16	5.56	6.06
May-16	8.85	5.94
Jun-16	5.70	7.41
Jul-16	8.66	6.65
Aug-16	8.99	7.67
Sep-16	7.67	8.30
Oct-16	7.17	7.99
Nov-16	8.04	7.61
Dec-16	7.20	7.83
Jan-17	8.80	7.55
Feb-17	9.65	8.16
Mar-17	8.08	8.84
Apr-17	10.40	8.44
May-17	6.02	9.32
Jun-17	5.45	7.71
Jul-17	5.74	6.68
Aug-17	6.20	6.32
Sep-17	5.98	6.36
Oct-17	5.91	6.28
Nov-17	5.72	6.21
Dec-17	5.18	6.09
Jan-18	6.26	5.78
Feb-18	5.88	6.13
Mar-18	6.11	6.12
Apr-18	4.79	6.23
May-18	8.31	5.67
Jun-18	7.59	7.03
Jul-18	8.65	7.35
Aug-18	7.40	7.99
Sep-18	12.53	7.72
Oct-18	10.13	9.97
Nov-18	11.45	9.93
Dec-18	9.45	10.52

Source: Fieldwork, 2022

Table 13: ARIMA (1,0,1) forecasted results of monthly claim denial rate (%) … continued

	Claim Denial Rate (%)	
Month	Actual	Forecasted
Jan-19	8.88	9.88
Feb-19	4.76	9.30
Mar-19	6.67	7.12
Apr-19	4.82	6.96
May-19	5.90	6.03
Jun-19	5.87	6.08
Jul-19	5.57	6.10
Aug-19	6.00	5.97
Sep-19	6.91	6.10
Oct-19	4.59	6.59
Nov-19	4.32	5.74
Dec-19	4.79	5.21
Jan-20	.	5.18
Feb-20	.	5.35

Source: Fieldwork, 2022

In a similar vein, the actual and predicted rates of claim denial in Ghana are depicted in Figure 26, which has a projection range of two months, from January 2020 to February 2020. The actual values (CDR) are shown by the blue line, while the forecast rates are shown by the red line (Forecasted CDR). Furthermore, the figure indicates that Ghana's CDR is likely to remain extremely low, hovering around a predicted rate of 5.35%, which is slightly lower than the benchmark rate of 7.79%. The most revealing aspect of this estimate is that CDR in Ghana is likely to stay very low over the projected period. According to Nsiah-Boateng et al. (2017a), this low CDR may be linked to the use of electronic medical records.

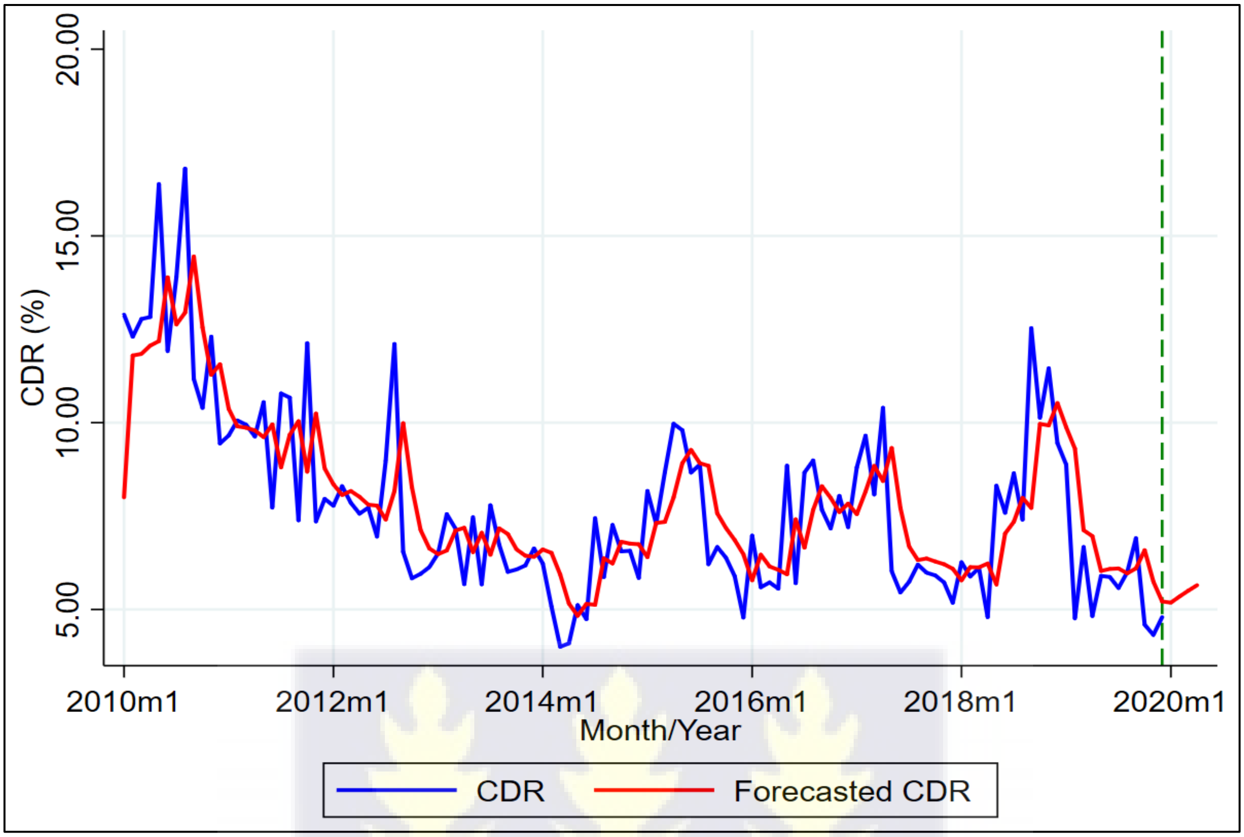

Figure 24: Time series plot for actual and forecasted claim denial rate (CDR)
Source: Fieldwork, 2022

4.3.8 Forecasting CDR based on sample CDR data

The forecasting was carried out based on a 70%/ 30% split of data. 70% was used to build the model and predicted for the omitted 30%. In this instance, the series CDR data from January 2010 to December 2017 was used to build the model and evaluated from January 2018 to January 2020.

4.3.8.1 ARIMA model selection based on sample CDR data

An Augmented Dickey-Fuller (ADF) test was conducted on the CDR data sample, revealing that the differential series exhibited stationarity (t= -4.973, p<0.001). Based on the ACF and PACF plots, the provisional values for the order of p and q were set as 1 or 2, and the value for P was established as 1 (Figure 25). After evaluating the AIC and BIC values of all candidate models in Table 14, the ARIMA model with parameters (1, 0, 1) was ultimately selected.

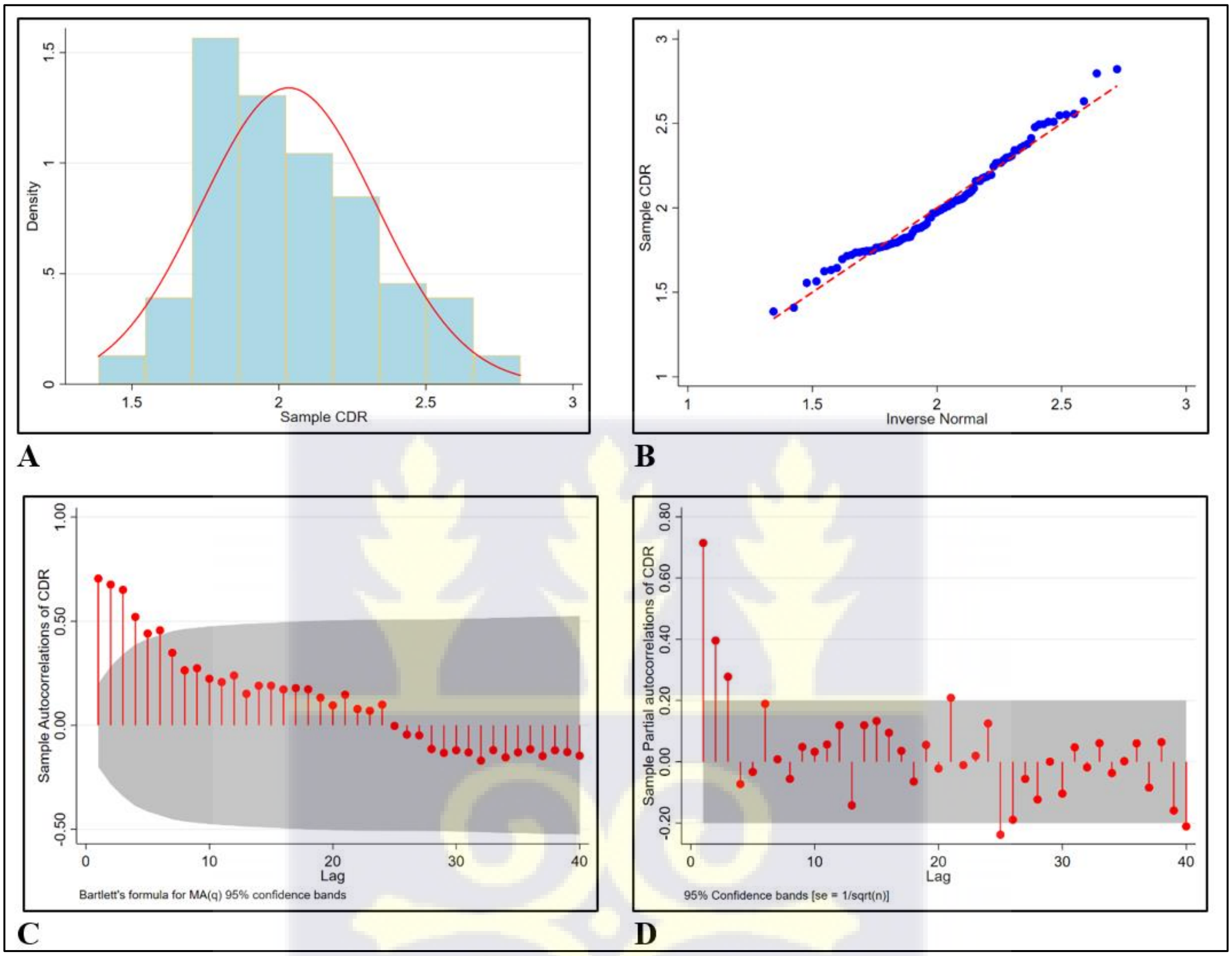

Figure 25 displays the normality and autocorrelation diagnostics of the residuals of the ARIMA model.

The histogram (A) shows the frequency distribution of standardised residuals. B depicts the QQ plots of the residuals from the ARIMA model, with the red dashed line indicating the standard normal distribution. The graphs C and D represent the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals, respectively. The stem plots illustrate the sample ACF and PACF values at various lags, with the grey-shaded portions indicating an interval of ± 2 times the standard deviation.

According to the information presented in Table 14, the ARIMA (1,0,1) model performs better than the other models, specifically ARIMA (1,0,2), ARIMA (1,0,3), ARIMA (3,0,1), ARIMA (3,0,2), and ARIMA (3,0,4), in terms of reliability. The ARIMA (1,0,1) model exhibited the most significant coefficients and the lowest Bayesian Criterion Information (BIC) value compared to other estimates, indicating its superiority. The AIC estimations suggest that the ARIMA (3,0,2) model is the most preferable, followed by the ARIMA (1,0,1) model. The ARIMA (3,0,4) model has the highest AIC value. The ARIMA (1,0,1) model is regarded as the optimal model with the most superior in-sample performance out of the six estimations.

Table 14: Model selection criteria for the sample CDR

Criteria	**Model**						**Best Model**
	Model A	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**	
	ARIMA (1,0,1)	**ARIMA (1,0,2)**	**ARIMA (1,0,3)**	**ARIMA (3,0,1)**	**ARIMA (3,0,2)**	**ARIMA (3,0,4)**	
Most Significant Coefficient (C, AR, MA)	3/3	3/4	3/5	2/5	2/6	6/8	A
SigmaSQ	1.577057	1.565718	1.56535	1.543742	1.527753	1.504304	F
Log-likelihood	-180.6976	-179.9646	-179.9248	-178.659	-177.6924	-178.0149	E
AIC	369.3951	369.9293	371.8496	369.318	369.3848	372.0299	D
BIC	379.6525	382.751	387.2357	384.7041	387.3352	392.5446	A
Best Model							A

Compare Akaike Criterion Information (AIC), lowest Bayesian Criterion Information (BIC) (**Smaller is better**); Maximum likelihood (**Bigger is better**); and SigmaSQ - an estimate of the error variance (**Smaller is better**). MAPE – Mean Absolute Percentage Error; RMSE – Root of Mean Squared Error; AR – Autoregressive; MA – Moving Average
Source: Fieldwork, 2022

4.3.8.2 Prediction of sample CDR

According to the projections in Figure 26, the CDR will be 5.90% in February 2018. This indicates that the CDR in Ghana will decrease from 8.43% in January 2010 to approximately 5.90% by February 2018. The use of electronic medical records may have contributed to the CDR's declining trend (Nsiah-Boateng et al., 2017a).

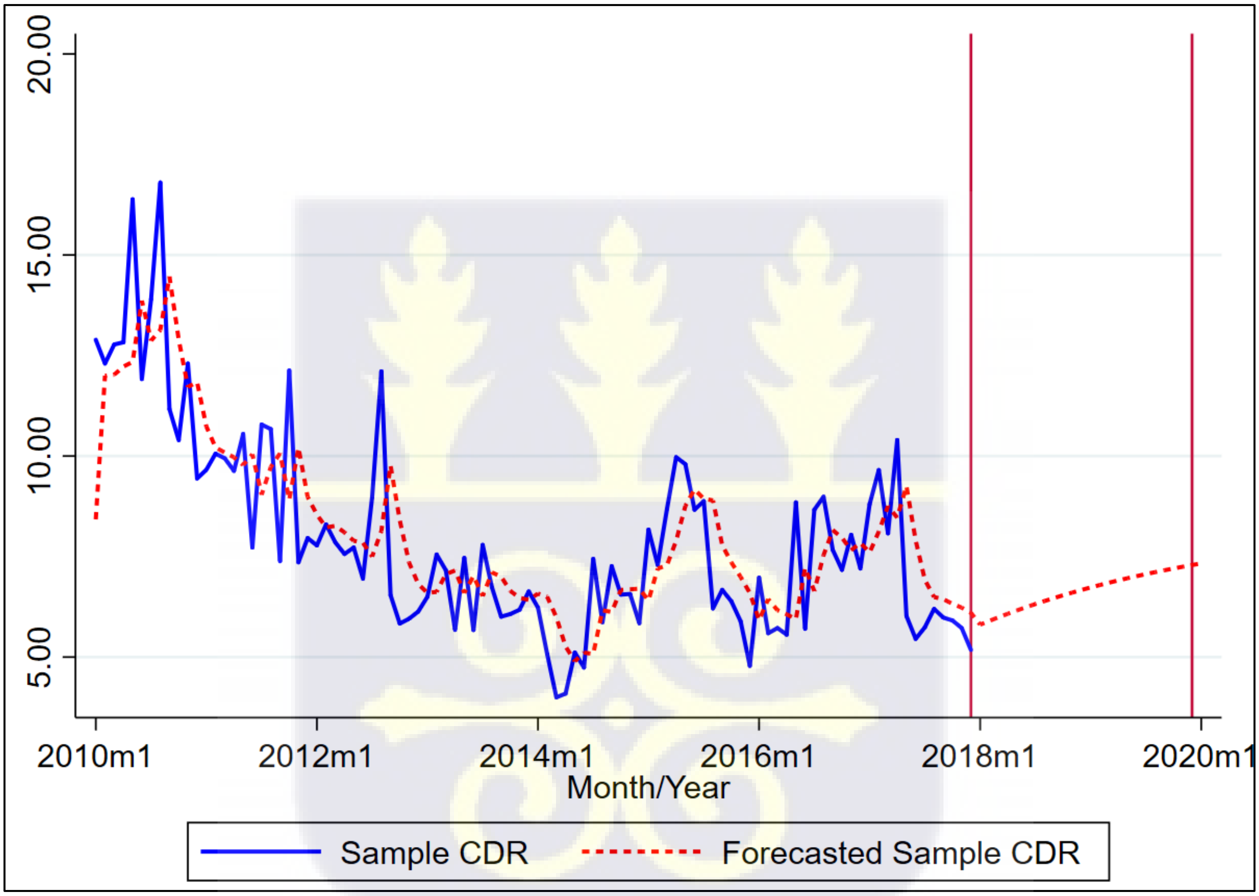

Figure 26 shows the forecast results of ARIMA models from January 2018 to December 2019. The blue line corresponds to the projected timeframe, while the red dashed curves show the forecast outcomes of the ARIMA model. The blue line represents the simulated results of the revised ARIMA model using 70% of the observed data from January 2010 to December 2017.

4.3.8.3 Evaluation of goodness-of-fit of ARIMA (1,0,1) model

The adequacy of the ARIMA model for the sample CDR data can be evaluated by examining the values of MAPE, RMSE, and MAE, as presented in Table 15. The projected sample CDR has a better overall performance, with a MAPE value of 85%, in contrast to the observed sample CDR's 84%.

Table 15: Evaluation of goodness-of-fit of ARIMA (1,0,1) model

	Observed sample CDR	Predicted sample CDR
RMSE	1.62323	1.62323
MAE	1.25466	1.25466
MAPE	0.16106	0.15370
Theil's U	0.89204	2.11409

MAPE – Mean Absolute Percentage Error; RMSE – Root of Mean Squared Error
Source: Fieldwork, 2022

4.4 Reasons accounting for deductions in claims due to errors in health insurance claims

Several reasons have accounted for deductions in claims due to errors. The analysis revealed that among the top 10 reasons were; treatment-to-diagnosis mismatch, Multiple ANC visits, Duplication of Claims, Inappropriate prescription, Oversupply of medication, Wrong application of Tariffs, No diagnosis, Inactive member, Unclear diagnosis and Age treatment mismatch (Table 16).

Table 16: Reasons accounting for deductions in claims due to errors in health insurance claims

		Reasons for claim deductions	
Reasons	Total	Yes n (%)	No n (%)
Treatment to diagnosis mismatch	2,713	2377 (87.62)	336 (12.38)
Multiple ANC visits	2,713	2361 (87.03)	352 (12.97)
Duplication of Claims	2,712	2360 (87.02)	352 (12.98)
Inappropriate prescription	2,713	2358 (86.91)	355 (13.09)
Oversupply of medication	2,713	2351 (86.66)	362 (13.34)
Wrong application of Tariffs	2,713	2338 (86.18)	375 (13.82)
No diagnosis	2,713	2338 (86.18)	375 (13.82)
Inactive member	2,712	2331 (85.95)	381 (14.05)
Unclear diagnosis	2,713	2330 (85.88)	383 (14.12)
Age treatment mismatch	2,712	2329 (85.88)	383 (14.12)
Duplication of Medication	2,711	2304 (84.99)	407 (15.01)
No diagnoses request evidence	2,713	2294 (84.56)	419 (15.44)
Wrong GDRG	2986	1195 (40.02)	1791 (59.98)
Wrong medicine code	2986	1194 (39.99)	1792 (60.01)

Fieldwork, 2022

4.5 To assess the impact of eClaims on Average number of days spent in submitting claims to NHIS in Health Facilities

4.5.1 Performance of Claims Submissions

The overall timely claims submissions based on Ghana's LI 1809 which stipulates a 60-day period for healthcare providers to submit claims to NHIS for reimbursement by healthcare providers was 78.7% out of 3000 monthly claims submitted over the period under consideration (Figure 27). The lowest performance, 22.5% was recorded in HP18. HP22 recorded 100% timely submissions for all the 120 monthly claims observed. More than two-thirds of the healthcare providers achieved at least 75% timely claims submissions (Figure 27).

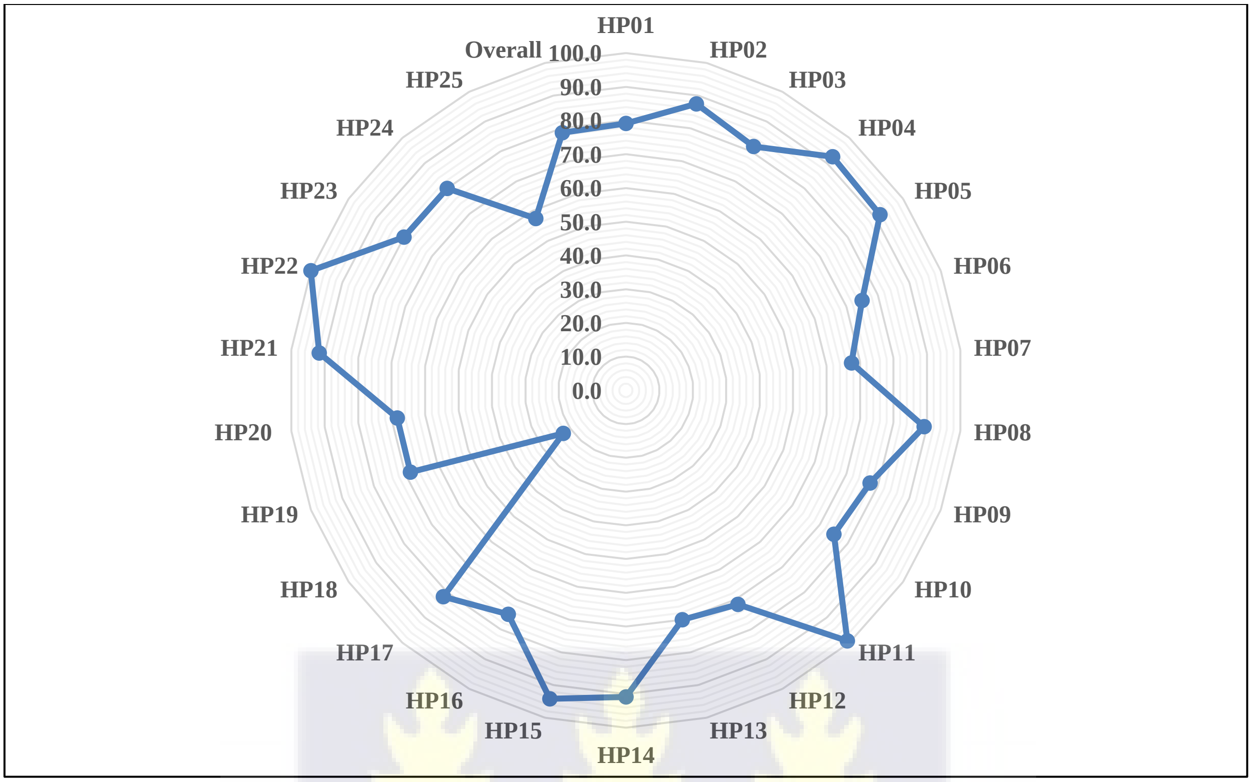

Figure 27: Percentage number of claims submitted on time by healthcare providers (HP) based on Ghana's LI 1809 stipulates a 60-day period for healthcare providers to submit claims to NHIS for reimbursement.
Each healthcare provider submitted a total of 120 monthly claims from January 2010 to December 2019. In all, 3000 monthly claims were submitted by the 25 healthcare providers.
Source: Authors' analysis, 2022.

4.5.2 Differences between Pre-eClaims and Post-eClaims Average number of days spent in submitting claims to NHIS in Health Facilities

Two independent Student's t-tests for two independent samples conducted revealed that average number of days spent in submitting claims in the pre-eClaims (paper-based systems) (56.51 days) was statistically significantly higher than the post-eClaims (electronic systems) (35.11 days) (p<0.0001) (Table 17). The significant reduction in average number of days spent in submitting claims in post-eClaims compared to the pre-eClaims periods was recorded in majority (75%) of health facilities (Table 17). Late claims submission was observed in few health facilities mostly in the pre-eClaims period using Ghana's LI 1809 stipulated 60-day period to healthcare providers to submit claims to NHIS for reimbursement (Figure 28). For the post-eClaims period, late claims submission was recorded in HP17 and HP18 respectively (Figure 28).

Table 17: Differences between Pre-eClaims and Post-eClaims Average number of days spent in submitting claims in healthcare providers

Healthcare Provider	Average number of days spent in submitting claims				*P*-value
	Pre-eClaims		Post-eClaims		
	Mean (se)	[95% CI]	Mean (se)	[95% CI]	
HP01	83.27 (8.11)	[66.98-99.57]	18.62 (0.83)	[16.97-20.27]	<0.0001**
HP02	35.88 (2.83)	[30.18-41.57]	32.49 (2.37)	[27.77-37.20]	0.3625
HP03	44.94 (2.12)	[40.73-49.14]	22.08 (2.32)	[16.98-27.18]	0.0005*
HP04	39.21 (0.79)	[37.57-40.85]	39.96 (1.57)	[36.84-43.08]	0.8137
HP05	36.02 (0.68)	[34.64-37.40]	37.71 (2.06)	[33.60-41.81]	0.536
HP06	54.01 (2.75)	[48.55-59.47]	39.18 (3.57)	[31.77-46.60]	0.0159*
HP07	46.32 (1.93)	[42.48-50.16]	53.50 (5.47)	[42.13-64.87]	0.1393
HP08	54.31 (4.52)	[45.21-63.41]	37.29 (1.59)	[34.12-40.47]	0.0001*
HP09	19.44 (1.47)	[16.42-22.47]	45.55 (2.81)	[39.98-51.12]	<0.0001**
HP10	35.19 (2.16)	[30.84-39.53]	55.46 (2.46)	[50.55-60.37]	<0.0001**
HP11	19.21 (0.75)	[17.70-20.72]	20.74 (0.83)	[19.08-22.39]	0.2006
HP12	108.83 (8.96)	[90.73-126.93]	24.63 (0.99)	[22.66-26.60]	<0.0001**
HP13	45.35 (3.53)	[38.26-52.45]	58.68 (2.85)	[53.00-64.36]	0.0039*
HP14	36.60 (1.55)	[29.48-35.73]	41.00 (2.13)	[36.75-45.25]	0.0046*
HP15	43.36 (2.67)	[38.08-48.64]	17.71 (0.84)	[16.67-19.76]	0.0187*
HP16	60.54 (3.55)	[53.51-67.58]	25.88 (2.31)	[20.41-31.34]	0.0106*
HP17	49.12 (1.80)	[45.56-52.68]	75.67 (6.48)	[61.40-89.93]	<0.0001**
HP18	79.79 (3.95)	[71.95-87.64]	76.38 (2.08)	[72.06-80.69]	0.6698
HP19	107.50 (8.43)	[90.53-124.47]	19.28 (0.83)	[17.62-20.93]	<0.0001**
HP20	109.50 (8.43)	[92.53-126.47]	19.76 (0.87)	[18.03-21.50]	<0.0001**
HP21	48.30 (1.20)	[45.93-50.68]	44.71 (3.93)	[35.09-54.34]	0.4674
HP22	38.56 (1.32)	[35.90-41.22]	26.10 (1.12)	[23.86-28.33]	<0.0001**
HP23	71.88 (4.46)	[62.64-81.11]	27.08 (1.44)	[24.22-29.94]	<0.0001**
HP24	61.81 (3.96)	[53.77-69.84]	25.27 (1.45)	[22.38-28.17]	<0.0001**
HP25	102.45 (11.78)	[78.87-126.03]	45.48 (5.85)	[33.78-57.18]	<0.0001**
Overall	56.51 (1.04)	[54.47-58.56]	35.11 (0.60)	[33.93-36.29]	<0.0001**

Note: Student's t-test was used to test differences between Pre-eClaims and Post-eClaims Average number of days spent in submitting claims
*p<0.05 and **p<0.0001 are considered statistically significant. se – Standard Error
CI – Confidence Interval
Source: Fieldwork, 2022

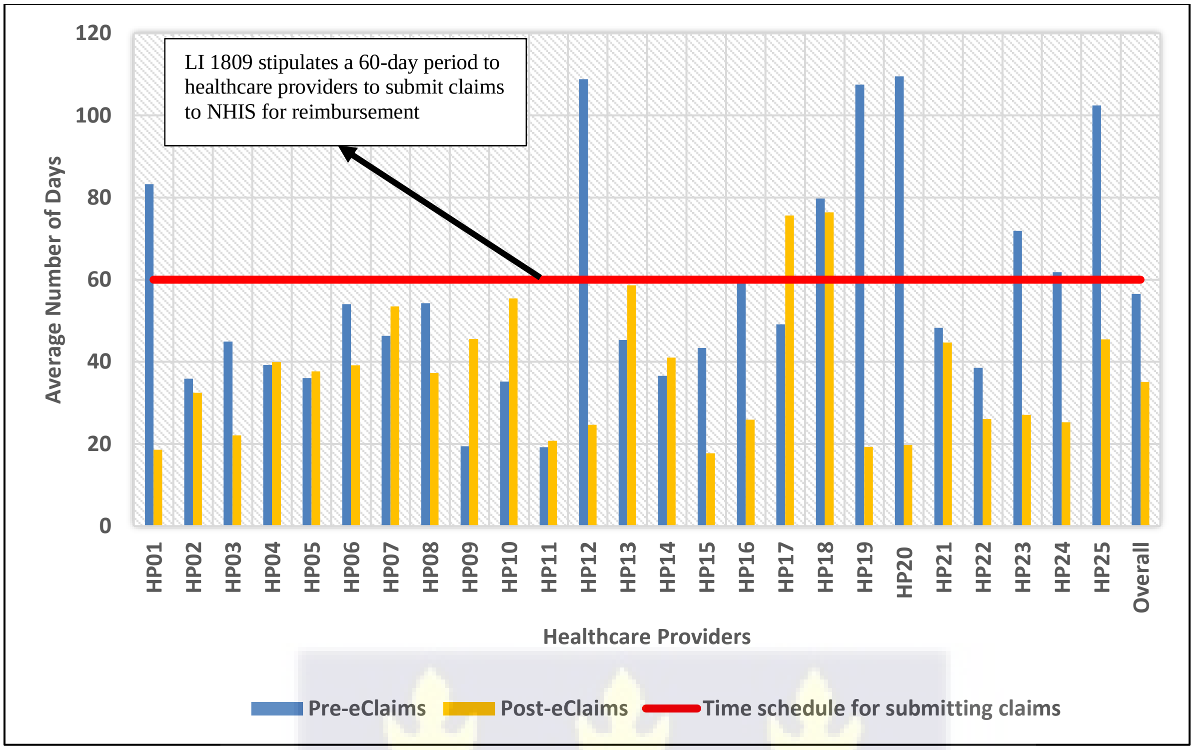

Figure 28: Average number of days spent by healthcare providers (HP) in submitting claims to NHIS for reimbursement for pre- and post-eClaims system.
Source: Authors' analysis, 2022.

4.5.3 Estimates for the Introduction of eClaims Effects on Average Number of Days Spent Submitting Claims and 95% Confidence Intervals Obtained Using Single-Group Interrupted Time Series Analysis

The segmented regression for the outcome variable of the average number of days spent in submitting claims in health facilities revealed that the baseline average number of days spent in submitting claims in these individual health facilities ranges from 14.74 days to 163.14 days (Table 18). The lowest baseline average number of days spent in submitting claims was observed at HP02 whilst the highest was recorded by HP20 (Table 18). However, 16 health facilities observed a reduction in monthly changes in the average number of days spent in submitting claims prior to the introduction of eClaims. These reductions range from 0.01 days to 2.23 days. Furthermore, these reductions were however statistically significant in 8 health facilities namely; HP01, HP20, HP19, HP12, HP25, HP24, HP16 and HP06 (Table 18). However, 9 health facilities observed increases ranging from 0.03 days to 0.86 days in the average number of days spent in submitting claims in monthly changes in the average number of days spent in submitting claims before the introduction of eClaims (Table 18). In the first month after the introduction of eClaims, 20 health facilities observed a reduction ranging from 0.04 day to 47.28 days in the average number of days spent submitting claims. Furthermore, these reductions were however statistically significant in 9 health facilities (i.e. HP25, HP12, HP23, HP20, HP19, HP07, HP15, HP03 and HP22) (Table 16). The highest statistically significant reduction in the average number of days spent submitting claims in the first month after the introduction of eClaims was observed at HP25 (Table 18). The analysis further revealed that 7 health facilities observed a reduction in the average number of days spent in submitting claims in the difference between pre-eClaims and post-eClaims slopes period (I. e HP21, HP15, HP02, HP22, HP04, HP23, and HP05) (Table 18). These reductions in the average number of days spent in submitting claims in the difference between pre-eClaims and post-eClaims slopes period were statistically significant in only three health facilities namely; HP15, HP02 and HP22 respectively (Table 18). Increases in the average number of days spent in submitting claims in the difference between pre-eClaims and post-eClaims slopes period were observed in 18 health facilities ranging from 0.02 days to 3.77 days. These increases were statistically significant in 9 health facilities (i.e. HP24, HP12, HP19, HP20, HP01, HP11, HP06. HP25 and HP07) (Table 18).

Table 18: Estimates for the Introduction of eClaims Effects on Average Number of days spent submitting Claims and 95% CIs Obtained Using Single-Group Interrupted Time Series Analysis

				Slope prior to intervention					Change in level in the period immediately following intervention initiation (compared with counterfactual)					Difference between preintervention and postintervention slopes				
ID	Hosp_Code	Region	Intercept (Baseline level) β_0	β_1	Robust SE	*P*-value	[95% CI] LCI	UCI	β_2	Robust SE	*P*-value	[95% CI] LCI	UCI	β_3	Robust SE	*P*-value	[95% CI] LCI	UCI
1	HP01	Eastern	140.49	-2.30	0.49	0.000	-3.27	-1.33	-3.01	10.96	0.784	-24.71	18.69	2.25	0.49	0.000	1.27	3.23
2	HP02	Eastern	14.74	0.86	0.27	0.002	0.33	1.40	-1.66	11.42	0.885	-24.27	20.96	-1.46	0.31	0.000	-2.07	-0.86
3	HP03	Central	50.53	-0.11	0.07	0.154	-0.25	0.04	-18.24	6.51	0.006	-31.15	-5.34	0.35	0.61	0.574	-0.87	1.56
4	HP04	Central	36.10	0.25	0.27	0.356	-0.28	0.77	-1.81	3.26	0.579	-8.27	4.64	-0.25	0.28	0.374	-0.81	0.31
5	HP05	Volta	35.38	0.03	0.03	0.369	-0.03	0.09	1.80	3.32	0.590	-4.78	8.37	-0.05	0.10	0.632	-0.25	0.15
6	HP06	Ashanti	73.57	-0.40	0.12	0.001	-0.63	-0.18	-12.04	6.09	0.050	-24.10	0.02	2.02	0.44	0.000	1.15	2.88
7	HP07	Volta	40.47	0.12	0.07	0.108	-0.03	0.26	-24.03	7.34	0.001	-38.56	-9.50	2.32	0.68	0.001	0.98	3.66
8	HP08	Western	67.32	-0.58	0.34	0.090	-1.25	0.09	-0.80	9.60	0.934	-19.82	18.22	0.53	0.39	0.182	-0.25	1.31
9	HP09	Eastern	20.60	-0.15	0.46	0.738	-1.06	0.76	-4.47	7.71	0.564	-19.74	10.81	0.89	0.52	0.088	-0.14	1.91
10	HP10	Eastern	36.08	-0.03	0.17	0.871	-0.37	0.31	12.61	7.49	0.095	-2.22	27.44	0.24	0.33	0.472	-0.42	0.89
11	HP11	Bono East	21.20	-0.08	0.05	0.069	-0.18	0.01	-1.06	2.33	0.649	-5.67	3.54	0.22	0.07	0.003	0.08	0.35
12	HP12	Bono East	149.36	-2.03	0.79	0.011	-3.60	-0.47	-37.57	16.95	0.029	-71.15	-3.99	1.94	0.79	0.016	0.36	3.51
13	HP13	Volta	41.92	0.14	0.44	0.747	-0.72	1.01	-0.04	9.87	0.997	-19.59	19.51	0.18	0.65	0.789	-1.12	1.47
14	HP14	Bono	34.52	-0.14	0.20	0.471	-0.53	0.25	9.63	5.30	0.072	-0.87	20.13	0.27	0.36	0.453	-0.44	0.97
15	HP15	Western	34.48	0.15	0.16	0.347	-0.17	0.48	-19.37	8.62	0.027	-36.45	-2.29	-3.18	1.35	0.020	-5.86	-0.50
16	HP16	Western	93.90	-0.62	0.16	0.000	-0.93	-0.30	5.85	3.48	0.095	-1.03	12.74	0.02	1.99	0.993	-3.93	3.97
17	HP17	Volta	50.43	-0.02	0.10	0.872	-0.22	0.19	19.28	13.50	0.156	-7.45	46.02	0.26	1.85	0.890	-3.42	3.93
18	HP18	Upper West	77.22	0.05	0.09	0.536	-0.12	0.23	-8.77	7.53	0.246	-23.68	6.14	0.19	0.20	0.361	-0.22	0.59
19	HP19	Oti	161.06	-2.29	0.57	0.000	-3.41	-1.17	-28.47	12.84	0.029	-53.91	-3.03	2.19	0.57	0.000	1.07	3.32
20	HP20	Savannah	163.14	-2.29	0.56	0.000	-3.40	-1.18	-31.10	12.76	0.016	-56.37	-5.83	2.23	0.56	0.000	1.11	3.35
21	HP21	Ahafo	41.51	0.12	0.10	0.208	-0.07	0.32	-0.59	3.41	0.864	-7.34	6.17	-3.71	2.82	0.190	-9.29	1.87
22	HP22	Ashanti	32.34	0.25	0.13	0.060	-0.01	0.52	-10.76	4.29	0.013	-19.24	-2.27	-0.47	0.15	0.002	-0.76	-0.17
23	HP23	Bono	72.39	-0.01	0.82	0.986	-1.65	1.62	-36.21	13.96	0.011	-63.86	-8.56	-0.17	0.83	0.836	-1.82	1.48
24	HP24	Oti	82.54	-1.21	0.33	0.000	-1.86	-0.55	-8.40	8.25	0.311	-24.75	7.94	1.08	0.34	0.002	0.40	1.76
25	HP25	Bono East	161.95	-2.02	0.62	0.001	-3.23	-0.80	-47.28	23.86	0.050	-94.53	-0.03	3.77	0.68	0.000	2.42	5.12

*$p<0.05$ and **$p<0.001$ are considered statistically significant
L/UCI – Lower/Upper Confidence Internal; SE – Standard Error
Source: Fieldwork, 2022

4.5.4 Meta-analysis pooling of aggregate data on Average number of days spent in submitting claims using the Random Effects

The pooled effect analysis of the average number of days spent in submitting claims in all 25 health facilities has been presented in Table 19. The segmented regression for the outcome variable of the average number of days spent in submitting claims in health facilities revealed that the baseline average number of days spent in submitting claims in these health facilities was 58.83 days. However, monthly changes in the average number of days spent submitting claims before the introduction of eClaims were reduced by 0.16 days with a confidence interval of [-0.29 - -0.033] and were statistically significant (Table 19). In the first month after the introduction of eClaims, a further reduction of 5.84 days was observed in the average number of days spent submitting claims in the 25 health facilities and was statistically significant (p=0.0071; and CI= [-10.09 - -1.59]). The difference between pre-eClaims and post-eClaims slopes observed an increase of 0.62 days in average number of days spent in submitting claims and was statistically significant (p=0.0004; and CI= [0.28 - 0.96]) (Table 19). In the analysis involving the 25 health facilities, the between study sites heterogeneity ranged from moderate, $I^2 \geq 50\%$ to high, $I^2 \geq 50\%$. The pooled meta-analysis produced the most precise estimate for Slope before the introduction of eClaims (Table 19), Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual) (Table 19) and Difference between pre-eClaims and post-eClaims slopes (Table 19) with corresponding significantly smaller confidence intervals (Table 19). However, it was observed that where there was substantial within study sites variability and high between-study-sites heterogeneity for post-eClaims linear trend, $I^2 \geq 75\%$, the pooled estimate goes with a wider confidence interval which was not significant (Table 19).

Table 19: Meta-analysis pooling of aggregate data on Average number of days spent in submitting claims using the Random Effects

Trends	N	Overall Effect Size	Standard Error of Effect Size	[95% CI]	*P*-value	Homogeneity Tests			
						Cochran's Q Value	df (Q)	*P*-value	I-squared (%)
Intercept (Baseline level)	25	58.83	4.04	[50.90 - 66.75]	<0.0001***	724.79	24	<0.001**	96.7
Slope prior to the introduction of eClaims	25	-0.16	0.07	[-0.29 - -0.033]	0.0143*	138.84	24	<0.001**	82.7
Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual)	25	-5.84	2.17	[-10.09 - -1.59]	0.0071*	67.19	24	<0.001**	64.3
Difference between pre-eClaims and post-eClaims slopes	25	0.62	0.17	[0.28 - 0.96]	0.0004*	173.34	24	<0.001**	86.2

*p<0.05, **p<0.001 and ***p<0.0001 are considered statistically significant

I^2 = Proportion of total variation in effect estimate due to between-study heterogeneity (based on Q)

df - Degrees of freedom

N - Number of Hospitals

Fieldwork, 2022

4.5.4.1 Assessing the immediate impact of HIS implementation on Average number of days spent in submitting health insurance claims

The pooled effect analysis of the average number of days spent in submitting claims in all 25 health facilities has been presented in Figure 29. In the first month after the introduction of eClaims, a reduction of 5.84 days was observed in the average number of days spent in submitting claims in the 25 health facilities and was statistically significant (p=0.0071; and 95%CI= [-10.09 - -1.59]) (Table 19). Further observation showed that 20 health facilities saw a reduction ranging from 0.04 days to 47.28 days in the average number of days spent submitting claims. These reductions were however statistically significant in 9 health facilities (i.e. HP25, HP12, HP23, HP20, HP19, HP07, HP15, HP03 and HP22) (Figure 29). The highest statistically significant reduction in the average number of days spent submitting claims in the first month after the introduction of eClaims was observed at HP25 (Figure 29). The analysis further revealed that 7 health facilities observed a reduction in the average number of days spent in submitting claims in the difference between pre-eClaims and post-eClaims slopes period (I. e HP21, HP15, HP02, HP22, HP04, HP23, and HP05) (Figure 29). These reductions in the average number of days spent in submitting claims in the difference between pre-eClaims and post-eClaims slopes period were statistically significant in only three health facilities namely; HP15, HP02 and HP22 respectively (Figure 29).

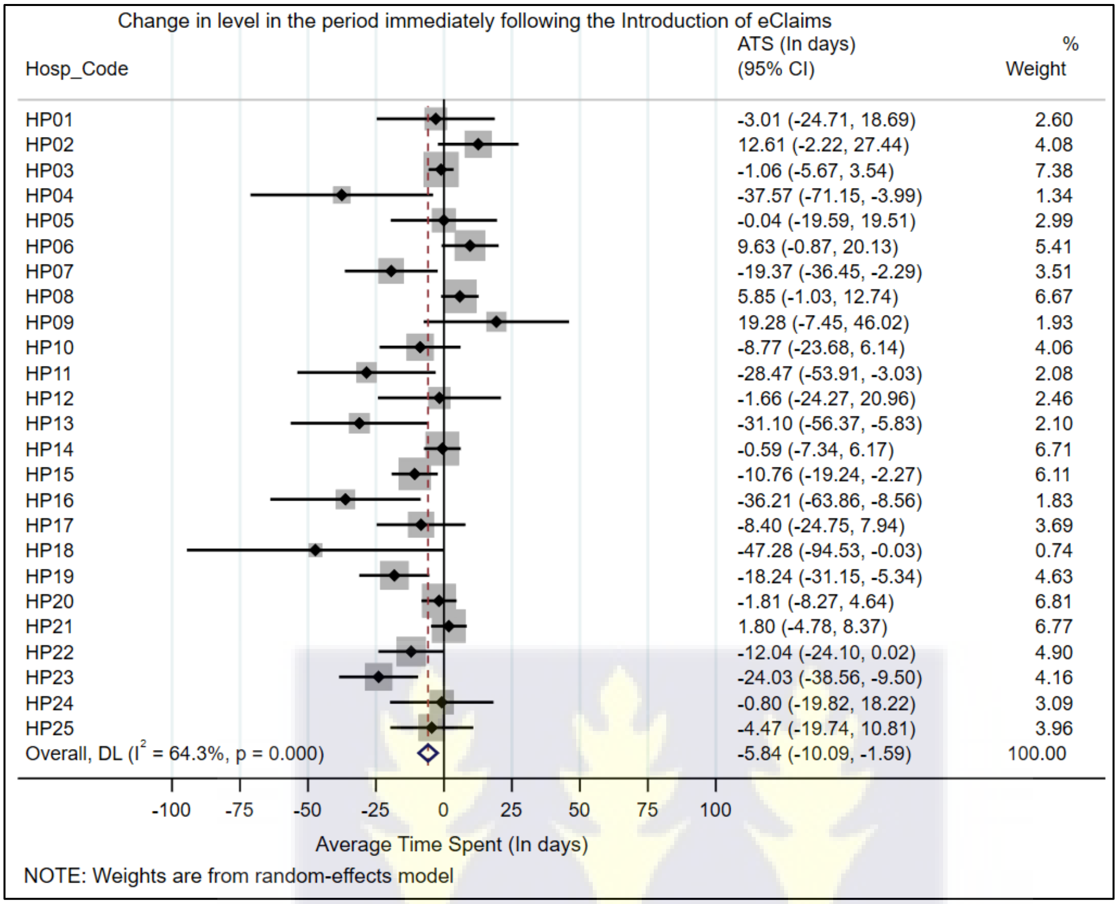

Figure 29: Forest plot for Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual) on Average number of days spent in submitting claims
ATS – Average Time Spent (In days); Hosp_Code – Hospital Code
Fieldwork, 2022

4.5.4.2 Assessing the sustained impact of HIS implementation on Average number of days spent in submitting health insurance claims

The difference between pre-eClaims and post-eClaims slopes observed an increase of 0.62 days in average number of days spent in submitting claims and was statistically significant (p=0.0004; and 95%CI= [0.28 - 0.96]) (Table 19). The analysis also revealed a sustained reduction in average number of days spent in submitting claims in 7 health facilities (I. e PH02, PH04, PH05, HP15, HP21, PH22 and PH23) (Figure 30). These reductions were statistically significant in only three health facilities namely; HP15, HP02 and HP22 respectively (Figure 30).

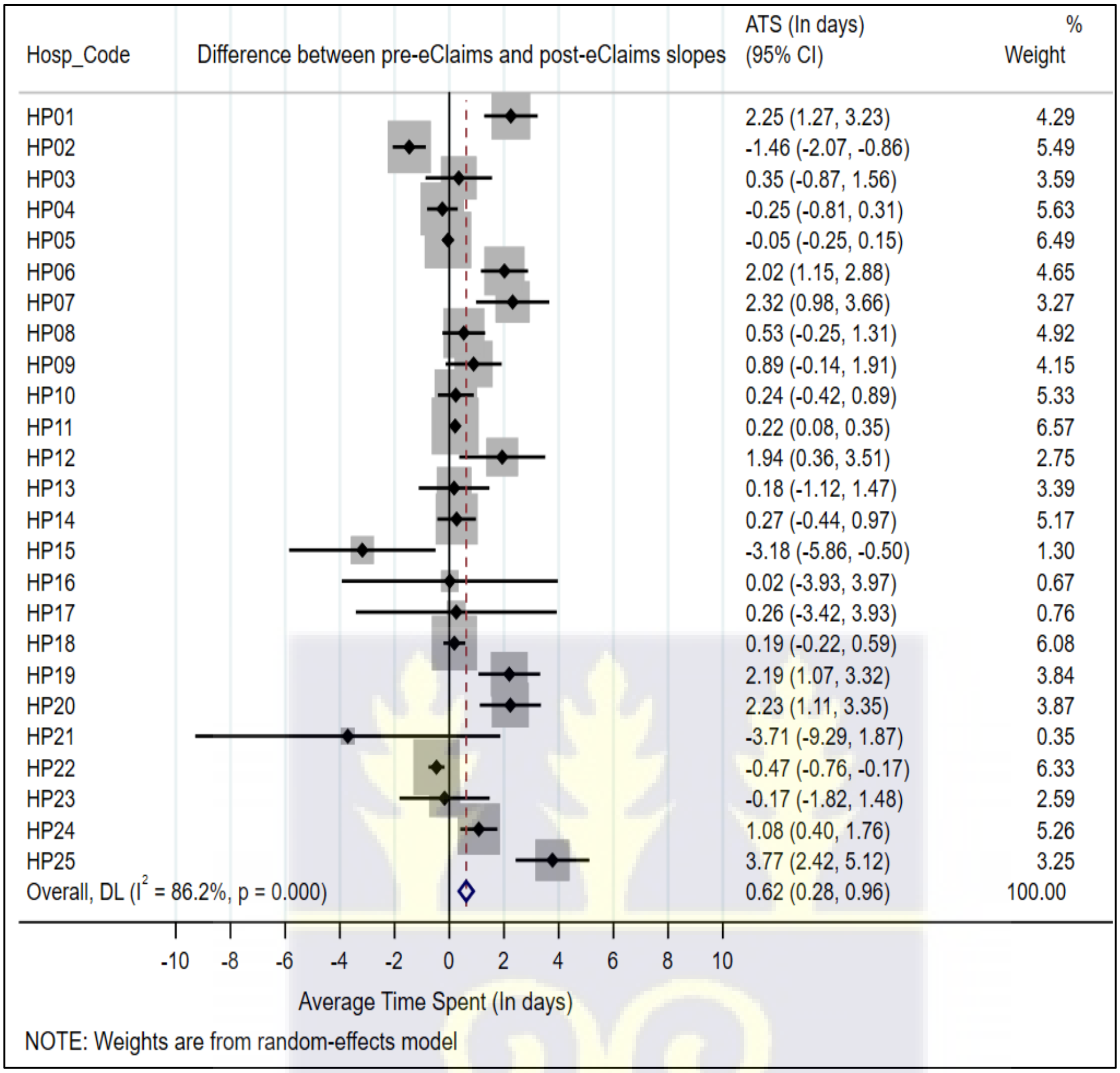

Figure 30: Forest plot for Difference between pre-eClaims and post-eClaims slopes on Average number of days spent in submitting claims
ATS – Average Time Spent (In days); Hosp_Code – Hospital Code
Fieldwork, 2022

4.5.5 Meta-analysis pooling of aggregate data on Average number of days spent in submitting claims using the Random Effects stratified by Ecological zones

The pooled effect analysis of the average number of days spent in submitting health insurance claims for slope before the introduction of eClaims in all the 25 health facilities stratified by regions has been presented in (Table 20). The segmented regression for the outcome variable of the average number of days spent in submitting health insurance claims in health facilities was statistically significantly high in Savannah (effect size=118.39; p=0.0058 and 95%CI= [34.27 - 202.52]), Forest (effect size=54.93; p<0.0001 and 95%CI= [42.28 - 67.58]) and Coastal (effect size=55.54; p=<0.0001 and 95%CI= [45.52 - 65.56]) zones in Ghana (Table 20). The segmented regression for the outcome variable of average number of days spent in submitting health insurance claims in health facilities revealed that the monthly changes in average number of days spent in submitting health insurance claims before the introduction of eClaims reduced by 0.07 to 0.81 days across the three ecological zones (Table 20). The highest reduction in the average number of days spent in submitting health insurance claims was observed in the Savannah zone (effect size=-0.81; p=0.4703 and 95%CI= [-3.03 - 1.40]) whilst the lowest was observed in the Forest zone (effect size=-0.07; p=0.3794 and 95%CI= [-0.24 - 0.09]) (Table 20). The analysis involving the 25 health facilities across the regions observed that there was high within-study-site variability and between-study-sites heterogeneity ($I^2 \geq 75\%$) for the three ecological zones (Table 20).

Table 20: Meta-analysis pooling of aggregate data on the Average number of days spent in submitting claims using the Random Effects stratified by Ecological zones

Ecological Zones	Trends	N	Overall Effect Size	Standard Error of Effect Size	[95% CI]	*P*-value	Homogeneity Tests			
							Cochran's Q Value	df (Q)	P-value	I-squared (%)
Savannah	Intercept (Baseline level)	2	118.39	42.92	[34.27 - 202.52]	0.0058*	20.39	1	<0.0001**	95.10
	Slope prior to the introduction of eClaims	2	-0.81	1.13	[-3.03 - 1.40]	0.4703	11.14	1	0.0010*	91.00
	Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual)	2	-18.28	21.85	[-61.11 - 24.55]	0.4029	3.49	1	0.0620	71.40
	Difference between pre-eClaims and post-eClaims slopes	2	1.14	1.02	[-0.86 - 3.14]	0.2642	11.41	1	0.0010*	91.20
Forest	Intercept (Baseline level)	12	54.93	6.46	[42.28 - 67.58]	<0.0001**	241.83	11	<0.0001**	95.50
	Slope prior to the introduction of eClaims	12	-0.07	0.09	[-0.24 - 0.09]	0.3794	65.37	11	<0.0001**	83.20
	Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual)	12	-2.78	3.19	[-9.02 - 3.47]	0.3836	28.7	11	0.0030*	61.70
	Difference between pre-eClaims and post-eClaims slopes	12	0.67	0.29	[0.10 - 1.25]	0.0223*	117.52	11	<0.0001**	90.60

Coastal	Intercept (Baseline level)	11	55.54	5.11	[45.52 - 65.56]	<0.0001**	120.44	10	<0.0001**	91.70
	Slope prior to the introduction of eClaims	11	-0.31	0.12	[-0.55 - -0.07]	0.0122*	53.66	10	0.0660	81.40
	Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual)	11	-9.92	3.65	[-17.08 - -2.77]	0.0066*	33.67	10	<0.0001**	70.30
	Difference between pre-eClaims and post-eClaims slopes	11	0.52	0.29	[-0.05 - 1.09]	0.0715	42.40	10	0.2540	76.40

*p<0.05 and **p<0.0001 are considered statistically significant

I^2 = Proportion of total variation in effect estimate due to between-study heterogeneity (based on Q)

df - Degrees of freedom

N - Number of Hospitals

Fieldwork, 2022

4.5.5.1 Assessing the immediate impact of HIS implementation on Average number of days spent in submitting health insurance claims stratified by Ecological zones

The pooled effect analysis of the average number of days spent in submitting health insurance claims for Change in level in the period immediately following the introduction of eClaims (compared with counterfactual) in all the 25 health facilities stratified by Ecological zones has been presented in Table 20. The segmented regression for the outcome variable of the average number of days spent in submitting health insurance claims in health facilities revealed that Change in level in the period immediately following the introduction of eClaims (compared with counterfactual) reduced in all three Ecological zones (Figure 31). The reduction observed in Savannah zone was 18.28 days in average number of days spent in submitting health insurance claims. Forest zone also reduced by 2.78 days in the average number of days spent in submitting health insurance claims. The reductions in Savannah and Forest zones were not statistically significant (Figure 31). The coastal zone saw a statistically significant reduction of 9.92 days in average number of days spent submitting health insurance claims (Figure 31). The highest pooled effect reduction in average number of days spent in submitting health insurance claims was recorded in Savannah zone whilst the least was observed in Forest zone (Figure 31). 100% of all the health facilities (HP18 and HP20) in the Savannah zone observed a reduction in average number of days spent in submitting health insurance claims (Figure 31). In the Forest zone it was observed that 75% (9 out of 12) of health facilities (HP03, HP04, HP05, HP07, HP08, HP13, HP15, HP16, HP17, HP19 and HP24) recorded a reduction in average number of days spent in submitting health insurance claims. In the Coastal zone it was observed that 91% (10 out of 11) of health facilities (HP01, HP10, HP11, HP12, HP14, HP21, HP22, HP23 and HP25) also recorded a reduction in average number of days spent in submitting health insurance claims (Figure 31).

The analysis involving the 25 health facilities across the three ecological zones observed that, there was moderate within study sites variability and between study sites heterogeneity ($I^2 \geq 50\%$) for Savannah, Forest and Coastal zones respectively (Figure 31).

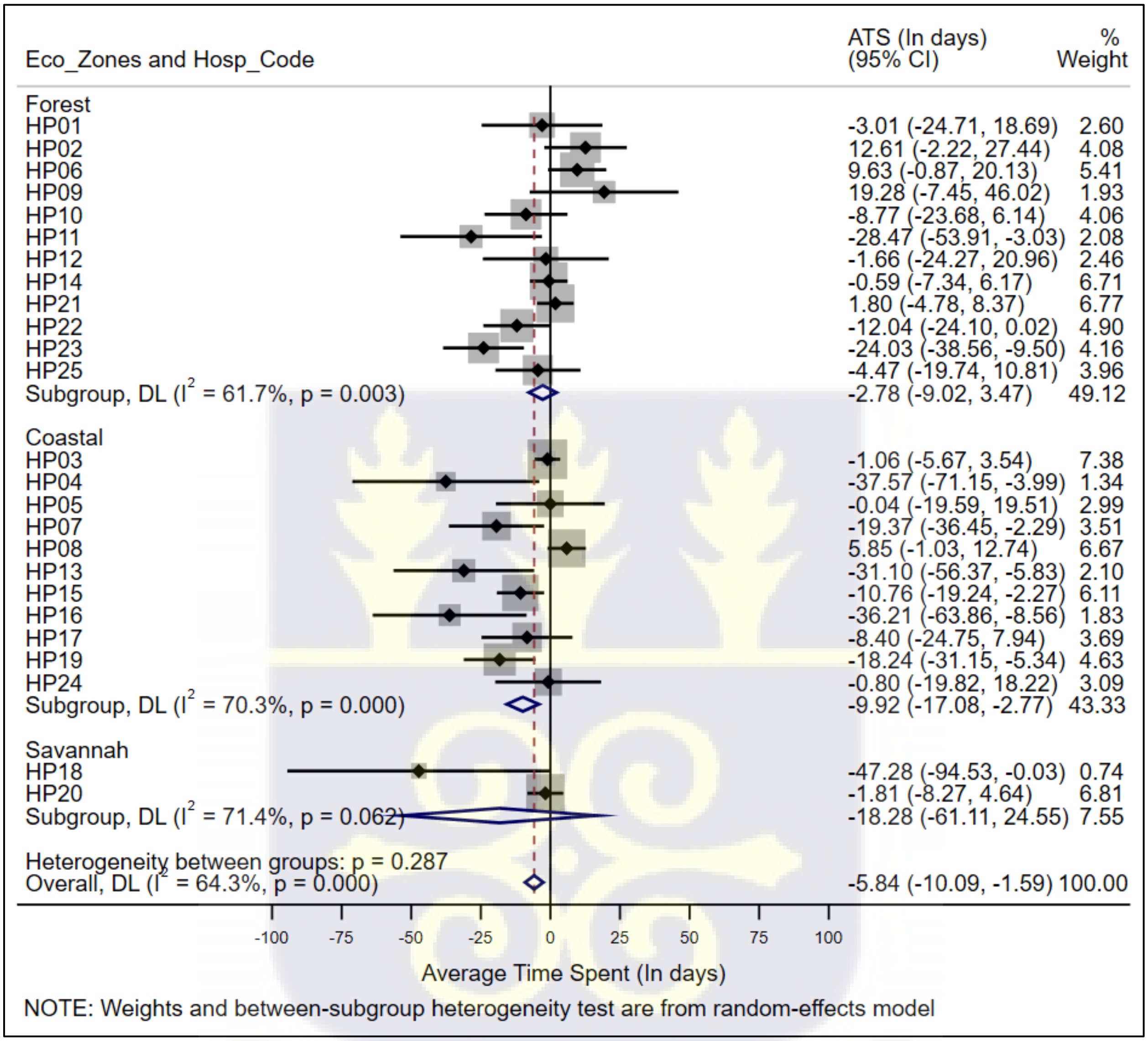

Figure 31: Forest plot for Change in level in the period immediately following the Introduction of eClaims (compared with counterfactual) on Average number of days spent in submitting claims stratified by regions

ATS – Average Time Spent (In days); Eco_zones – Ecological zones; Hosp_Code – Hospital Code

Fieldwork, 2022

4.5.5.2 Assessing the sustained impact of HIS implementation on Average number of days spent in submitting health insurance claims

The pooled effect analysis of average number of days spent in submitting health insurance claims for Difference between pre-eClaims and post-eClaims slopes in all the 25 health facilities stratified by regions have been presented in Table 20. The segmented regression for the outcome variable of the average number of days spent in submitting health insurance claims in health facilities revealed that the Difference between pre-eClaims and post-eClaims slopes increased by 0.52 to 1.14 days across the three ecological zones in Ghana (i.e. Savannah, Forest and Coastal zones) with the highest increase in Savannah zone (effect size=1.14; p=0.2642 and 95%CI=[-0.86 - 3.14]) and the lowest in Coastal zone (effect size=0.52; p=0.0715 and 95%CI=[-0.05 - 1.09]). These reductions were however not statistically significant. (Table 20). The increase observed in the Forest zone was however statically significant (effect size=0.67; p=0.0223 and 95%CI= [0.10 - 1.25]) (Table 20). 100% of all the health facilities (HP18 and HP20) in the Savannah zone observed an increase in the average number of days spent submitting health insurance claims (Figure 32). However, it was observed in the Forest zone that, 33% (4 out of 12) of health facilities (HP02, HP21, HP22 and HP23) recorded a reduction in the average number of days spent submitting health insurance claims (Figure 32). In the Coastal zone, it was observed that 27% (3 out of 11) of health facilities (HP04, HP05 and HP15) also recorded a reduction in the average number of days spent submitting health insurance claims (Figure 32). The analysis involving the 25 health facilities across the regions, the between study sites heterogeneity were high, $I^2 \geq 75\%$ for Savannah, Forest and Coastal zones respectively (Table 18; Figure 32).

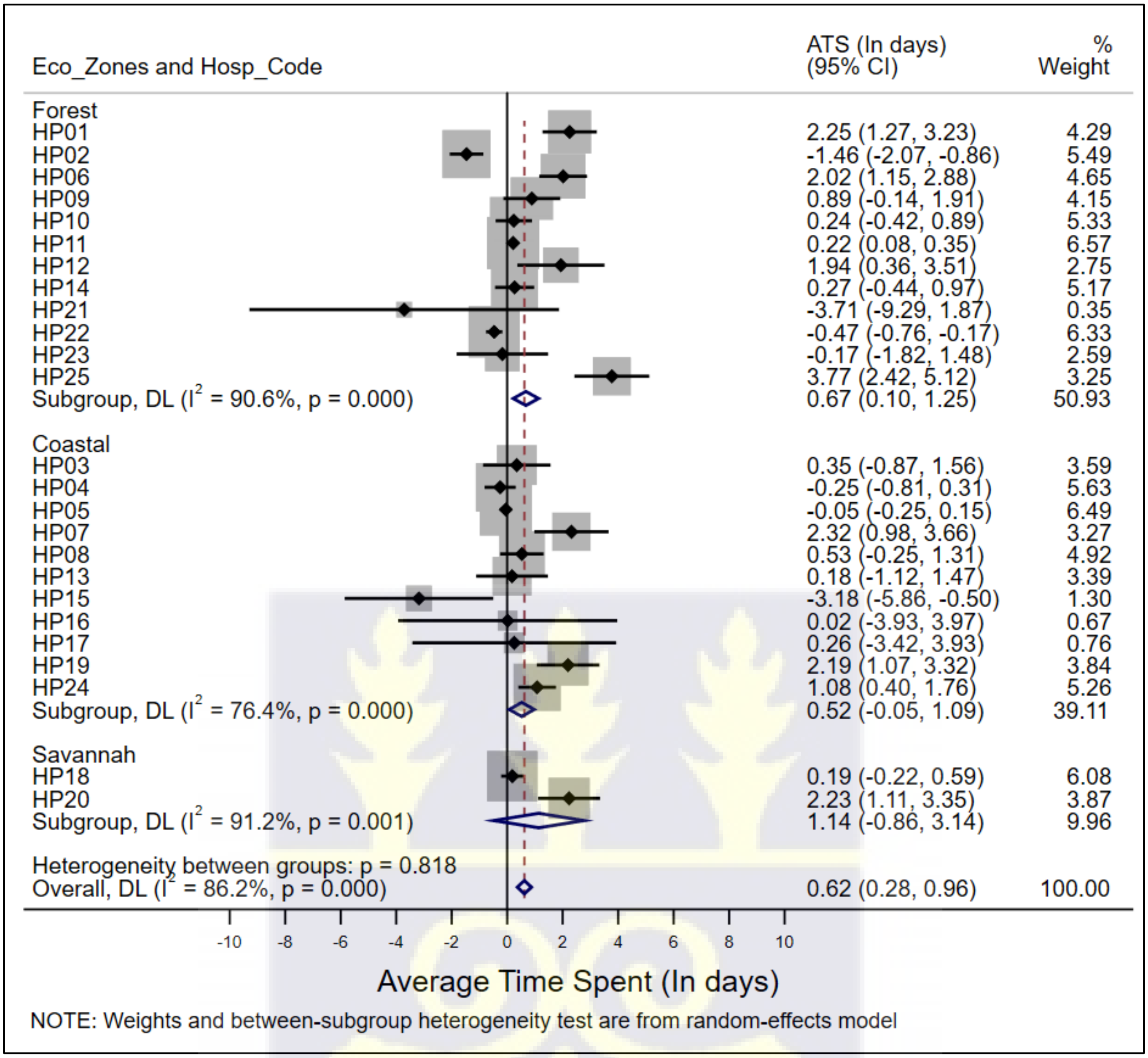

Figure 32: Forest plot for Difference between pre-eClaims and post-eClaims slopes on Average number of days spent in submitting claims stratified by regions

ATS – Average Time Spent (In days); Eco_zones – Ecological zones; Hosp_Code – Hospital Code

Fieldwork, 2022

4.6 Efficiency of Hospital Information Systems

4.6.1 Background characteristics

In this study, 1416 target healthcare professionals out of 1738 in 25 NCHS hospitals using hospital information system (HIS) were interviewed representing an 81% response rate. Table 19 shows the results of demographic characteristics of respondents. More than 50% of respondents came from the nursing department. The majority 729 (51.48%) of the respondents were males. More than 77% are within the age bracket 30-44 years. Over 90% had acquired tertiary education. Only 8% of the users do not have a university degree. The majority 1232 (87%) of the users had over 6 years of HIS experience. The majority 600 (42%) of the users also Working hours spent 2 – 3 hours a day using HIS for-service provision. Only 4 (0.3%) of users spent less than 30 minutes using HIS for-service provision (Table 21).

Table 21: Background characteristics of all users from the 25 healthcare facilities

Users' characteristics	Frequency	Percentage
Age-group		
Below 30	130	9.18
30-44	1,100	77.68
45 plus	186	13.14
Gender		
Male	729	51.48
Female	687	48.52
Level of education		
SHS	120	8.47
Diploma	906	63.98
Degree	307	21.68
Masters or Higher	83	5.86
Work experience		
Below 1 year	0	0
1-5 years	177	12.5
6-10 years	528	37.29
More than 10 years	711	50.21
HIS usage experience		
Below 1 year	5	0.35
1-5 years	94	6.64
6-10 years	1232	87.01
More than 10 years	85	6
Working hours spent on using HIS for-service provision by HP		
Less than 30 minutes	4	0.28
Between 30 minutes and 1 hour	24	1.69
Between 1 and 2 hours	298	21.05
Between 2 and 3 hours	600	42.37
Between 3 and 4 hours	108	7.63
More than 4 hours	382	26.98
Department		
Nursing	748	52.82
Physicians/Doctors	122	8.62
Dispensary	114	8.05
Medical Laboratory	140	9.89
Accounts/Claims	168	11.86
Health Information	124	8.76

Data is presented as numbers and percentages. HP – Healthcare Providers; HIS – Hospital Information System

Source: Fieldwork, 2022

4.6.2 Hospital Information System (HIS) Efficiency Rate

Table 22 presents an analysis of the mean HIS efficiency Rate for all dimensions used for E-ISSM and U-DM models for the assessment. The analysis shows that System use, Service quality and System quality recorded the highest mean HIS efficiency rate of 80% and more for the E-ISSM model whilst System quality, Information quality, User satisfaction, System use and Potential net benefits obtained the highest score of 80% and above for the U-DM model. Only Service quality recorded a score of less than 80% using the U-DM model. In the case of the E-ISSM model, Information quality and User satisfaction had scores less than 80%.

Further analysis for E-ISSM model shows that there is statistically significant mean variation in System use HIS efficiency rate among professional categories; Nursing (85%, 95%CI [84 - 87]); Physicians (80%, 95%CI [77 - 84]); Dispensary staff (86%, 95%CI [83 - 89]); Medical laboratory staff (87%, 95%CI [83 - 91]); Accounts/Claims officers (86%, 95%CI [82 - 90]) and Health Information Officers (91%, 95%CI [87 - 94]) with (p-value=0.0147) (Table 22). The U-DM model analysis revealed that there is a statistically significant mean variation in System use (p-value=0.0159) and Perceived net benefits (p-value=0.0002) HIS efficiency rate among professional categories. The total HIS efficiency rate for the professional categories were ranging from 80% to 85% for respective the E-ISSM and U-DM models respectively (Table 22). Further analysis of the U-DM model shows a statistically significant mean variation in the total HIS efficiency rate for the professional categories (p-value=0.0040) with the highest HIS efficiency rate coming from the health Information cadre group (85%, 95%CI [84 - 87]) (Table 22).

Table 22: Mean HIS Efficiency Rate of dimensions stratified by profession

Dimensions	Mean % [95%CI]							
	All users	Nursing	Physicians/ Doctors	Dispensary	Medical Laboratory	Accounts/ Claims	Health Information	F-value; p-value
E-ISSM model								
System Quality	80 [79 - 80]	80 [79 - 81]	79 [76 - 81]	80 [77 - 82]	80 [78 - 82]	81 [79 - 83]	79 [75 - 80]	1.05; 0.3886
Information Quality	78 [77 - 79]	79 [78 - 79]	78 [76 - 80]	78 [76 - 80]	77 [76 - 80]	80 [78 - 82]	78 [76 - 80]	0.72; 0.6079
Service Quality	84 [83 - 85]	84 [83 - 85]	85 [82 - 88]	85 [82 - 88]	85 [82 - 87]	84 [82 - 87]	84 [81 - 87]	0.10; 0.992
System use	85 [84 - 86]	85 [84 - 87]	80 [77 - 84]	86 [83 - 89]	87 [83 - 91]	86 [82 - 90]	91 [87 - 94]	2.84; 0.0147*
User satisfaction	78 [77 - 79]	78 [77 - 80]	77 [74 - 80]	79 [76 - 82]	76 [72 - 79]	79 [77 - 81]	81 [76 - 84]	1.27; 0.275
Total HIS Efficiency rate	81 [80 - 82]	81 [81 - 82]	80 [78 - 82]	82 [80 - 83]	82 [80 - 84]	83 [81 - 84]	83 [81 - 85]	1.81; 0.1073
U-DM model								
System Quality	84 [83 - 85]	84 [83 - 86]	83 [81 - 87]	84 [80 - 87]	83 [80 - 86]	82 [80 - 85]	87 [85 - 90]	1.35; 0.2406
Information Quality	83 [82 - 84]	83 [82 - 84]	84 [82 - 87]	83 [80 - 86]	85 [82 - 88]	83 [81 - 86]	87 [84 - 90]	1.45; 0.2027
Service Quality	79 [78 - 80]	79 [78 - 81]	78 [75 - 81]	79 [76 - 82]	80 [77 - 83]	76 [75 - 80]	83 [80 - 86]	1.75; 0.1203
System use	81 [80 - 82]	81 [80 - 82]	79 [76 - 82]	83 [80 - 86]	82 [80 - 85]	79 [76 - 82]	85 [82 - 87]	2.80; 0.0159*
User satisfaction	82 [81 - 83]	81 [80 - 83]	82 [79 - 85]	84 [81 - 88]	85 [82 - 87]	80 [78 - 83]	84 [81 - 88]	1.62; 0.1518
Perceived net benefits	80 [79 - 81]	78 [77 - 80]	80 [77 - 83]	82 [79 - 85]	83 [80 - 86]	80 [76 - 82]	86 [83 - 88]	4.82; 0.0002*
Total HIS Efficiency rate	82 [81 - 82]	81 [80 - 82]	81 [79 - 83]	82 [80 - 85]	83 [81 - 85]	80 [78 - 82]	85 [84 - 87]	3.48; 0.0040*

p-value<0.05 was considered statistically significant
CI - Confidence Interval
Source: Fieldwork, 2022

4.6.3 Overall HIS Efficiency Rate Categories

The overall mean total HIS efficiency rate for E-ISSM and U-DM models was 81% with 95%CI [80 - 82] and 82% with 95%CI [81 - 82] respectively (Table 19 and Table 20). Considering the E-ISSM model, only one (4%) out of 25 healthcare providers was in the moderate HIS efficiency rate category (Moderate – 50%<=HIS Efficiency rate<75%) and the rest 24 (96%) out of 25 health care providers were in high HIS Efficiency rate category (High – 75%<=HIS Efficiency rate) (Table 23).

Table 23: Hospital Information System (HIS) Efficiency Rate based on E-ISSM model

Hospital Code	Hospital Information System (HIS) Efficiency Rate categories*			
	Very low Mean % [95%CI]	Low Mean % [95%CI]	Moderate Mean % [95%CI]	High Mean % [95%CI]
HP01	–	–	–	80 [78 - 82]
HP02	–	–	–	85 [84 - 87]
HP03	–	–	–	83 [81 - 84]
HP04	–	–	–	84 [82 - 86]
HP05	–	–	–	77 [75 - 78]
HP06	–	–	–	84 [83 - 84]
HP07	–	–	–	79 [72 - 87]
HP08	–	–	–	82 [80 - 84]
HP09	–	–	–	82 [81 - 84]
HP10	–	–	68 [65 - 70]	–
HP11	–	–	–	82 [80 - 84]
HP12	–	–	–	83 [80 - 85]
HP13	–	–	–	82 [80 - 83]
HP14	–	–	–	81 [79 - 84]
HP15	–	–	–	78 [70 - 85]
HP16	–	–	–	84 [81 - 87]
HP17	–	–	–	84 [81 - 88]
HP18	–	–	–	81 [75 - 86]
HP19	–	–	–	87 [84 - 89]
HP20	–	–	–	78 [75 - 81]
HP21	–	–	–	81 [73 - 90]
HP22	–	–	–	82 [80 - 84]
HP23	–	–	–	77 [76 - 79]
HP24	–	–	–	81 [78 - 84]
HP25	–	–	–	84 [82 - 86]
Overall	–	–	–	81 [81 - 82]

*The overall mean HIS Efficiency rate category; High – 75%<=HIS Efficiency rate; Moderate – 50%<=HIS Efficiency rate<75%, low – 25%<=HIS Efficiency rate<50% and very low - HIS Efficiency rate<25%
HP – Healthcare Provider
Source: Fieldwork, 2022

Analysis of the U-DM model shows that four (16%) out of 25 healthcare providers were in the moderate HIS Efficiency rate category (Moderate – 50%<=HIS Efficiency rate<75%) and the rest 21 (84%) out of 25 health care providers were in high HIS Efficiency rate category (High – 75%<=HIS Efficiency rate) (Table 24).

Table 24: Hospital Information System (HIS) Efficiency Rate based on the U-DM model

Hospital Code	Hospital Information System (HIS) Efficiency Rate categories*			
	Very low Mean % [95%CI]	Low Mean % [95%CI]	Moderate Mean % [95%CI]	High Mean % [95%CI]
HP01	–	–	–	75 [73 - 78]
HP02	–	–	–	79 [77 - 81]
HP03	–	–	–	81 [79 - 84]
HP04	–	–	–	88 [86 - 90]
HP05	–	–	–	80 [79 - 81]
HP06	–	–	–	84 [72 - 97]
HP07	–	–	74 [64 -84]	–
HP08	–	–	–	83 [79 - 87]
HP09	–	–	–	85 [83 - 87]
HP10	–	–	–	85 [81 - 88]
HP11	–	–	–	89 [86 - 88]
HP12	–	–	–	84 [81 - 88]
HP13	–	–	–	83 [80 - 86]
HP14	–	–	–	83 [80 - 87]
HP15	–	–	–	78 [67 - 88]
HP16	–	–	–	81 [79 - 84]
HP17	–	–	–	85 [83 - 88]
HP18	–	–	71 [61 - 80]	–
HP19	–	–	–	87 [84 - 90]
HP20	–	–	–	78 [74 - 82]
HP21	–	–	70 [57 - 83]	–
HP22	–	–	–	82 [80 - 83]
HP23	–	–	74 [72 - 75]	–
HP24	–	–	–	78 [75 - 81]
HP25	–	–	–	82 [80 - 84]
Overall	–	–	–	82 [81 - 82]

*The overall mean HIS Efficiency rate category; High – 75%<=HIS Efficiency rate; Moderate – 50%<=HIS Efficiency rate<75%, low – 25%<=HIS Efficiency rate<50% and very low - HIS Efficiency rate<25%
HP – Healthcare Provider
Source: Fieldwork, 2022

4.6.4 Measuring agreement between Composite Index and DeLone and McLean tools using the Bland-Altman method

Figure 33 shows the Bland-Altman plot of the difference between the E-ISSM and U-DM models against the mean of E-ISSM and U-DM models in the 25 health facilities in the study. Only 1 (4%) out of the 25 hospitals falls outside the limits of agreement. The majority 24 (96%) of the hospitals lie between averages 75.5% and 87.0%. The regression between the mean difference and the average of the E-ISSM and U-DM model shows that there is no statistically significant proportional bias between the application of E-ISSM and U-DM model to measure the efficiency of Hospital Information System (HIS) (coefficient=-0.50; 95%CI [-1.14 to 0.14] and p-value=0.1228) (Figure 33).

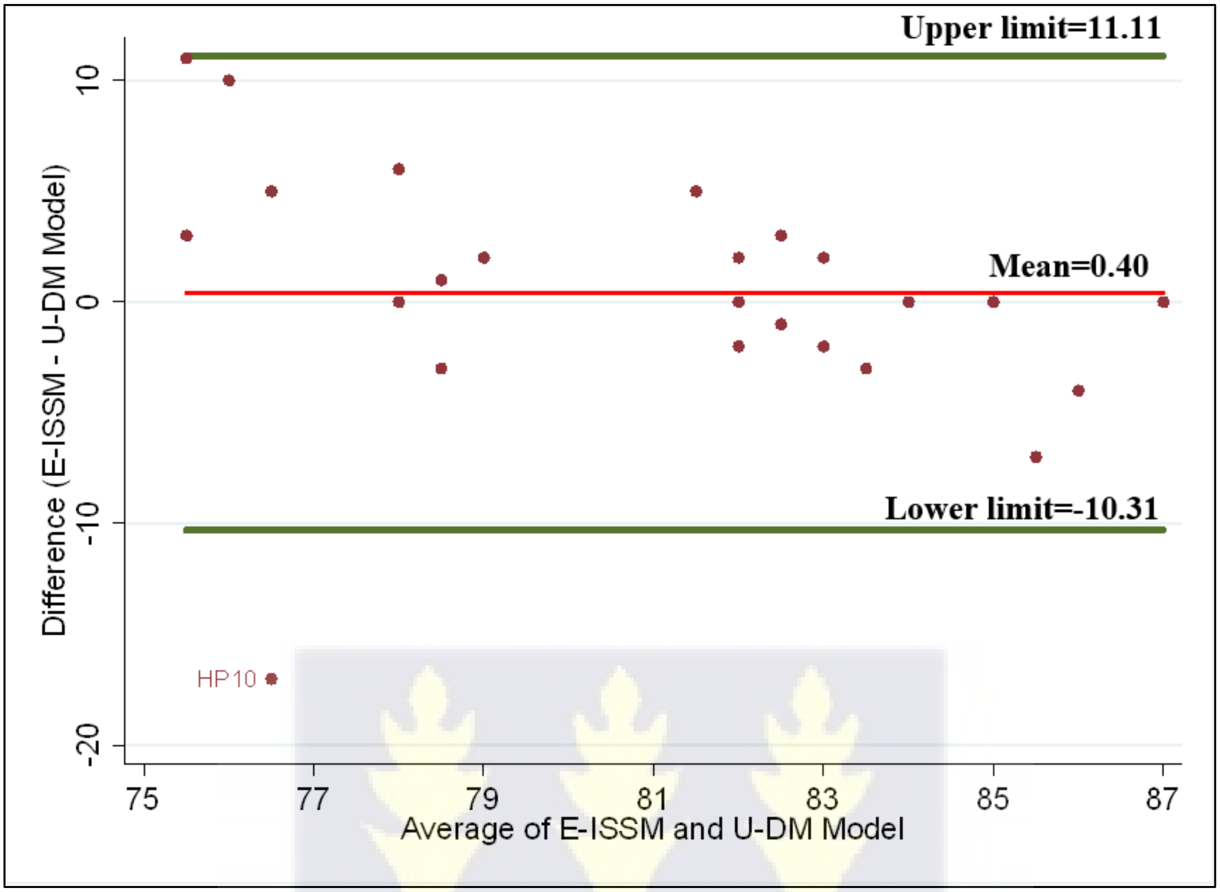

Figure 33: Bland-Altman plot of the difference between E-ISSM and U-DM model against the mean of E-ISSM and U-DM model in the 25 health facilities in the study. Point outside limits **is** labelled by the hospital code

4.6.5 Validation of the E-ISSM and U-DM mean HIS Efficiency rates

According to Otieno et al. (2008), the construct validity of the mean HIS efficiency rate can be validated against it internal dimensions (System quality, Information quality, Service quality, System use, User satisfaction and Potential net benefits) using correlation analysis. This was done for the outcomes of the two models used in this study. The E-ISSM revealed a strong statistically significant correlation between the total mean HIS efficiency rate and it dimensions (Figure 34). Similarly, the U-DM model also revealed a strong statistically significant correlation between the total mean HIS efficiency rate and it dimensions (Figure 34).

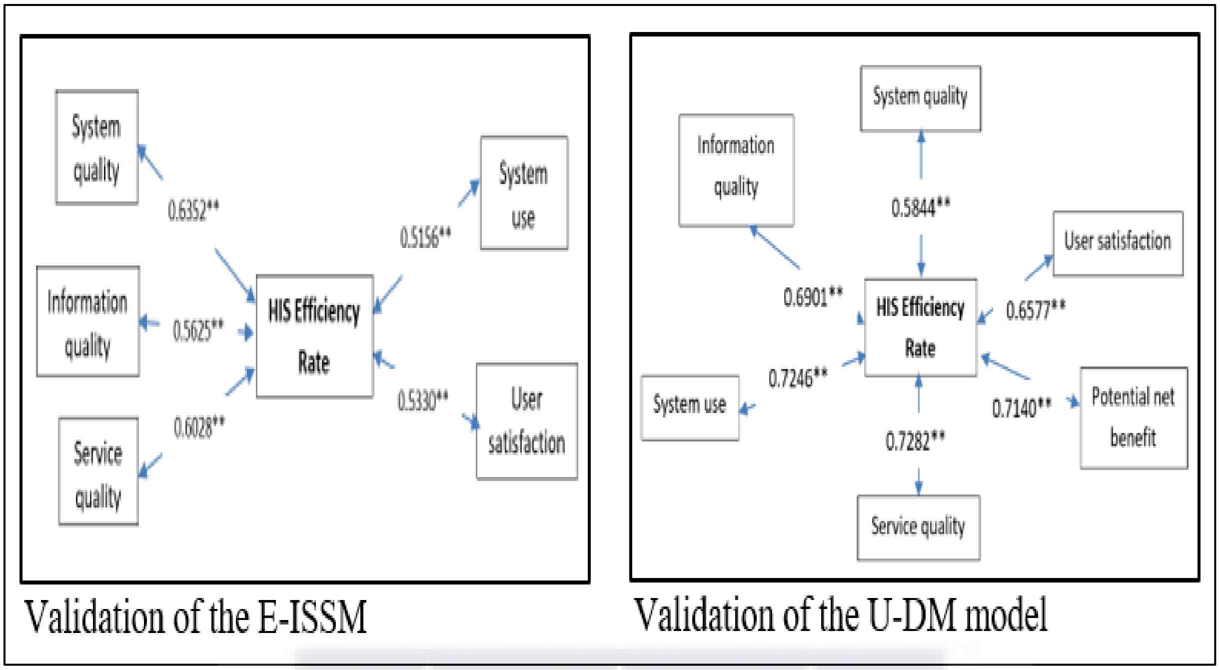

Figure 34: Validation of the E-ISSM and U-DM models HIS Efficiency Rate using Spearman correlation analyses.
**Statistically significant at p-value<0.0001
Source: Fieldwork

Discussion

This study quantified the impact of the HIS system on error margins of Health Insurance claims in Ghana. The analysis shows that HIS claims processing saves costs in terms of denied claims compared to manual claims processing. The overall average error margins of claims are lower for HIS systems compared to paper-based systems. Our study is in agreement with studies conducted by Nsia-Boateng et, al (Nsiah-Boateng et al., 2017b) who compared health insurance claim reviews for paper-based and electronic systems by the NHIS. This could be attributed to the laborious nature of processing paper-based claims which requires more labour force to accomplish. On the other hand, the HIS proves to be efficient due to its ability to flag some errors that cannot be identified by the paper-based system. In general, the use of HIS to process claims benefits healthcare providers by minimizing error margins in health insurance claims compared to paper-based ones. The trend analysis revealed that in the first month after the introduction of electronic claims, a reduction of 1.31% was observed in percentage error margins of health insurance claims but was not statistically significant. This shows that if care providers monitor and invest in information systems to enhance electronic claims processing the gains can be overwhelming. This reduction can be attributed to the dedication attached to every go-live information system implementation because implementers would want to see the change yield the needed dividend. Further analysis revealed that the difference between pre-electronic claims and post-electronic claims trends observed an increase of 0.09% in error margins of health insurance claims. This was statistically insignificant. This study did not see a sustained significant effect of HIS in reducing error margins of claims submitted by some health facilities to the NHI authority, and this may be attributed to the rate decline in the efficient use of HIS, the complex architecture of the different system, inadequate knowledge of how the systems operate and the potential illegal manipulation of the systems to financially benefit the service providers. The analysis of the 25 health facilities across the regions revealed significant variation within each site and differences between the sites. The wide range of variations can be attributed to errors made by personnel during data entry, differences in the size of healthcare facilities, variations in training, and the use of different eClaims systems by healthcare facilities. Managing these factors could enhance the variation between study sites.

The study also estimated and predicted the claim denial rate in Ghana. To accomplish this, a Box-Jenkins-based Autoregressive Integrated Moving Average (ARIMA) model was used to forecast Ghana's 120-month denial rate of health insurance claims. The minimum number of deductions was 4.0 percent. This low CDR is supported by Rostami and Nasiripour (2019). On the other hand, the highest CDR (16.8%) reported in this study is supported by Khanlari, Janati, Gholamzadeh Nikjoo, and Asadi (2017) in the public hospitals of Tabriz. Additionally, an average CDR of 7.79 percent has been estimated. This means that, on average, 7.79% of the requested amount of the hospital claim is deducted by the national health insurance scheme. Depending on the amount claimed by the hospital, this 7.79% may differ (Khanlari et al., 2017). According to Nsiah-Boateng et al. (2017a), this low CDR may be linked to the use of electronic medical records.

Regarding the validation of the model's accuracy, numerous indicators exist for determining the forecast accuracy. The Root of Mean Squared Error (RMSE), the Mean Absolute Percentage Error (MAPE), and the Mean Absolute Error (MAE) are examples. MAPE is preferred for the accuracy check because it accounts for errors that are between 0 and 1 percent (Matyjaszek, Fernández, Krzemień, Wodarski, & Valverde, 2019; Namawejje & Geofrey, 2020). The MAPE value of the expected model is 5.71 percent. This indicates that the model accurately predicts the CDR's 120-month future values by 94.29%.

The study also revealed that denied claims can be attributed to treatment to diagnosis mismatch, multiple antenatal visits, duplication of claims, inappropriate prescription, oversupply of medication, wrong application of tariffs, no diagnosis, inactive member, unclear diagnosis, and age treatment mismatch. The findings from this study are corroborated by other studies conducted elsewhere (Leikin, 2019; Matson et al., 2020; Pal et al., 2022; Zarei, Najafi, & Arabi, 2020). These causes of denied claims can be avoided if providers undertake thorough vetting of their claims before submitting them to the insurers (NHIS). Training and supervision are required to enable the electronic claims processing system to function efficiently and effectively.

Healthcare providers' financial well-being could be jeopardized because of claim deductions, which have the potential to reduce hospital revenues. Short-term deductions may limit hospitals' liquidity and pose a challenge to their operations due to rising production costs. In the long run, the government's budget resources may be put under pressure to support both public and quasi-hospitals because of lower revenues caused by claim deductions. The hospital has lost money on insurance deductions despite providing services to patients and incurring production costs for those services. Therefore, hospital administrators ought to place a high priority on preventing such a waste of resources. The first step toward achieving this objective is to determine what triggers and causes claim deductions in hospitals.

Few studies have reported a variety of hospital deduction reasons that can be broken down into two primary categories: technical factors and documentation factors (Karimi, Vesal, Saeedfar, & Rezayatmand, 2011; Khanlari et al., 2017). Patients' prolonged hospital stays and excessive use of medical supplies and drugs are correlated with technical factors. The treatment team's failure to adhere to established and accepted guidelines could be the cause of this excessive use. Vulnerability in the treatment cycle should likewise be viewed as such. Rotter and co. also carried out a meta-analysis and systematic review of the use of clinical pathways, as well as their relationship to a decrease in hospital complications and improved documentation (Rotter et al., 2012). Notably, public hospitals' educational programs may also be the cause of resource overuse. Khanlari and others (2017) added that incorrect surgery coding, the absence of the physician's signature, incorrect dates, and the illegibility of documents are the root causes of claim deductions (Khanlari et al., 2017). Furthermore, Aryankhesal, Kalantari, Raeissi, and Shahidi (2019), reported computational errors, a lack of hospital supervision, and file-related issues are the most significant causes of hospital deductions. However, numerous issues with documentation have straightforward solutions.

Interventions should focus on both the technical and documentation aspects to eliminate or minimise claim deductions. Additionally, providing others with the advantages of lower deduction costs and providing training on the documentation procedure could eventually result in lower claim deductions. Adapting treatment procedures to clinical guidelines is another way to reduce resource overuse to some degree. Specifically, Kimiaeimehr, Hosseini, Alimohammadzadeh, Bahadori, and Maher (2019) concluded that standards for work processes, access to information, motivation, attitude change, effective management, developing a systematic vision, providing appropriate feedback, and creating a systematic vision are effective solutions for the implementation of guidelines.

This study also assesses the health information system impact assessment on the timeliness of healthcare provider claim submission to NHIS for reimbursement. To the best of our knowledge, no prior comparable research has been identified on the electronic claim management system's impact on the timeliness of claims submission in Ghana. The study expands the scope of literature for other developing countries. Timely medical claim submission was observed to be very high (at least 75%) in more than 2-thirds of the health facilities showing compliance with NHIA guidelines on medical claim submission. This outcome is similar to what was observed by Sodzi-Tettey et al. (2012) in the Kassena Nankana and Builsa districts of the Northern region of Ghana. The current study shows that the implementation and use of HIS have improved the timeliness of medical claim submission. This study is supported by a similar study conducted by Sockolow, Bowles, Adelsberger, Chittams, and Liao (2014) which shows that the introduction of point-of-care EHR has improved early Medicare payment due to timely claims submission. The pooled effect based on the trend analysis revealed a reduction of an average of 5.84 days in the timeliness of claim submission in the first month after the introduction of an HIS. This outcome is an indication to healthcare providers consider the use of HIS to improve electronic medical claims processing and submission. This reduction can be attributed to the dedication attached to every go-live information system implementation because implementers would want to see the change yield the needed dividend. However, the gains observed immediately after the HIS implementation could not be sustained in most health facilities. The difference between pre-electronic claims and post-electronic claims trends observed a marginal increase of 0.62 days in the timeliness of health insurance claims submission. This can sometimes be attributed to the diminishing euphoria that characterised every HIS implementation where there is adequate technical support, motivation and management support, monitoring and evaluation throughout the first few days after implementation. Other challenges such as misunderstanding of claims submission processes such as unclear vetting procedures and frequent change of claims forms, use of unqualified staff (e.g. National Service Personnel) to process claims, and lack of adequate staff to process claims as reported elsewhere (Akweongo et al., 2021). Though, there was no sustenance of the reduction in timeliness of medical claim submission, few health facilities sustained the reduction in timeliness in the difference between pre-electronic claims and post-electronic claims trends. Consistent monitoring, training and supervision are necessary for users of the HIS to help sustain gains made after the implementation and use of an HIS. The use of HIS for claims management can increase the accuracy of claims submitted and reduce the cost associated with the manual printing of claims forms or invoices and time spent in manual filling and processing claims (Haule, Dida, & Sam, 2019).

The current study adapted an extended ISSM and upgraded DM models to assess hospital information systems in 25 selected national catholic health service hospitals across the 16 regions in Ghana. A high rate of validity and reliability was found to be realized from the application of the two tools. The outcomes from this study show that the tools can be used in subsequent studies in Ghana and other low- and middle-income countries. HIS efficiency rate in different hospitals was determined based on the perspective of health professionals using the HIS for-service provision. The Bland-Altman method used to measure the agreement in HIS efficiency rate between the two tools was also investigated. The current study highlights the perspectives of hospital information system users in Ghana and also confirms several studies (Alharthi, Youssef, Radwan, Al-Muallim, & Zainab, 2014; Lambooij, Drewes, & Koster, 2017; Ojo, 2017; Tilahun & Fritz, 2015; Top & Gider, 2012) conducted to validate the ISSM. The analysis also revealed a significant correlation between the study constructs (system quality, information quality, service quality, system use, user satisfaction and potential net benefits) used in this study.

The results of this study show that health professionals using HIS hold favourable opinions on the HIS Efficiency rate in hospital settings. The outcomes from the use of the two ISSM tools revealed that the HIS Efficiency rate in all the hospitals was high. Majority of the users indicated that the dimensions such as system quality, information quality, service quality, system use, user satisfaction and potential net benefits as satisfactory. This was confirmed by a study conducted by Zahra. Ebnehoseini et al. (2019) that users of HIS indicated that system quality, system use and user satisfaction success rate were appropriate. Studies conducted by Top and Gider (2012) and Lambooij et al. (2017) revealed that an electronic health record system was very important and key of improving information quality and reliable workflow of a hospital information system. Their study also revealed that the users were able to input data easily, retrieve and use the data using electronic health record systems as well as working more faster with the EHRs.

Other studies conducted by Ebnehoseini et al. (2021) and Bossen, Jensen, and Udsen (2013) on health information system evaluation also revealed similar outcomes found in this study. In all, they indicated that health professionals using the health information system had favourable encounters with their systems in terms of quality, system use, service support and satisfaction. Furthermore, the EHR success rate was appropriate and above average.

The findings from this study also shows that there is a significant difference mean HIS efficiency rate among health professionals. These were observed in system use and potential net benefits. The rate was higher among dispensaries, accounts/claims and health information professionals than nurses and physicians. According to Ebnehoseini et al. (2019) and Asadi, Moghaddasi, Rabiei, Rahimi, and Mirshekarlou (2015), computer facilities are more easily provided to finance and administrative professionals compared to other health professionals confirming the findings of this study. This means that health professionals in the administrative and financial departments use hospital information system more compared to other cadres within the health facilities. The findings of a study done by Lu, Hsiao, and Chen (2012) also emphasized that the presence of computer facilities is very important in hospital information system use.

Strengths and limitations of the study

This study offers some strengths which are worth mentioning. One significant advantage of utilising ITS to evaluate the impact of the eClaims system with observational data is its ability to account for the influence of long-term trends in a variety of outcome indicators. Another notable feature of ITS is the ability to conduct analysis based on population rates rather than individual-level data. When there is a distinct linear pattern in the population rates, it is recommended to use population rates as the basis for data modelling, rather than relying on the log odds (McDowall, McCleary, & Bartos, 2019). The ITS technique assesses changes in outcome rates at the population level, therefore the influence of individual-level variables on the results will not generate significant bias unless it coincides with the intervention. Standardisation (Briesacher et al., 2011) is commonly employed to account for temporal population fluctuations, specifically changes in the mix of individuals' attributes or features. One further advantage of ITS is the investigator's ability to perform stratified analyses to assess the varying effects of an intervention or policy change on specific subgroups of individuals (i.e. by geographical location, facility size, etc.). Furthermore, ITS offers lucid and straightforward graphical outcomes that are effortless to comprehend. Even without the statistical results from a segmented regression model, showing graphs like Appendix II Figure 35 to administrators and policy-makers can be a powerful way to convey a message. It is easy for the reader to determine the date of the change, the circumstances leading up to it, what happened immediately following it, and what transpired throughout the follow-up time.

Undeniably, this study has limitations. First, the time series model is typically used for short-term forecasting and its accuracy decreases when used for long-term predictions. Hence, it is necessary to regularly update the data to enhance the model's performance, as it depends on analysing existing data to make future projections. In addition, the study did not examine specific treatment claims, such as outpatient and inpatient claims, that care providers submitted to NHIS, in-depth. However, by analysing the total corrections made due to mistakes every month for each healthcare provider in the study, we can gain a comprehensive understanding of the costs related to rejected insurance claims, regardless of whether they were submitted through paper-based or electronic systems. Third, data on medical claims resubmission was not accessible since there was no available data on that concerning time-lapse. Reasons accounting for the delays in meeting the Insurer's submission deadline were also not collected. Fourth, the HIS efficiency was measured based on health professionals' perspectives. This was because the situation in most health facilities visited is that, all users in the department were not assigned to individual computers. Hence, a user logs into the system to get the computer operational and other colleagues use the HIS alongside. Therefore, the current study could not measure the HIS system use based on user log-in data. Furthermore, this study used random effects to mitigate bias and account for variations, while there remains the possibility of concealed factors linked to both computerised and paper-based claims systems that contribute to claim rejection. There are numerous methods available to researchers for studying and mitigating the occurrence of claims denial in information systems. Six, a cost-benefit analysis of the HIS can also be evaluated since the study falls short in that regard. Finally, variations in claim denial rate (due to facility size, locations, and other provider characteristics) were also not investigated.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Introduction to the chapter

Chapter Four provided important information on the findings and discussions on the research objectives. This chapter summarizes the findings in the context of the conclusion, suggestions, limitations, and ideas for further investigation.

5.1 Summary

Hospital Information Systems (HIS)'s ability to reduce the rate of error margins in health insurance claims submitted by Ghanaian health facilities to the National Health Insurance Authority is the subject of this investigation. The study also aims to determine how HIS affects how quickly medical claims are submitted in Ghana's National Catholic Health Service. The healthcare providers and other stakeholders would be more likely to make investments in health information technology for a more effective healthcare delivery system if the HIS efficiency rate was evaluated. Using two information system success model (ISSM) tools, the current study also measures the agreement between the two ISSM tools and assesses the HIS efficiency rate from the perspective of users. From 2010 to 2019, the study used longitudinal data on monthly claims adjustments due to errors from both paper-based and different HIS-submitted claims. Each month, an estimate was made for the rate of error margins. By comparing claims data for each facility before and after the system was implemented, Prais-Winsten Segmented Interrupted Time-Series analysis was used to estimate the impact of HIS. A pooled impact estimate of HIS on the error margins of health insurance claims was produced by employing methods of meta-analysis. The study also used longitudinal data from 2010 to 2019 using various forms of HIS on the timeliness of monthly medical claims from both paper-based and electronic systems. For each month, the number of days required to submit medical claims was calculated. The Prais-Winsten method, based on Segmented Interrupted Time-Series analysis, was used to compare the average number of days each facility spent submitting claims data before and following the implementation of HIS. The pooled effect estimates of HIS on the average number of days spent submitting claims were estimated using meta-analysis methods. The survey method was used to conduct the study in 25 Ghanaian NCHS hospitals regarding the HIS efficiency rate.

The study also estimates and forecasts CDR using Autoregressive Integrated Moving Average (ARIMA) based on time series data on CDR from January 2010 to December 2019 from 25 National Catholic Health Service (NCHS) hospitals. At a 5% level of significance, our diagnostic tests like the Augmented Dickey-Fuller (ADF) showed that the CDR series is stationary. This study provides the ARIMA (1, 0, 1) model, the ARIMA (2, 0, 1) model, and the ARIMA (3, 0, 1) model, with the ARIMA (1, 0, 1) model being unquestionably the best optimal model based on parsimonious considerations and the minimal Theil's U prediction evaluation statistic. Additionally, our diagnostic tests revealed that the offered models are stable and thus reliable. The study's findings showed that by the end of February 2020, Ghana's CDR is anticipated to drop from a benchmark rate of 7.79% to around 5.35%.

This study also adapted two self-administered structured data collection tools based on the upgraded DeLone and McLean models, which each cover seven dimensions, and extended ISSM, which covers six dimensions. The study included 1416 users from 25 hospitals across the country. The content validity indices and content validity ratios of the two instruments were found to be valid. Both tools' Cronbach's alpha values were also above 0.75. For continuous variables, descriptive statistics like means and standard deviations were calculated, and for categorical variables, percentages were calculated. Cronbach's alpha was used to evaluate the study's internal validity. The Shapiro-Wilk test was used to determine whether the data were normal. The weighted mean was used to determine the HIS efficiency rate for the two models. The agreement between the two models was assessed using the Bland-Altman method.

The HIS had a significantly lower total cost of deductions caused by errors than the paper-based system. When compared to the paper-based system, the error margins for health insurance claims were immediately reduced by 1.31 percentage points thanks to HIS.

In most health facilities, claim submission times were greater than 75% of the time. When compared to the paper-based system, the average number of days required to submit medical claims in HIS has significantly decreased. The trend analysis revealed that when compared to the manual system, HIS reduced the average number of days required to submit medical claims by 5.84.

The high efficiency of the HIS can be seen in the overall mean HIS efficiency rate of more than 80%. According to the Bland-Altman method, the mean HIS efficiency rate for 24 (or 96%) of 25 hospitals ranges from 75.5% to 87.0% on average. The coefficient of the regression between the mean difference and the average of the two tools demonstrates that there is no statistically significant proportional bias between their use to measure HIS efficiency rate.

5.2 Conclusion

Compared to the paper-based claims system, the HIS recorded lower costs for denied claims. The rate of claim denials will decrease, the provision of healthcare services will remain viable, and the insurer will be reimbursed promptly if an HIS is expanded for claim submission.

The use of HIS systems by healthcare providers has a significant effect in reducing the likelihood of errors associated with rejected claims compared to the paper-based claims system. The use of large-scale longitudinal data from both the manual claims and electronic claims systems over time confirm that the adoption of HIS claims system by healthcare providers reduces the tendency of a health insurance claim to be denied by the insurers.

The study's findings from the ARIMA (1, 0, 1) model indicate that, as of February 2020, the anticipated CDR was lower (5.35%) than the benchmark rate of 7.79%. The model employed to forecast claim denial rate is ARIMA (1, 0, 1). When it comes to estimating and forecasting the CDR trend of health insurance claim deductions, ARIMA models are a great tool that may help healthcare providers to make an evidence-based decision on the hospital’s financial health.

The timely submission of medical claims was improved by the use and implementation of HIS. The findings from the study indicate that HIS use has a significant effect on timeliness of claims submission immediately after the introduction of the HIS. In terms of long-term operations, HIS use had a sustained impact on timeliness in a few health facilities but was not sustained in most health facilities.

The focus of this study's findings is on the perspective of Ghanaian healthcare professionals regarding the HIS efficiency rate in a hospital setting. Since there was no proportional bias between the two models, the adapted tools can be used to evaluate hospital information systems in any subsequent studies.

Furthermore, this study investigates the effects of electronic claims processing technologies on resolving challenges within the healthcare system in Ghana. The escalating healthcare expenses in Ghana, worsened by denied claims, are not possible to be maintained in the long term. The study demonstrates that the use of electronic claims processing can enhance accuracy and compliance in health insurance claims, thereby making a valuable contribution to the field of Information Systems.

Finally, the study offers healthcare providers and policymakers significant insight that may be implemented to decrease errors in claims processing, resulting in a reduction of denied claims. This would enhance the reserves and enhance the financial sustainability of healthcare providers and medical programs. In the end, these cost reductions can be redirected towards healthcare services, leading to improved healthcare quality.

Contribution to knowledge

The following findings have been made to improve the adoption and use of hospital information systems:

1. This study is the first of its kind in assessing the impact of HIS on-error margins of health insurance claims in Ghana. The findings from the study show that an HIS has an impact in

reducing denied claims compared to the paper-based system. This evidence can add to existing knowledge of research concerning the effect of HIS in improving the quality and safety of healthcare delivery in low and middle-income countries.

2. This study is also the first of its type to evaluate how HIS affects the timely filing of claims to offer an evidence-based conclusion about HIS use in health facility-based claims management. The results of the study show that immediately following the implementation of the HIS, HIS use significantly affects the timeliness of claim filing. Regarding long-term operations, only a small number of healthcare facilities' usage of HIS had a sustained influence on timeliness, but it was sustained in most facilities. The impact of factors impacting timely claim processing and submissions in a wider population and various study settings needs to be investigated in other studies. These assessment outcomes can inform the development and implementation of medical claims management HIS in our healthcare facilities as HIS rollout expands to meet the growing demands for prudent and efficient management of healthcare facilities.
3. The current study concludes that the used of the extended ISSM tool and upgraded DM model can be used to evaluate hospital information system efficiency rate since there was no proportional bias between the two instruments. The findings also revealed the perspectives of health professionals on HIS efficiency rate in a hospital setting in Ghana. Future studies can quantitatively assess and compare users' opinions on the success rate of HIS in other low-and-middle-income countries. It is important to note that this study could not ascertain the factors influencing HIS efficiency rate and future studies can be conducted to determine that.

5.3 Recommendations

As a result of the study's findings, the following recommendations are made:

1. The cost to healthcare providers of denied claims would be reduced if the Ministry of Health and healthcare providers collaborate to scale up and strengthen HIS implementation in all facilities across the nation. These savings can be reinvested in improving the quality of care for the populace, particularly in rural areas, by expanding healthcare services.
2. Hospital Administrators should be encouraged to extensively incorporate eClaims systems into HIS for claims processing and submission. This will expedite claims processing and submission to ensure prompt reimbursement by the NHIA.
3. To improve service delivery around claims management and submissions, managers of healthcare facilities should establish a robust system for claims processing and management, as well as train and hire the right staff.
4. Hospital Administrators can prevent reasons for denied claims by thoroughly reviewing their claims before presenting them to the insurers (NHIS) for reimbursement. By carefully monitoring and explaining, for example, the prescription writing process and tariffs application process, the hospital should be able to identify the staff responsible for these deductions. The Claims department within the hospital must also develop a plan to eliminate the root causes of these deductions, which are typically the result of administrative errors. Training and supervision of all responsible cadres are required to enable the electronic claims processing system to function efficiently and effectively. Quality improvement initiatives can be adopted by hospital managers to reduce errors and enhance patient care. Addressing these issues can lead to improved health outcomes, reduced costs, and enhanced patient satisfaction.

5. The study examines the viewpoints of healthcare professionals in Ghana regarding the efficiency of Health Information Systems (HIS) in a hospital environment. It offers useful insights into the user experience and emphasises the significance of considering the needs and perspectives of end-users throughout the design and implementation of HIS. Given the absence of any proportional bias between the two models (ISSM/DM), the potential of the ISSM/DM tools to evaluate hospital information systems in future studies presents a good opportunity for further research and evaluation.

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APPENDICES

Appendix I: Table 25: Before-and-After eClaims system implementation Health Insurance Data from Health Facilities in the 11 Selected Regions in Ghana from Jan 2010 to Dec 2019

		Before eClaims system Implementation					After eClaims system Implementation			
Regions	Number of Health Facilities	Number of claims submitions	Amount Submitted [GH₵]	Amount Deducted [GH₵]	Claims Rejection Rate (%)	Number of claims submitions	Amount Submitted [GH₵]	Amount Deducted [GH₵]	Claims Rejection Rate (%)
Ashanti	2	146	9,680,000.00	209,496.20	2.16	94	38,000,000.00	183,668.40	0.48
Bono East	3	149	37,800,000.00	1,979,473.00	5.24	211	70,300,000.00	4,240,309.00	6.03
Central	2	132	16,900,000.00	2,095,532.00	12.40	108	35,100,000.00	2,215,890.00	6.31
Eastern	4	174	30,100,000.00	1,606,317.00	5.34	306	91,000,000.00	4,988,283.00	5.48
Volta	4	299	38,200,000.00	8,189,402.00	21.44	181	40,100,000.00	6,849,335.00	17.08
Western	3	273	32,800,000.00	6,536,967.00	19.93	87	20,100,000.00	1,177,475.00	5.86
Bono	2	72	14,900,000.00	894,447.70	6.00	168	50,400,000.00	485,842.20	0.96
Savannah	1	48	6,000,000.00	671,503.60	11.19	72	12,000,000.00	1,542,633.00	12.86
Oti	2	84	9,480,000.00	666,547.40	7.03	156	19,300,000.00	954,870.30	4.95
Ahafo	1	113	26,000,000.00	392,336.70	1.51	7	1,840,000.00	80,956.31	4.40
Upper West	1	96	17,800,000.00	515,173.10	2.89	24	5,260,000.00	139,634.40	2.65
Total	25	1586	239,660,000.00	23,757,195.70	9.91	1414	383,390,000.00	22,858,896.61	5.96

Data are presented as numbers and percentages.
Source: Fieldwork, 2022

Appendix II: Publication from objective one and three

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Impact of digital health technology on health insurance claims rejection rate in Ghana: a quasi-experimental study

Godwin Adzakpah & Duah Dwomoh

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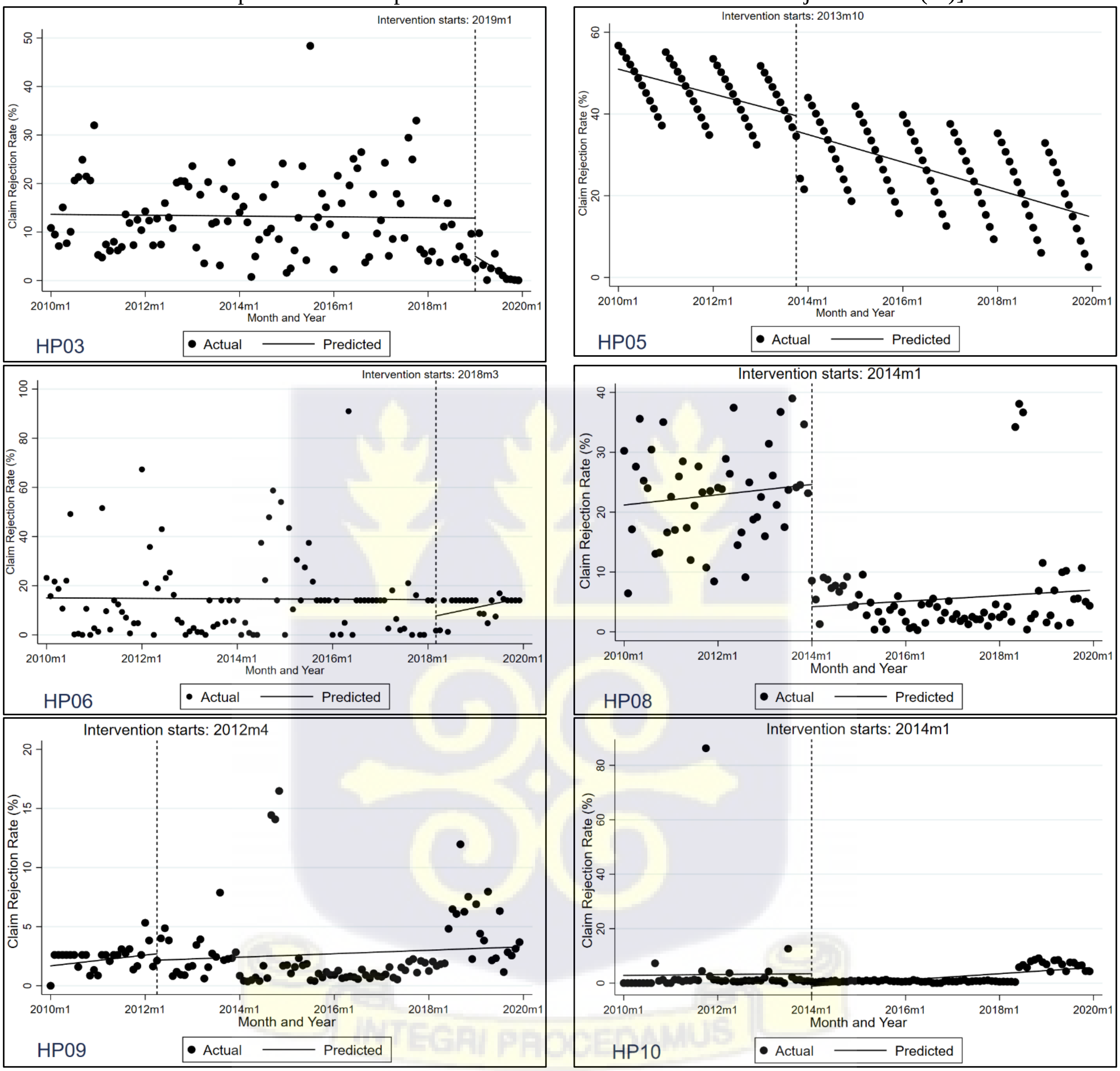
Appendix III: Figure 35: The trend analysis of the before-and-after DHT implementation depicts health facilities showing a reduction in health insurance claim rejection rate (%) in the first month immediately following the Introduction of DHT (compared with counterfactual) [i.e. the immediate impact of DHT implementation on health insurance claim rejection rate (%)]

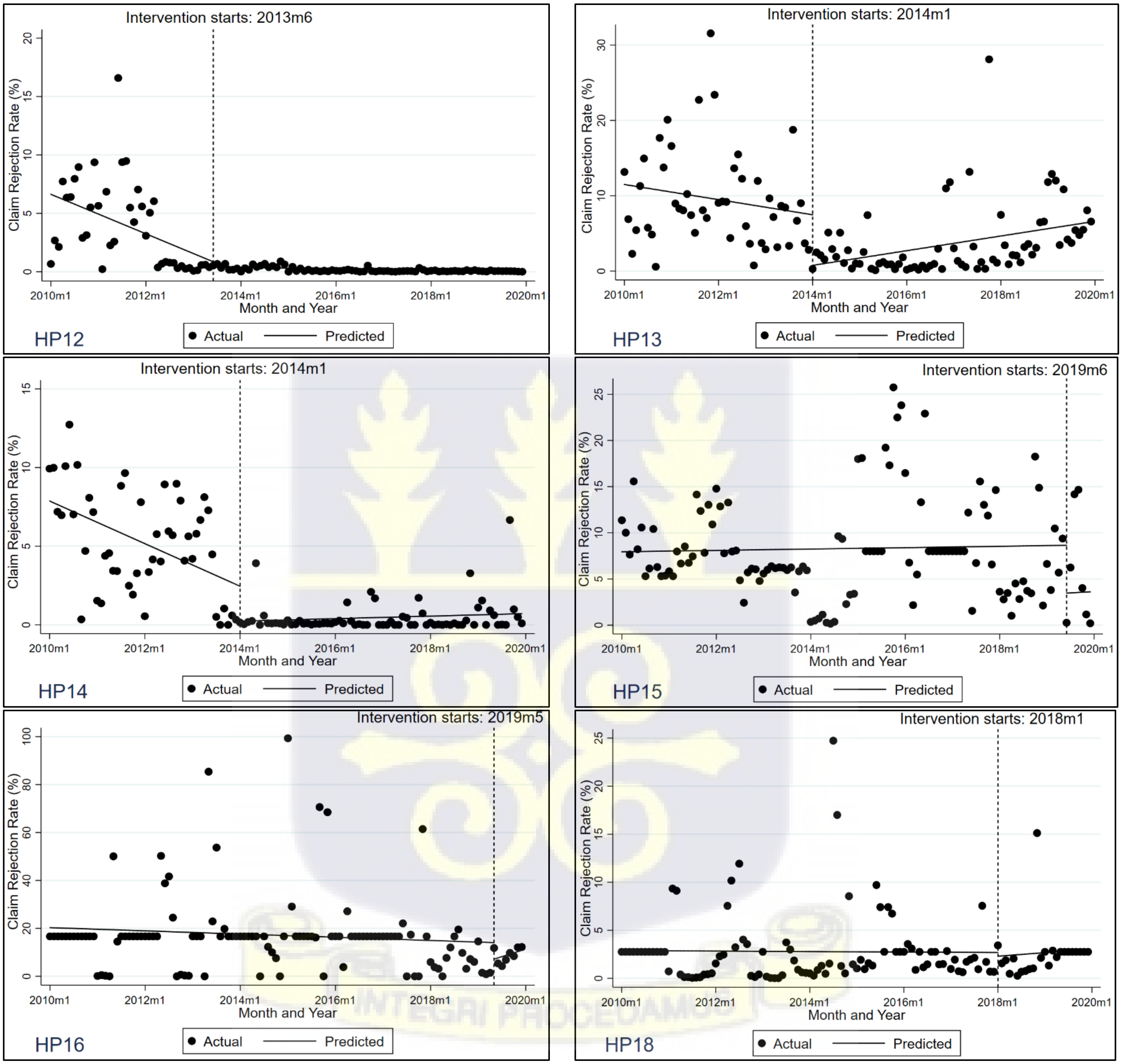


The reduction in health insurance claim rejection rate (%) in the first month immediately following the Introduction of DHT was statistically significant (p-value<0.05) in HP03, HP08 and HP10

These graphs were drawn using "Prais-Winsten and Cochrane-Orcutt regression - lag(1)"

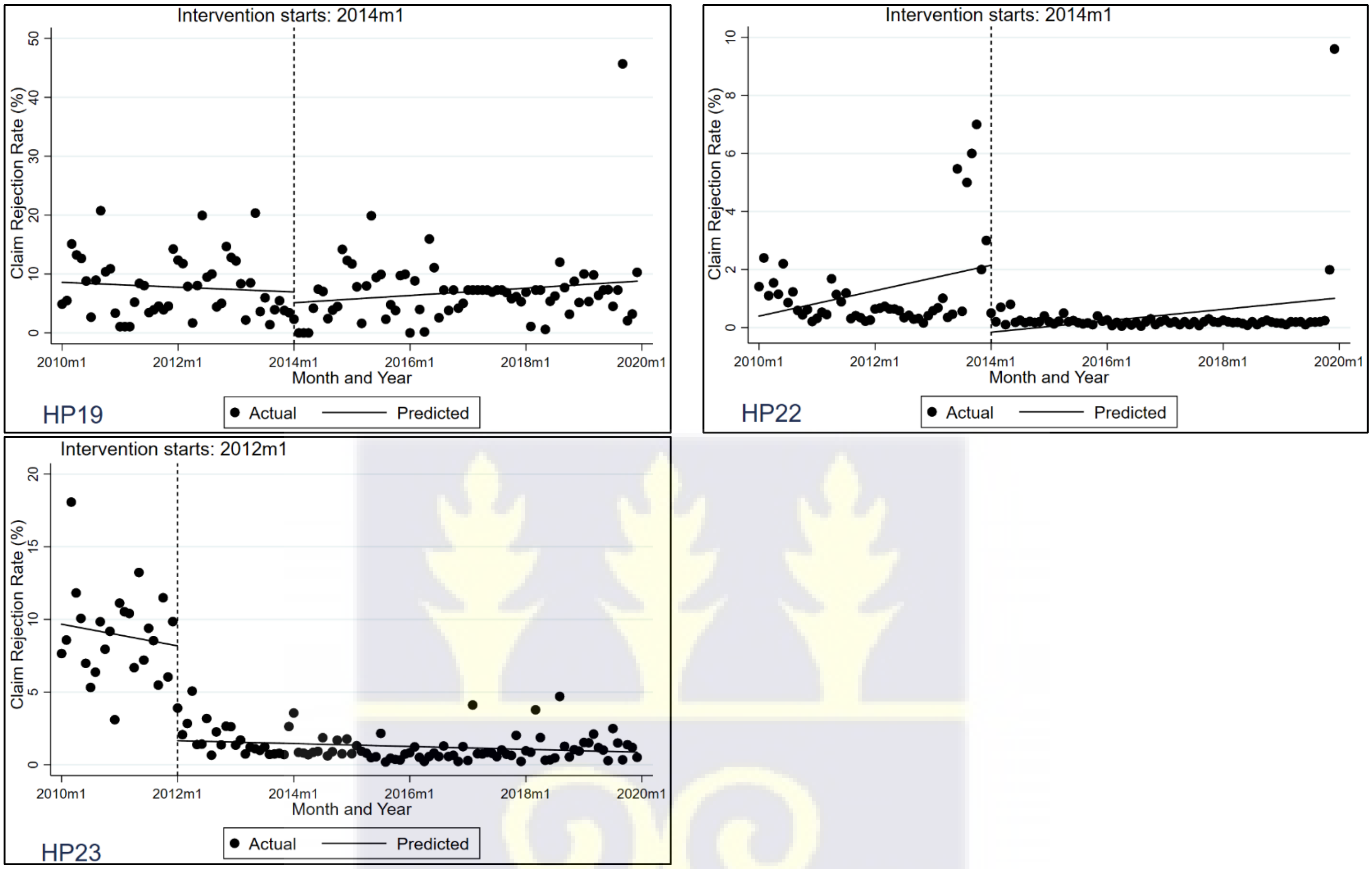
HP – Healthcare Provider

Appendix II: Figure 35: The trend analysis of the before-and-after DHT implementation depicts health facilities showing a reduction in health insurance claim rejection rate (%) in the first month immediately following the Introduction of DHT (compared with counterfactual) [i.e. the immediate impact of DHT implementation on health insurance claim rejection rate (%)] …continued



The reduction in health insurance claim rejection rate (%) in the first month immediately following the Introduction of DHT was statistically significant (p-value<0.05) in HP13, HP14, and HP16
These graphs were drawn using "Prais-Winsten and Cochrane-Orcutt regression - lag(1)"'
HP – Healthcare Provider

Appendix II: Figure 35: The trend analysis of the before-and-after DHT implementation depicts health facilities showing a reduction in health insurance claim rejection rate (%) in the first month immediately following the Introduction of DHT (compared with counterfactual) [i.e. the immediate impact of DHT implementation on health insurance claim rejection rate (%)] …continued



The reduction in health insurance claim rejection rate (%) in the first month immediately following the Introduction of DHT was statistically significant (p-value<0.05) in HP22 and HP23

These graphs were drawn using "Prais-Winsten and Cochrane-Orcutt regression - lag(1)"

HP – Healthcare Provider

Appendix IV: Table 26: ARIMA (1,0,1) forecasted results of sample monthly CDR (%)

	Sample Claim Denial Rate (%)	
Month/Year	Actual	Forecasted
Jan-10	12.89	8.43
Feb-10	12.30	12.00
Mar-10	12.78	12.02
Apr-10	12.83	12.22
May-10	16.39	12.34
Jun-10	11.92	13.86
Jul-10	13.90	12.87
Aug-10	16.80	13.13
Sep-10	11.17	14.46
Oct-10	10.40	12.90
Nov-10	12.30	11.72
Dec-10	9.44	11.84
Jan-11	9.66	10.74
Feb-11	10.06	10.21
Mar-11	9.94	10.09
Apr-11	9.63	9.97
May-11	10.55	9.78
Jun-11	7.73	10.04
Jul-11	10.78	9.04
Aug-11	10.67	9.73
Sep-11	7.39	10.07
Oct-11	12.13	8.91
Nov-11	7.36	10.21
Dec-11	7.96	8.98
Jan-12	7.78	8.54
Feb-12	8.30	8.23
Mar-12	7.85	8.26
Apr-12	7.56	8.10
May-12	7.73	7.89
Jun-12	6.95	7.84
Jul-12	8.98	7.50
Aug-12	12.11	8.14
Sep-12	6.54	9.77
Oct-12	5.83	8.40
Nov-12	5.95	7.35
Dec-12	6.13	6.82

Source: Fieldwork, 2022

Appendix IV: Table 26: ARIMA (1,0,1) forecasted results of sample monthly CDR (%)… Continuation

	Sample Claim Denial Rate (%)	
Month/Year	Actual	Forecasted
Jan-13	6.50	6.60
Feb-13	7.55	6.62
Mar-13	7.16	7.07
Apr-13	5.68	7.15
May-13	7.47	6.59
Jun-13	5.67	7.02
Jul-13	7.79	6.52
Aug-13	6.74	7.11
Sep-13	6.01	7.00
Oct-13	6.07	6.65
Nov-13	6.18	6.47
Dec-13	6.63	6.42
Jan-14	6.23	6.58
Feb-14	5.08	6.50
Mar-14	4.00	5.99
Apr-14	4.09	5.26
May-14	5.11	4.90
Jun-14	4.74	5.11
Jul-14	7.44	5.08
Aug-14	5.87	6.16
Sep-14	7.26	6.12
Oct-14	6.55	6.67
Nov-14	6.57	6.69
Dec-14	5.84	6.70
Jan-15	8.17	6.41
Feb-15	7.29	7.20
Mar-15	8.68	7.28
Apr-15	9.97	7.89
May-15	9.80	8.76
Jun-15	8.66	9.17
Jul-15	8.88	8.94
Aug-15	6.21	8.90
Sep-15	6.67	7.78
Oct-15	6.39	7.35
Nov-15	5.89	6.99
Dec-15	4.78	6.59

Source: Fieldwork, 2022

Appendix IV: Table 26: ARIMA (1,0,1) forecasted results of sample monthly CDR (%) … Continuation

	Sample Claim Denial Rate (%)	
Month/Year	Actual	Forecasted
Jan-16	6.98	5.92
Feb-16	5.59	6.44
Mar-16	5.72	6.17
Apr-16	5.56	6.07
May-16	8.85	5.94
Jun-16	5.70	7.22
Jul-16	8.66	6.64
Aug-16	8.99	7.53
Sep-16	7.67	8.16
Oct-16	7.17	7.97
Nov-16	8.04	7.66
Dec-16	7.20	7.84
Jan-17	8.80	7.60
Feb-17	9.65	8.12
Mar-17	8.08	8.76
Apr-17	10.40	8.47
May-17	6.02	9.26
Jun-17	5.45	7.90
Jul-17	5.74	6.92
Aug-17	6.20	6.49
Sep-17	5.98	6.44
Oct-17	5.91	6.32
Nov-17	5.72	6.23
Dec-17	5.18	6.10
Jan-18	.	5.81
Feb-18	.	5.90
Mar-18	.	5.99
Apr-18	.	6.08
May-18	.	6.16
Jun-18	.	6.24
Jul-18	.	6.32
Aug-18	.	6.39
Sep-18	.	6.47
Oct-18	.	6.54
Nov-18	.	6.60
Dec-18	.	6.67

Source: Fieldwork, 2022

Appendix IV: Table 26: ARIMA (1,0,1) forecasted results of sample monthly CDR (%) … Continuation

	Sample Claim Denial Rate (%)	
Month/Year	Actual	Forecasted
Jan-19	.	6.73
Feb-19	.	6.79
Mar-19	.	6.85
Apr-19	.	6.91
May-19	.	6.96
Jun-19	.	7.01
Jul-19	.	7.06
Aug-19	.	7.11
Sep-19	.	7.16
Oct-19	.	7.20
Nov-19	.	7.25
Dec-19	.	7.29
Jan-20	.	7.33

Source: Fieldwork, 2022

Appendix V: NCHS letter of authorisation

NATIONAL CATHOLIC HEALTH SERVICE

Tel : 233-302-500491/2
Fax : 233-302-500493
E-mail : admin@nchs.org.gh
Web site: www. nchsgh.org

Health Directorate
National Catholic Secretariat
P. O. Box KA 9712
Airport - Accra
Ghana

Our Ref: **NCS/DOH/B2/2021/01**

April 28, 2021

To All (NCHS) Hospital Administrators and Clinic In-Charges

Dear Colleague,

LETTER OF INTRODUCTION – MR. ADZAKPAH GODWIN

The bearer of this letter is a student of University of Ghana, Legon. He is researching into **"The Impact of eClaims on National Health Insurance Claims Management and Reimbursement: A Case Study of National Catholic Health Service in Ghana"** as part of his Doctor of Philosophy studies.

It will be highly appreciated if you could accord him the needed courtesies and assistance to collect data for this assignment please.

Thank you.

Yours faithfully,

for: DIRECTOR, HEALTH
IVAN T. ESSEGBEY
(CBO)

Appendix VI: Secondary data extraction form (Claims Data)

Data Extraction Sheet for Claims Data When complete, please email to: godwin.adzakpah@ucc.edu.gh	
1. Name of Facility	
2. Date of EMR Implementation	
3. Full Name of Software Being Used	
4. Period of Data Collection:	**From January 2010 to December 2019**
PI contact details This is the lead investigator/ PI responsible for the Study	
5. Study PI (name)	**Godwin Adzakpah**
6. Study PI (email address)	**godwin.adzakpah@ucc.edu.gh**
7. Study PI (Phone number)	**+233 (0) 24 417 0155**

NHIS Claims Metadata (please refer to sheet "Instructions" for details of meaning and acceptable value for each field)

Month/Year of Claims	Claims Submission Date	Amount Submitted	Amount Paid	Reason for the deduction
Jan-10				
Feb-10				
Mar-10				
Apr-10				
May-10				
Jun-10				
Jul-10				
Aug-10				
Sep-10				
Oct-10				
Nov-10				
Dec-10				
Jan-11				
Feb-11				
Mar-11				
Apr-11				
May-11				
Jun-11				
Jul-11				
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Nov-18				
Dec-18				
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Feb-19				
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Jun-19				
Jul-19				
Aug-19				
Sep-19				
Oct-19				
Nov-19				
Dec-19				

Appendix VII: Questionnaire

Tool Number One: Extended ISSM (Otieno, Hinako, Motohiro, Daisuke, & Keiko, 2008)

	Dimensions	Strongly Disagree	Disagree	Neither Agree/ Disagree	Agree	Strongly Agree
		1	2	3	4	5
	System Quality					
E-ISSM_SQ1	The EMR system is friendly to me					
E-ISSM_SQ2	The EMR system is easy to use					
E-ISSM_SQ3	I believe that it is easy to get the EMR system to do what I want					
E-ISSM_SQ4	My interaction with the EMR system is clear and understandable					
E-ISSM_SQ5	Learning to operate the EMR system is easy for me					
E-ISSM_SQ6	The operational speed of the EMR system is satisfactory					
E-ISSM_SQ7	The EMR system operates at a satisfactory pace					
E-ISSM_SQ8	The EMR system runs very quickly					
E-ISSM_SQ9	The speed of the EMR system is satisfactory					
E-ISSM_SQ10	I believe that the screen layouts of the EMR system are well designed					
E-ISSM_SQ11	I believe that the screen colours of the EMR system are pleasant					
E-ISSM_SQ12	I believe that the volume of output per screen is suitable					
E-ISSM_SQ13	I generally believe that the screen interface is easy to customize					
E-ISSM_SQ14	The function of the EMR system to correct a mistake is simple					
E-ISSM_SQ15	The EMR system has the ability to correct an incorrect information in a fast way					
E-ISSM_SQ16	The methods and policies governing correction and rerun of EMR system outputs that are incorrect are complete					
	Information Quality					
E-ISSM_IQ1	I believe that the EMR system provides the precise information I need					
E-ISSM_IQ2	I believe that the information content meets my needs					
E-ISSM_IQ3	I believe that the EMR system provides reports that seems to be just about exactly to what I need					
E-ISSM_IQ4	The information provided by the EMR system fit my needs					

E-ISSM_IQ5	The EMR system provides me the right amount of information for my needs					
E-ISSM_IQ6	I believe that the EMR system is accurate					
E-ISSM_IQ7	The accuracy of the EMR system is satisfactory					
E-ISSM_IQ8	I believe that the EMR system provides accurate information					
E-ISSM_IQ9	I believe that the EMR system provides reliable information					
E-ISSM_IQ10	I believe that the output is presented in a useful format					
E-ISSM_IQ11	I believe that the information provided is clear					
E-ISSM_IQ12	The layout of the output is satisfactory					
E-ISSM_IQ13	The format of the output is satisfactory					
E-ISSM_IQ14	I believe that the information is presented to me in a satisfactory way					
E-ISSM_IQ15	I believe that I get the information I need in time					
E-ISSM_IQ16	The EMR system provides up-to-date information					
E-ISSM_IQ17	I believe that the EMR system provides me with the information in a timely manner					
E-ISSM_IQ18	The EMR system provides information that it is too old to be useful					
E-ISSM_IQ19	I believe that the EMR system provide some information that it is too late for my needs					
E-ISSM_IQ20	The EMR system secures data against physical loss or damage					
E-ISSM_IQ21	The EMR system secures data against unauthorized alteration					
E-ISSM_IQ22	Generally, the safeguarding of the EMR system from unauthorized access is satisfactory					
	Service Quality					
E-ISSM_SerQ1	I believe that the IT Unit provides satisfactory support to all users of the EMR system					
E-ISSM_SerQ2	I believe that staffs suggestions for future enhancements of the EMR system are responded to by IT Unit cooperatively					
E-ISSM_SerQ3	I believe that there is availability of IT staff for consultation					
E-ISSM_SerQ4	I believe that the amount of support provided by the vendor is satisfactory					
E-ISSM_SerQ5	The vendor is available for assistance with software difficulties					

E-ISSM_SerQ6	The vendor is available for assistance with hardware difficulties					
	System use					
E-ISSM_SU1	EMR system enables me to complete my tasks successfully in a few easy steps					
E-ISSM_SU2	EMR system allows me to prevent misdiagnosis					
E-ISSM_SU3	EMR system allows me to provide the right medications to patients					
	User satisfaction					
E-ISSM_US1	Overall, I am satisfied with EMR system					
E-ISSM_US2	In general, I am pleased to use the EMR system.					
E-ISSM_US3	I am positive to use the EMR system.					
E-ISSM_US4	Overall, I am comfortable to use the EMR system					

Tool Number Two: Upgraded DeLone and McLean (DeLone & McLean, 2003)

	Dimensions	Strongly Disagree	Disagree	Neither Agree/ Disagree	Agree	Strongly Agree
		1	2	3	4	5
	System Quality					
U-DM_SQ1	I find the EMR system easy to use					
U-DM_SQ2	I find it easy to get the EMR system do what I want					
U-DM_SQ3	The EMR system is flexible to interact with					
U-DM_SQ4	Learning to operate the EMR system was easy for me					
	Information Quality					
U-DM_IQ1	The information generated by the EMR system is correct					
U-DM_IQ2	The information generated by the EMR system is useful for its purpose					
U-DM_IQ3	The EMR system generates information in a timely manner					
U-DM_IQ4	I trust the information output of the EMR system					
	Service Quality					
U-DM_SerQ1	There is adequate technical support from the system’s provider					
U-DM_SerQ2	The overall infrastructure in place is adequate to support the EMR system					
U-DM_SerQ3	The EMR system can be relied on to provide information as when needed					
U-DM_SerQ4	The output of the EMR system is complete for work processes					

	System Use					
U-DM_SU1	Using the EMR system enables me accomplish tasks more quickly					
U-DM_SU2	Using the EMR system has improved my job performance					
U-DM_SU3	Using the EMR system has made my job easier					
U-DM_SU4	I find the EMR system useful in my job					
	User satisfaction					
U-DM_US1	I am satisfied with the functions of the EMR system					
U-DM_US2	The EMR system has eased work processes					
U-DM_US3	I am generally satisfied using the EMR system					
	Perceived net benefits					
U-DM_PNB1	The EMR system will help overcome the limitations of the paper-based system					
U-DM_PNB2	Using the EMR system will cause an improvement in patient care delivery					
U-DM_PNB3	The EMR system facilitates easy access to patient's information					
U-DM_PNB4	The EMR system will enhance communication among workers					
U-DM_PNB5	The EMR system use will cause improved decision making					

Issues of concern	
Trust in the EMR software	
IoC_TrustEMR	In general, how much would you trust the EMR systems to enable you execute your tasks? **1. Not at all 2. A little 3. Some 4.A lot**
Information security beliefs	
IoC_ISB1	How confident are you that safeguards (including the use of technology) are in place to protect your patients' clinical and financial records from being seen by people who aren't permitted to see them? **1. Not confident 2. Somewhat confident 3. Very confident**
IoC_ISB2	How confident are you that having safeguards (including the use of technology) in place has to do with the security of your clinical and financial records? **1. Not confident 2. Somewhat confident 3. Very confident**
Privacy concerns	
IoC_Privacy	If your patients' clinical and financial information is sent electronically from one health care provider to another, how concerned are you that an unauthorized person would see it? Electronically means from computer to computer, instead of by telephone, mail, or fax machine. **1. Not concerned 2. Somewhat concerned 3. Very concerned**
Support for electronic medical record	
IoC_Support	Please indicate how important it is that [Doctors and other healthcare providers should be able to share your patients' clinical information with each other electronically]. **1. Not at all important 2. Somewhat important 3. Very important**
Patient access to health records	
IoC_PAHR	How will you rate patients' access to personal health information from the EMR system? **1. Poor 2. Fair 3. Good 4. Very good 5. Excellent**
Patient care quality	
IoC_PCQ	Overall, how would you rate the quality of healthcare you provided in the past 12 months? **1. Poor 2. Fair 3. Good 4. Very good 5. Excellent**

Background Characteristics

1. Age group: ☐ Below 30 years old ☐ 30-50 years ☐ More than 50 years
2. Gender: ☐Male ☐Female
3. Select your education level: ☐ SHS ☐Diploma ☐Degree ☐ Masters
4. How long have been working in this hospital? ☐ Below 1 year ☐ 1-5 years ☐ 6-10 years ☐ More than 10 years
5. How long have you been using the EMR system (Years of experience)? ☐ Below 1 year ☐ 1-5 years ☐ 6-10 years ☐ More than 10 years
6. What is the average amount of time you spend during each working day in the use of the system? ☐Less than 30 minutes ☐Between 30 minutes and 1 hour ☐Between 1 and 2 hours ☐Between 2 and 3 hours ☐Between 3 and 4 hours ☐More than 4 hours