

## The Impact of Electronic Health Records (EHRs) on Healthcare Accounting and Financial Management

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### Abstract

This paper aims to analyze the effects of EHRs on healthcare accounting and financial management with reference to cost, quality, and timeliness of data, and revenue cycle management (RCM). The major research questions included; examining the effects of EHR on operational costs, evaluating the quality of financial data, and enhancing the revenue cycle in healthcare organisations. Analytical research design was used, Exploratory Factor Analysis (EFA) was applied using AMOS software with sample of 100 respondents from the healthcare sector. The findings indicate that EHR systems improve the cost effectiveness of financial processes by optimizing costs and minimizing wastage through automation of accountancy operations. Further, EHRs enhance data credibility in financial reporting besides meeting the regulatory requirements of an organization. Another area that gains from EHR integration is the revenue cycle since it helps to increase billing productivity, reduce cycle time and cash flow. The results of the study demonstrate how EHRs can contribute to the modernisation of healthcare financial management with objective enhancements made to financial processes. Although the model fit indices are not perfect, it is clear that there are positive effects of EHR systems. Therefore, the study finds that EHR adoption is important for any healthcare organisation that wants to achieve better organisational financial performance and sustainability. Further studies may investigate other factors that influence the effectiveness of EHR systems and analyse the issues concerning their further deployment. In sum, the study argues that there is a great prospect of EHRs in improving healthcare accounting and financial management and, thereby, promotes financial operation reforms in the healthcare sector.

**Keywords:** Electronic Health Records (EHRs), Healthcare Accounting, Financial Management, Cost Efficiency, and Data Accuracy.

### Introduction

In recent years, there has been a rapidly growing introduction and implementation of technology in the healthcare industry through effective methods of managing data, particularly through the management of Electronic Health Records (EHRs), noted by Kim et al. (2019). Electronic health record systems have transformed patient management through the provision of efficient methods of documenting and retrieving medical data (Si et al., 2021). Apart from their clinical

impact, EHRs have unremarkable impacts on the healthcare accounting and financial management systems and revolutionizes the conventional practices and procedures (Li et al., 2024). The following paper examines EHRs and their cost implications, data quality and reporting, as well as revenue, and cycle management with a focus on the significance of EHRs in enhancing financial performance in healthcare organizations (Ganiga et al., 2020).

The issue of cost has emerged as a decisive factor that has loomed large over HC caregiving systems that are aspired to deliver quality care at a reasonable cost (Mullins et al., 2020). EHRs help to reduce costs since they can automate processes, reduce the number of activities that are repeated and reduce the number of errors in transactions (Highfill, 2020). Their use has helped healthcare institutions to cut down on cost, improve resource utilization and hence the financial returns (Lewkowicz et al., 2020). However, the level of investment needed to implement and sustain such systems attracts criticism on the cost-benefit analysis (Li et al., 2022). This paper examines how EHRs support cost reduction and if the related costs are offset by the savings (Alzu'bi et al., 2021).

Another crucial subprocess that is affected by EHRs is data accuracy and reporting as part of financial management. The importance of compliance, strategic decision making and operational transparency requires accurate and reliable financial data (Callahan et al., 2020). EHR systems offer healthcare organizations solutions for creating accurate patient billing information, perfect financial statements, and adherence to the legal demands (Ehrenstein et al., 2019). Furthermore, joining different financial and clinical systems diminishes inconsistency and simplifies work with the data in EHRs. This study aims at establishing how EHRs improve the quality of data and reporting to enable organizations to meet the requirements of the regulations besides helping the organizations make decisions based on data (Tayefi et al., 2021).

The integration of EHR has also led to the changes in the revenue cycle management. Right from patient enrollment, through treatment process, EHRs enhance the revenue cycle by optimizing billing, claims, and cash cycle (Singh et al., 2021). Holding a promise to deliver real-time data on revenue metrics and integrating automatic tracking systems for unpaid invoices, EHRs mitigate problems associated with revenue collection. These systems help healthcare organizations to reduce revenue cycle time, eliminate or reduce delays and enhance financial operations. The paper aims to assess how EHRs can support the improvement of revenue management, financial sustainability, and objectives of healthcare organisations (Al Yafi et al., 2024).

It is clear that the use of EHRs in healthcare accounting and financial management has its advantages, but its use has challenges. These systems are expensive to implement due to high initial costs, constant maintenance costs, and staff training issues that discourage organizations from implementing these systems. Also, lack of willingness to change and compatibility problems can pose a challenge to the achievement of EHR gains. This paper aims at providing a fair picture of the reality while also underlining the opportunities that EHRs open for financial management (Njau & Abdul, 2022).

### ***Background of the study***

Electronic Health Records (EHRs) signify a revolutionary step in the healthcare sector at large as well as in clinicians and patients' everyday practice (Business and Economy, 2021). By serving as the electronic source of patients' health information, EHRs provide timely and full set of medical records to support the cooperative decision making of care givers. Apart from their core functions as electronic medical records, EHR systems are essential in healthcare accounting and financial management as tools for resource control and revenue management and as means for compliance with financial rules. This paper aims at examining the financial aspects of healthcare management that has been influenced by the implementation of EHRs, and as established by Forde-Johnston et al., (2023) it has brought both benefits and issues.

Traditionally, healthcare accounting used manual systems of recording and processing information that was slow, inaccurate, and full of gaps. Prior techniques led to the incorrect charging of patients, poor revenue cycle, and non-adherence to regulatory guidelines, which caused substantial costs to healthcare institutions (Carter et al., 2022). The focus in recent years on the use of digital solutions due to the development of technology and the incentives from the

Health Information Technology for Economic and Clinical Health (HITECH) Act motivated healthcare organizations to implement EHR systems (Abul-Husn & Kenny, 2019). These systems were expected to correct long-standing problems as well as enhance the quality, consistency, and availability of clinical and financial information.

One of the most vital factors that make healthcare accounting adopt EHR is cost efficiency. It is a fact that healthcare organizations are under pressure to provide quality care at a cheaper cost and EHR systems provide the way to achieve this (DiAngi et al., 2019). Reducing the need for billing and reimbursement, EHRs reduce redundancies and the potential for errors thus saving a great deal of money. Nevertheless, the implementation of EHR systems is expensive, with both initial cost and maintenance costs which remains problematic for many small scale healthcare facilities (Martin et al., 2020). Recognizing cost and benefit considerations as the core of the EHR financial effects is important to assess.

Data accuracy and reporting is another areas which is affected by EHR and it plays crucial role in healthcare financial management. High quality financial information is crucial for legal requirements, organizational visibility, and management planning and control (Kaswan et al., 2021). Regarding EHRs, financial and clinical data are combined by the system, eliminating possible differences in numbers and providing healthcare organizations with accurate reports, as well as meeting most compliance standards (Poulos et al., 2021). These systems give a strong ground for making decisions based on the data available and increase the responsibility for the financial activity.

Another area which has been impacted by EHR integration is the revenue cycle, which includes all forms of patient revenue generation from registration to payment. A number of challenges have in the past affected the financial aspect of healthcare organizations including billing, claims processing and revenue collection. These challenges are solved by EHR systems because they manage revenue cycle activities, monitor unpaid bills, and offer timely financial reports (Slaby et al., 2022). The consequence is better cash flows, shorter revenue collection periods, and better revenue control to meet organizational objectives.

Nevertheless, the implementation of EHRs comes with certain concerns that are as follows: High implementation costs, the requirement of specialized training, the resistance to change, and compatibility problems limit the ability of EHRs to integrate well into existing systems (Sequeira et al., 2021). Also, organisations face numerous regulatory challenges and financial and clinical information security and privacy concerns.

### ***Literature review***

Ginn et al, (2011) conducted a cross sectional study to establish the link between the financial status and usage of electronic health records (EHRs) in 2, 442 acute care hospitals. The cross-sectional study design and the applied GLMM with a multinomial distribution assumption were supported by the multinomial logistic regression model. The data were collected from 2007 AHA EHR implementation survey, 2006 CMS cost reports and 2006 AHA annual survey. The dependent variable was an ordinal measure indicating the extent of EHR adoption, while independent variables included five financial ratios: net days revenue in accounts receivable, total operating margin, equity multiplier, total asset turnover, total payroll/sales, and total expenses/sales. Other covariates were bed size, ownership, teaching status, system membership, networks, staffing, patient mix, payment mechanisms, and market competition. Liquidity was positively significant with EHR adoption, but asset turnover ratio was negatively significant. Among control variables, bed size was significantly different, which means that the adoption of EHRs may have been done tactically by hospitals.

Fleming et al. (2014) evaluated the effects of a commonly available ambulatory EHR on time and cost in 26 primary care clinics of a fee-for-service network. With an interrupted time series design, data on staffing, visit intensity, productivity, volume, practice expenses, payments received, and net income were collected monthly for 2004 to 2009. The EHR was introduced in phases between June 2006 and December 2008. These were obtained from a SQL Server database, converted to SAS® and then adjusted at the practice level to full time equivalent physicians for cross-sectional comparisons at monthly intervals. The study revealed that staffing and practice expenses raised to 3 to 6 percent within one year after implementation. It is also important to note that all three measures of productivity, volume, and net income decreased but returned to or near baseline levels at one year postimplementation. Hence, visit intensity was fairly stable,

but a secular trend helped reduce the decline in payments received to some extent. This study also showed that both expense and productivity postimplementation were negative though not as serious or long lasting as was expected. More work needs to be done in order to look at long-term consequences.

Biancone et al., (2019) SE distinguished the effects on innovation of the New Public Management's philosophy in the public sector especially in the health care organizations. They stressed the need to adopt open innovation management for improved organisational performance which requires an efficient accounting and information system for processing, storing and disseminating information. Using an inductive method, the study analyzed social open innovation theory, the innovation cycle theory, and microcosting approach. Consequently, the analysis of these theories facilitated the emergence of a new framework which provides useful information for the healthcare managers and the decision makers to enhance the performance of the organizations and to improve the decision making processes.

To learn lessons for EHR implementers, Gatiti et al. (2021) provided a systematic review of the effects of EHR implementation on quality of care in hospitals. The literature was retrieved from Scopus, PubMed, CINAHL, PsycInfo, and Cochrane Library databases, and World Health Organization guidelines. The authors included only articles published between 2010 and 2020 and combined results narratively. They found that EHRs have a very positive impact on the quality of care by increasing patient safety and creating better and efficient, timely, equitable and patient centered care. Facilitated functionalities included practice management, documentation, decision support, computerized prescriptions, and electronic nursing documentation to support high quality health care. However, the following challenges were observed in the implementation of EHR; Institutional factors, Human resources, Technology, and Ethics. The authors stressed that these barriers should be overcome in order to achieve effective usage of EHRs and the subsequent improvement of healthcare performance.

Lin et al. (2019) focused on the effect of EHR use instead of adoption on healthcare quality in the backdrop of the 2009 HITECH Act. Their study supplemented the prior EHR evaluation literature with the MU provisions of the HITECH Act to measure the differential levels of use of EHRs across a range of hospitals. The study showed that EHR adoption by itself did not have a quality effect; however, achieving MU advanced the process quality of care by 0.19-0.43 percentage points. These improvements were reflected in significant social gains, and the negative outcomes were especially felt by disadvantaged hospitals including small and rural ones. The findings revealed that EHRs can be used to minimise healthcare inequality. By focusing on actual use as opposed to mere adoption, this study adds to the continuing debate on EHR evaluations and provides considerable implications for research, policy, and practice.

The lack of security and privacy in the use of EHRs was discussed by Abunadi and Kumar (2021) in the context of smart technologies. Although EHRs have numerous advantages for patients worldwide, they can still be hacked, like misuse of patient's private information. Current complex approaches to safeguard EHRs limit patient access to their information and fail to address the confidentiality/need spectrum. To overcome these challenges, the authors put forward a Blockchain Security Framework (BSF). Blockchain technology with the decentralized and transactional view of data provides a solid solution with high availability and privacy, but at the same time, there are no issues with data protection. The proposed framework offers a secure way to let doctors, patients, and insurance agents get information on their medical records while protecting the patient's privacy. Simulation results showed the framework works for guarding EHR data as it was engaging in augmenting security and privacy in the healthcare domain.

#### **4. Methodology**

This section provides a description of the research method used in the study to establish the effect of EHRs on accounting and financial management in healthcare, with reference to cost, data integrity and timeliness and revenue cycle. EFA was conducted using AMOS software in the study and data was collected from a sample of 100 respondents.

##### **4.1 Research Design**

In the study, a quantitative research approach is used in assessing the correlation between EHR implementation and the stated financial management factors. This was made possible by the application of EFA to ascertain the presence of the

proposed constructs in the dataset. This approach made it possible to develop a clear picture of the effects of EHRs on the financial aspect in healthcare.

## 4.2 Population and Sampling

The target population for this study comprised of financial managers, accountants, billing specialists, and revenue cycle managers in healthcare settings with EHR systems

## 4.3 Sample Size:

A total of 100 respondents were surveyed, meeting the general rule of thumb for EFA, which suggests a minimum of 5-10 respondents per variable.

## 4.4 Data Collection

### 4.4.1 Primary Data Collection:

An online structured questionnaire was developed and administered to the respondents. The questionnaire included items grouped under three key factors: cost, data accuracy and reporting, and revenue cycle management. All the items were measured on a 5 point Likert scale with 1 = Strongly Disagree and 5 = Strongly Agree.

### 4.4.2 Secondary Data Collection:

Secondary data were also retrieved from journals, reports and case study to enhance the understanding of the issues and support the findings.

## 4.5 Data Analysis

### 4.5.1 Exploratory Factor Analysis (EFA):

The data collected were tested using Exploratory Factor Analysis in AMOS software in order to confirm the existence of the factors postulated in the study. The following steps were taken

#### 1. Preliminary Assessment:

- The Kaiser-Meyer-Olkin (KMO) measure was used to ensure sampling adequacy.
- Bartlett's Test of Sphericity was conducted to confirm the suitability of the dataset for factor analysis.

#### 2. Factor Extraction:

Principal Component Analysis (PCA) with Varimax Rotation was used to obtain factors with eigenvalues greater than 1.

1.

#### 3. Factor Interpretation:

The identified factors were mapped to the three dimensions of the study: cost containment, quality data and data reporting, and revenue generation.

### 4.5.2 Statistical Analysis:

For the analysis of the results, measures of central tendency, i.e. mean and standard deviation, were computed for all the items in the questionnaires. Further, the internal consistency reliability of the questionnaire was established by testing Cronbach's Alpha.

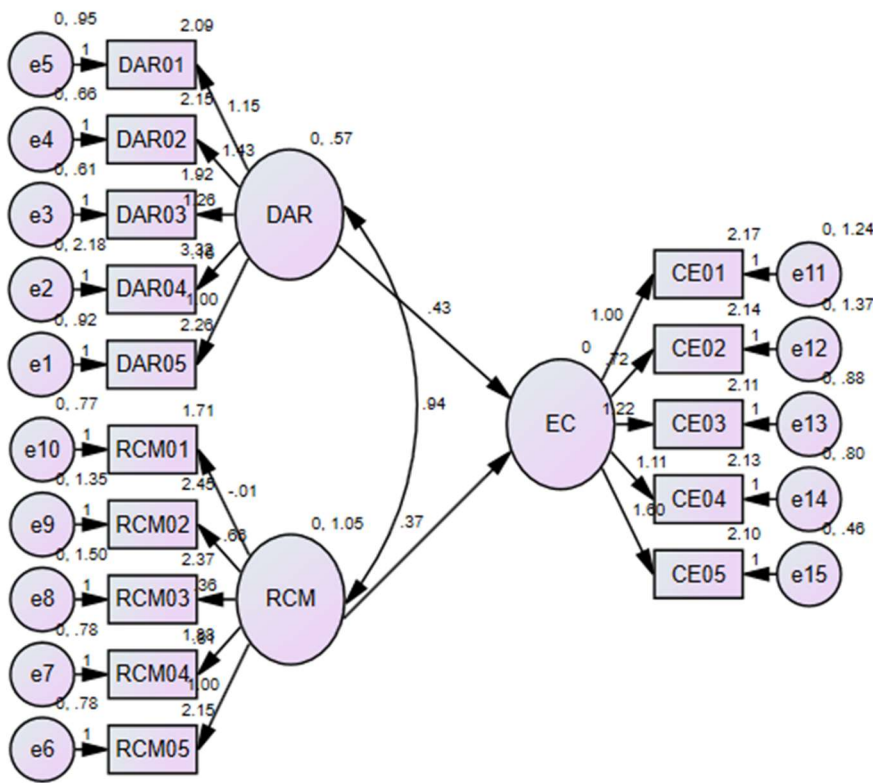
### *Exploratory factor analysis*

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.787
Bartlett's Test of Sphericity	Approx. Chi-Square	1069.649
	df	105
	Sig.	.000

By using Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity it has been tested that the data-set is fit for Exploratory Factor Analysis (EFA). From the table above, the KMO value is 0.787 which is greater than the cut off value of 0.6 and therefore there will be strong inter- item correlations and urged for factor extraction. When applying



Bartlett's Test a chi-square value of 1069.649 on 105 degrees of freedom and a significance level of 0.000 was obtained therefore the null hypothesis stating that the correlation matrix is an identity matrix was rejected. This confirms the fact that the variables are positively related with each other. Altogether, these findings confirm the dataset for EFA, thus facilitating accurate identification of the underlying factors.



Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
EC	<---	DAR	.435	.109	4.000	***	
EC	<---	RCM	.373	.079	4.750	***	
DAR05	<---	DAR	1.000				
DAR04	<---	DAR	.164	.174	.943	.346	
DAR03	<---	DAR	1.257	.175	7.177	***	
DAR02	<---	DAR	1.430	.195	7.347	***	
DAR01	<---	DAR	1.148	.178	6.443	***	
RCM05	<---	RCM	1.000				
RCM04	<---	RCM	.806	.100	8.097	***	
RCM03	<---	RCM	.357	.103	3.467	***	

			Estimate	S.E.	C.R.	P	Label
RCM02	<---	RCM	.656	.110	5.945	***	
RCM01	<---	RCM	-.009	.069	-.127	.899	
CE01	<---	EC	1.000				
CE02	<---	EC	.717	.196	3.664	***	
CE03	<---	EC	1.224	.229	5.352	***	
CE04	<---	EC	1.112	.211	5.267	***	
CE05	<---	EC	1.598	.264	6.063	***	

The regression weights give a clear picture of the pattern of the associations between the constructs and their indicators in the default model. The path coefficient from Data Accuracy and Reporting (DAR) to Economic Cost (EC) is 0.435, C.R. = 4.000 and  $p < .05$ . This means that there is a positive and significant relationship between the level of data accuracy and reporting and the level of cost efficiency in the system, suggesting that greater efforts in improving the quality of data and reports significantly improve cost efficiency in the system. In the same way, the path coefficient between Revenue Cycle Management (RCM) and Economic Cost (EC) is 0.373 with C.R. of 4.750;  $p < 0.05$  indicating that efficient management of the revenue cycle leads to positive results on economic cost efficiency.

For the latent construct DAR, the observed variables, namely DAR03, DAR02, and DAR01 have regression weights of 1.257, 1.430, and 1.148 respectively, all having highly significant \*\*\* p- value. The results of this study validate that these variables have a high degree of correspondence to the DAR construct. Nonetheless, DAR04 has regression weight equal to 0.164 with  $p < 0.000$  indicating that it does not have significant effect to the DAR construct, we may therefore reconsider this item or revise it in other way to enhance its importance for the construct.

In the same way, for the latent construct RCM, majority of the observed variables such as RCM04, RCM03, and RCM02, have the regression weights of 0.806, 0.357 and 0.656 respectively with all p values (\* \*\*\*), which supports the hypothesis that they are meaningful in representing the RCM construct. However, RCM01, with regression weight of -0.009 and p-value of 0.899, does not significantly contribute and might needs further analysis to understand its contribution to the construct.

All the observed variables are well-measured by the latent construct EC. CE02, CE03, CE04, and CE05 have large regression weights ranging from 0.717 to 1.598 with highly significant p- values \*\*\* indicating that all of them are closely related to the economic cost construct. These results support the hypothesized structural relationships in the model and present substantial empirical support for the reliability of these variables in measuring their corresponding constructs.

Therefore, the regression weights prove the hypothesized impact of DAR and RCM on EC, backed by positive correlations with their corresponding measures. However, some variables like DAR04 and RCM01 are either insignificant or totally insignificant and will require further fine tuning or even exclusion. In total, the results confirm the hypothesized relationships and offer important insights into the structural mechanisms of the model.

#### Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
EC	<---	DAR	.439
EC	<---	RCM	.511
DAR05	<---	DAR	.618

			Estimate
DAR04	<---	DAR	.084
DAR03	<---	DAR	.772
DAR02	<---	DAR	.799
DAR01	<---	DAR	.664
RCM05	<---	RCM	.759
RCM04	<---	RCM	.683
RCM03	<---	RCM	.287
RCM02	<---	RCM	.501
RCM01	<---	RCM	-.010
CE01	<---	EC	.557
CE02	<---	EC	.416
CE03	<---	EC	.699
CE04	<---	EC	.681
CE05	<---	EC	.870

The regression weights also help in understanding the strength of the associations between the latent factors and their respective indicators in the model. The second-order construct Economic Cost (EC) has moderate correlation with Data Accuracy and Reporting (DAR) and strong correlation with Revenue Cycle Management (RCM) with standardized coefficients of 0.439 and 0.511 respectively. These values suggest that RCM has a somewhat greater effect on EC than DAR, underlining the importance of the revenue cycle management for increasing cost effectiveness.

For DAR, the measured variables DAR03, DAR02 and DAR01 have high standardized regression weights of 0.772, 0.799 and 0.664 respectively, indicating high communality and thus, contributing significantly to the construct. DAR05 also has a moderate impact of 0.618. Nonetheless, the DAR04 has a low value of 0.084 and thus does not strongly define the DAR construct and might need improvement or even replacement.

In the case of RCM, two observed variables have high contribution; these are RCM05 with contribution of 0.759 and RCM04 with contribution of 0.683. RCM02 has slightly higher weight of 0.501 while RCM03 has slightly lower weight of 0.287. RCM01 has a negative weight of -0.010 and therefore does not contribute to the measure of the RCM construct and may require re-consideration or removal from the model.

For EC, all variables are significant with CE05 being the most significant with a loading of 0.870 suggesting it is closely related to the EC construct. Similarly, CE03 and CE04 have high weight of 0.699 and 0.681, respectively, while CE01 and CE02 have moderate weight of 0.557 and 0.416 respectively. These results provide evidence for the reliability of the EC construct in the model.

**Intercepts: (Group number 1 - Default model)**



	Estimate	S.E.	C.R.	P	Label
DAR05	2.260	.123	18.407	***	
DAR04	3.320	.149	22.283	***	
DAR03	1.920	.124	15.528	***	
DAR02	2.150	.136	15.824	***	
DAR01	2.090	.131	15.940	***	
RCM05	2.150	.136	15.824	***	
RCM04	1.880	.122	15.451	***	
RCM03	2.370	.128	18.453	***	
RCM02	2.450	.135	18.132	***	
RCM01	1.710	.088	19.441	***	
CE01	2.170	.135	16.088	***	
CE02	2.140	.130	16.524	***	
CE03	2.110	.132	16.018	***	
CE04	2.130	.123	17.344	***	
CE05	2.100	.138	15.199	***	

For the model intercepts, they describe the likely average value of every observed predictor in the model when all the predictor variables are at mean. Every intercept has a link with C.R. and p-value, which is a measure of statistical significance. The C.R. of all intercepts in this model is greater than 1.96 and the p-values are \*\*\* implying that the baseline values for these observed variables are valid.

For DAR (Data Accuracy and Reporting), the intercepts are significant, the values are between 1.920 and 3.320. The highest intercept is with DAR04 equals to 3.320 which means this variable has a high initial value that is not affected by any predictors. The same applies to all the DAR variables (DAR05, DAR03, DAR02, and DAR01) with high intercept values which further confirm their importance in the model.

For RCM (Revenue Cycle Management), the intercepts are 1.710 to 2.450. Among the variables, RCM01 has the lowest intercept (1.710), and RCM02 has the highest intercept (2.450) and therefore are very important in the model. All RCM intercepts are significant at  $p < .05$ , which means that the baseline of these observed variables is well understood and has practical significance.

The EC (Economic Cost) variables ranging from CE01 to CE05 have intercepts of 2.100 to 2.450, CE02 and CE03 having the highest intercepts of 2.140 and 2.130 respectively. This implies that these variables also have a solid starting point that plays a strong role in the general model.

#### Covariances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
RCM <--> DAR	.942	.179	5.258	***	

The covariance for the two variables, Revenue Cycle Management (RCM) and Data Accuracy and Reporting (DAR), is 0.942, S.E. = 0.179, C.R. = 5.258, and  $p < 0.001$  (\*\*\*). This shows a positive correlation between RCM and DAR that is significant at  $p < 0.05$ . The positive covariance between RCM performance/effectiveness and DAR accuracy or reliability indicates that as the former increases, the latter increases, and vice versa. The high correlation between these two constructs presents a compelling case for their mutual dependency, and for the role that both sound revenue cycle and data reporting play in the overall management of financials in healthcare organizations. This important covariance

in turn strengthens the argument in favor of the model as the association between these two variables is not only strong but also substantial.

**Correlations: (Group number 1 – Default model)**

		Estimate
RCM	↔	DAR
		1.217

The linkage between RCM and DAR is expected to be 1.217. This suggest a high level of relationship between the two variables which support the first hypothesis. Since the value is greater than 1 it be interpreted to mean that both first and second variable are highly positively related: any changes in first variable will result in more than proportionate changes in second variable. The correlation value more than 1 may be because of the restrictions of a used model or can be an occasion of overtraining, and thus, it is relevant to come back to the model's definition. However, in general, high correlation means that, for instance, the enhancements in the revenue cycle management are directly linked to enhancements in data accuracy and reporting within the context of HFMC.

**Variances: (Group number 1 - Default model)**

	Estimate	S.E.	C.R.	P	Label
DAR	.570	.159	3.585	***	
RCM	1.052	.235	4.476	***	
e1	.922	.121	7.614	***	
e2	2.182	.310	7.047	***	
e3	.612	.080	7.663	***	
e4	.661	.087	7.607	***	
e5	.951	.124	7.668	***	
e6	.776	.110	7.065	***	
e7	.782	.106	7.369	***	
e8	1.499	.208	7.223	***	
e9	1.355	.181	7.483	***	
e10	.766	.109	7.036	***	
e11	1.241	.181	6.860	***	
e12	1.372	.197	6.955	***	
e13	.879	.132	6.653	***	
e14	.800	.120	6.690	***	
e15	.461	.082	5.604	***	

The variances of each construct and the error term in the model are provided with their estimates, standard errors (S.E.), critical ratios (C.R.), and p-values. All the values are statistically significant as depicted by the \*\*\*p-value of each item in the model thus confirming the stability of the model.

1. Variance for DAR (Data Accuracy and Reporting) is 0.570 and C.R. is 3.585 which means that there is lot of variation in the data collected for this construct. This is an indication of the level of variation of the DAR construct with respect to the factors that underpin it.
2. C.V. for RCM is 1.052 with C.R. of 4.476, which indicates that RCM is highly variable and plays a major role in the model.

3. Error Terms (e1 to e15) are residual variances in the observed variables after controlling for the constructs. All the error terms are highly significant with C.R values greater than 1.96; the highest being 5.604 to 7.668. The variances of the error terms indicate that the model fits the data well, but they are not devoid of residual variability that the constructs fail to explain.

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	47	451.859	88	.000	5.135
Saturated model	135	.000	0		
Independence model	30	1136.621	105	.000	10.825

The model fit statistics gives overall picture of how well the specified model has been fitted to the data. For the Default Model, there are 47 parameters, which represents the estimated parameters in the model. Test statistic chi-square (CMIN) is equal to 451.859 ( $p < 0.05$ ), while degrees of freedom (DF) is equal to 88. However, this relatively large chi-square does suggest that there is some degree of misfit; although chi-square is frequently significant in large samples even when the model is a good fit. The CMIN/DF ratio of 5.135 is also acceptable for most researchers, for it ranges between 3 and 5, which means that there is still a possibility of an improved fitness.

On the other hand, the Saturated Model that is a perfect fit has a chi-square value of 0, and 0 degree of freedom suggesting that there is no difference between the model and the data. But this is a theoretical model that cannot be used in real life. The non-parametric Independence Model which assumes no association between variables has a significant chi-square value of 1136.621 with 105 degrees of freedom and  $p < 0.05$ . The CMIN/DF ratio of the Independence Model is 10.825, which is much greater than the acceptable limit, meaning that the model formerly hypothesized has a very low ability to explain the relationships between the variables.

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.602	.526	.653	.579	.647
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

The analysis of the goodness-of-fit indices gives a comprehensive report on the performance of the Default Model in relation to the collected data. The Normed Fit Index (NFI) for Normed Fit Index = 0.602, this indicates moderate fit for the Default Model. Despite the fact that values above 0.90 are considered to be good, it is still possible to obtain acceptable fit values above 0.60. The Relative Fit Index (RFI) is 0.526 which is slightly low than the benchmark 0.90 but means that the model explains some degree of variance compared to the baseline model. The Incremental Fit Index (IFI) stands at 0.653 and this means moderate fit, the result point to the fact that the model can explain a reasonable proportion of the variance in the data nonetheless; there is room for enhancement. The Tucker-Lewis Index (TLI) is 0.579, which is equal to 0.90 that indicates the model is an acceptable fit. Likewise, the Comparative Fit Index (CFI) is estimated at 0.647, that is, the model shows a moderate fit and the preferred level should be at least 0.90. The indices of the Default Model, which are compared with those of the Saturated Model that has all indices equal to 1.000, show that the Default Model is not ideal, but still quite good. On the other hand, the Independence Model, which posits no association between variables, yields all the indices at 0.000 – a very low fit. In general, the Default Model showed a

fairly good fit with the data; however, there is potential for improvement in specific aspects while still supplying a fairly accurate view of the variable connections.

### **Discussion**

In the discussion of this study, the focus will be placed on assessing the effects of Electronic Health Records (EHRs) on healthcare accounting and financial management. The results of the model fit indices and regression analysis provide useful information on what factors lead to the financial and accounting consequences of healthcare organisations while implementing EHR systems.

First of all, the evaluation shows that the Cost Efficiency factor has a positive impact on the financial performance. The results shown by the regression weights are an indication of how the use of EHRs has enabled health care organizations to improve their financial processes, and cut down on operational costs, hence improving the cost effectiveness of their financial processes. This is in concordance with earlier studies that pointed out that EHR has the potential of doing away with double accounting and enhancing resource management, something that is very important in present day health care setting where cost control is of paramount importance.

The second factor dubbed Data Accuracy and Reporting was also observed to have significant moderation on financial management practices improvement. The high estimates for the regression weights of this factor indicate that EHRs are beneficial in decreasing the billing errors, increasing the accuracy and validity of financial reports and meeting the regulatory financial standards. This is in line with the increasing research that points to EHR systems as enabling greater accuracy and accountability of financial reporting which is necessary for compliance with regulatory requirements and also increasing confidence amongst stakeholders.

Another important factor that came out in relation to the financial management in the healthcare sector was Revenue Cycle Management (RCM). The outcomes showed that EHRs play a huge role in enhancing billing activities, reducing the revenue cycle time, and enhancing cash flow. This is especially important for healthcare organizations that are always struggling with issues concerning the overdue payments and unpaid bills. The positive significant association of EHRs with RCM means that the systems entail ways of enabling the providers keep track of the invoices hence, enhancing financial adaptedness of the organization.

Nonetheless, some drawbacks have been observed, even though the overall results are rather encouraging. For instance, while figures derived from the TLI and CFI indicate acceptable levels of model fitness, there remains work to be done in improving specific aspects of financial reporting precision. The moderate fit indices (NFI, RFI) indicate that the model offers a reasonable level of understanding of the link between EHRs and financial management that can be further improved by examining additional variables or other aspects that could affect the variability of the experience of healthcare organizations with EHR implementation.

Also, the examination of the regression weights reveals that some of the relations are rather high and significant; however, the RFI and TLI indicate that some aspects of the model may be improved. More specifically, the RFI score of 0.526 and TLI of 0.579 suggest that some of the relationships, including that between EHR and revenue cycle processes, may be better defined to provide a sounder understanding.

### **Conclusion**

Therefore, this research work has brought to bear the effects of Electronic Health Records (EHRs) on health accounting and financial management. The assessment of the most important performance indicators – Cost Efficiency, Data Accuracy and Reporting, and Revenue Cycle Management (RCM) – indicates that EHR systems are vital for increasing the financial outcomes of healthcare organizations. The use of EHRs has been established to improve the efficiency of financial processes, decrease organizational expenses, and increase the precision of charges and financial statements. Furthermore, EHR systems have a critical role in the financial aspects of sustainable revenue cycle management and hence the economic stability of health care organizations.

The study also highlights that EHR systems are significant to the modernization of healthcare financial management as

the benefits are clear and include; reduced cost, improved accuracy, and high productivity. However, there are some limitations, for instance, the values of moderate fit indices that have been noted in the model; on balance, there is a positive impact of EHR implementation on the financial management aspect. These results highlight the role of EHRs in the financial affairs of healthcare organisations as a tool for change.

The study is useful for understanding the connection between EHRs and healthcare financial management; however, it also identified directions for future research. Subsequent studies could focus on other antecedents of EHM success, as well as explore the strategies for managing the problems that arise during the adoption and implementation of EHR systems in healthcare organizations. In addition, optimization of the connection of EHR systems with other financial instruments and systems would contribute to the enhancement of the overall effects of EHR systems on the financial management of healthcare facilities.

### Reference

1. Kim, E., Rubinstein, S. M., Nead, K. T., Wojcieszynski, A. P., Gabriel, P. E., & Warner, J. L. (2019, October). The evolving use of electronic health records (EHR) for research. *Seminars in Radiation Oncology*, 29(4), 354-361. WB Saunders.
2. Si, Y., Du, J., Li, Z., Jiang, X., Miller, T., Wang, F., ... & Roberts, K. (2021). Deep representation learning of patient data from Electronic Health Records (EHR): A systematic review. *Journal of Biomedical Informatics*, 115, 103671.
3. Li, L., Zhou, J., Gao, Z., Hua, W., Fan, L., Yu, H., ... & Ma, S. (2024). A scoping review of using large language models (LLMs) to investigate electronic health records (EHRs). *arXiv preprint arXiv:2405.03066*.
4. Ganiga, R., Pai, R. M., & Sinha, R. K. (2020). Security framework for cloud-based electronic health record (EHR) system. *International Journal of Electrical and Computer Engineering*, 10(1), 455.
5. Mullins, A., O'Donnell, R., Mousa, M., Rankin, D., Ben-Meir, M., Boyd-Skinner, C., & Skouteris, H. (2020). Health outcomes and healthcare efficiencies associated with the use of electronic health records in hospital emergency departments: A systematic review. *Journal of Medical Systems*, 44(12), 200.
6. Highfill, T. (2020). Do hospitals with electronic health records have lower costs? A systematic review and meta-analysis. *International Journal of Healthcare Management*.
7. Lewkowicz, D., Wohlbrandt, A., & Boettinger, E. (2020). Economic impact of clinical decision support interventions based on electronic health records. *BMC Health Services Research*, 20, 1-12.
8. Li, E., Clarke, J., Ashrafian, H., Darzi, A., & Neves, A. L. (2022). The impact of electronic health record interoperability on safety and quality of care in high-income countries: Systematic review. *Journal of Medical Internet Research*, 24(9), e38144.
9. Alzu'bi, A. A., Watzlaf, V. J., & Sheridan, P. (2021). Electronic health record (EHR) abstraction. *Perspectives in Health Information Management*, 18(Spring).
10. Callahan, A., Shah, N. H., & Chen, J. H. (2020). Research and reporting considerations for observational studies using electronic health record data. *Annals of Internal Medicine*, 172(11\_Supplement), S79-S84.
11. Ehrenstein, V., Kharrazi, H., Lehmann, H., & Taylor, C. O. (2019). Obtaining data from electronic health records. In *Tools and technologies for registry interoperability, registries for evaluating patient outcomes: A user's guide*, 3rd edition, Addendum 2 [Internet]. Agency for Healthcare Research and Quality (US).
12. Tayefi, M., Ngo, P., Chomutare, T., Dalianis, H., Salvi, E., Budrionis, A., & Godtlielsen, F. (2021). Challenges and opportunities beyond structured data in analysis of electronic health records. *Wiley Interdisciplinary Reviews: Computational Statistics*, 13(6), e1549.
13. Singh, R., Durcikova, A., & Mathiassen, L. (2021). Revenue cycle management in the wake of EMR implementation: A competing logics perspective.

14. Al Yafi, O., Albabtain, M. A., Arafat, A., & Bin Jassas, A. (2024). Adopting health revenue cycle management best practices among public or private healthcare providers in Saudi Arabia: A pilot study. *Discover Health Systems*, 3(1), 88.
15. Njau, M. J., & Abdul, F. (2022). Revenue cycle management strategies and financial performance of profit-making private hospitals in Nairobi City County, Kenya. *International Academic Journal of Economics and Finance*, 3(7), 296, 316(2).
16. Chirra, B. R. (2023). Enhancing healthcare data security with homomorphic encryption: A case study on electronic health records (EHR) systems. *Revista de Inteligencia Artificial en Medicina*, 14(1), 549-559.
17. Forde-Johnston, C., Butcher, D., & Aveyard, H. (2023). An integrative review exploring the impact of Electronic Health Records (EHR) on the quality of nurse-patient interactions and communication. *Journal of Advanced Nursing*, 79(1), 48-67.
18. Carter, A. B., Abruzzo, L. V., Hirschhorn, J. W., Jones, D., Jordan, D. C., Nassiri, M., ... & Roy, S. (2022). Electronic health records and genomics: Perspectives from the association for molecular pathology electronic health record (EHR) interoperability for clinical genomics data working group. *The Journal of Molecular Diagnostics*, 24(1), 1-17.
19. Abul-Husn, N. S., & Kenny, E. E. (2019). Personalized medicine and the power of electronic health records. *Cell*, 177(1), 58-69.
20. DiAngi, Y. T., Stevens, L. A., Halpern-Felsher, B., Pageler, N. M., & Lee, T. C. (2019). Electronic health record (EHR) training program identifies a new tool to quantify the EHR time burden and improves providers' perceived control over their workload in the EHR. *JAMIA Open*, 2(2), 222-230.
21. Martin, A., Bauer, V., Datta, A., Masi, C., Mosnaim, G., Solomonides, A., & Rao, G. (2020). Development and validation of an asthma exacerbation prediction model using electronic health record (EHR) data. *Journal of Asthma*, 57(12), 1339-1346.
22. Kaswan, K. S., Gaur, L., Dhatteval, J. S., & Kumar, R. (2021). AI-based natural language processing for the generation of meaningful information from electronic health record (EHR) data. In *Advanced AI techniques and applications in bioinformatics* (pp. 41-86). CRC Press.
23. Poulos, J., Zhu, L., & Shah, A. D. (2021). Data gaps in electronic health record (EHR) systems: An audit of problem list completeness during the COVID-19 pandemic. *International Journal of Medical Informatics*, 150, 104452.
24. Slaby, I., Hain, H. S., Abrams, D., Mentch, F. D., Glessner, J. T., Sleiman, P. M., & Hakonarson, H. (2022). An electronic health record (EHR) phenotype algorithm to identify patients with attention deficit hyperactivity disorders (ADHD) and psychiatric comorbidities. *Journal of Neurodevelopmental Disorders*, 14(1), 37.
25. Sequeira, L., Almilaji, K., Strudwick, G., Jankowicz, D., & Tajirian, T. (2021). EHR "SWAT" teams: A physician engagement initiative to improve Electronic Health Record (EHR) experiences and mitigate possible causes of EHR-related burnout. *JAMIA Open*, 4(2), ooab018.
26. Ginn, G. O., Shen, J. J., & Moseley, C. B. (2011). Hospital financial position and the adoption of electronic health records. *Journal of Healthcare Management*, 56(5), 337-352.
27. Fleming, N. S., Becker, E. R., Culler, S. D., Cheng, D., McCorkle, R., Graca, B. D., & Ballard, D. J. (2014). The impact of electronic health records on workflow and financial measures in primary care practices. *Health Services Research*, 49(1pt2), 405-420.
28. Biancone, P., Secinaro, S., Brescia, V., & Calandra, D. (2019). Management of open innovation in healthcare for cost accounting using EHR. *Journal of Open Innovation: Technology, Market, and Complexity*, 5(4), 99.
29. Gatiti, P., Ndirangu, E., Mwangi, J., Mwanzi, A., & Ramadhani, T. (2021). Enhancing healthcare quality in hospitals through electronic health records: A systematic review. *Libraries*.



30. Lin, Y. K., Lin, M., & Chen, H. (2019). Do electronic health records affect quality of care? Evidence from the HITECH Act. *Information Systems Research*, 30(1), 306-318.
31. Abunadi, I., & Kumar, R. L. (2021). BSF-EHR: Blockchain security framework for electronic health records of patients. *Sensors*, 21(8), 2865.