



Regulatory Pressure and Perceived Threats in Indonesian Electronic Medical Records Adoption



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Authors

Ghozali M.^{*1} PhD

Dewi C.K.² PhD

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¹Department of Quranic Studies and Interpretation, Faculty of Islamic Theology and Thought, Sunan Kalijaga State Islamic University, Yogyakarta, Indonesia

²Department of Biomedical Sciences, Faculty of Science and Technology, Sunan Kalijaga State Islamic University, Yogyakarta, Indonesia

*Correspondence

Address: Department of Quranic Studies and Interpretation, Faculty of Islamic Theology and Thought, Sunan Kalijaga State Islamic University, Caturtunggal, Laksda Adi Sucipto Street, Sleman, Yogyakarta Special Region, Indonesia. Postal Code: 55281

Phone: +62 (857) 859577770

mahbub.ghozali@uin-suka.ac.id

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ABSTRACT

Aims This study explored the dynamics of electronic medical records adoption and use in primary healthcare facilities in Indonesia, specifically examining the role of regulatory pressure and perceived technological threats within the framework of mandatory national health policies.

Instrument & Methods This multisite cross-sectional survey was conducted among 688 healthcare workers from 27 community health centers in Bantul Regency, Indonesia. An analytical framework was used to examine regulatory pressure, perceived threat, performance expectancy, effort expectancy, facilitating conditions, behavioral intention, and actual use, with the latter analyzed through structural equation modeling.

Findings Perceptions of utility, ease of use, and organizational support played a vital role in shaping the intention to adopt electronic medical records. Regulatory pressure emerged as a primary driver shaping facility readiness and practitioners' psychological response, directly strengthening behavioral intention. Notably, actual system usage was driven by the synergy between regulatory mandates and institutional readiness.

Conclusion Successful digital transformation in primary healthcare requires coherence among regulatory enforcement, institutional readiness, and healthcare workers' adaptive responses to technological change.

Keywords Electronic Medical Records; Primary Healthcare; Regulatory Pressure; Health Belief Models; Digital Health

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Introduction

Digital transformation has become a strategic priority in health system reform across many developing countries, including Indonesia. In this context, Indonesia's Ministry of Health (Kementerian Kesehatan Republik Indonesia—Kemenkes) is actively promoting the adoption of Electronic Medical Records (EMRs) as part of the national agenda to strengthen the health system. This initiative is outlined in the 2020-2024 National Medium-Term Development Plan (RPJMN) and will continue through the 2025-2029 RPJMN. The agenda is supported by various regulatory frameworks, including Law (Undang-Undang—UU) Number 17 of 2023 concerning Health, the Health Digital Transformation Strategy policy, and Minister of Health Regulation (Peraturan Menteri Kesehatan—Permenkes) No. 24 of 2022, Article 45, which mandates that all health facilities implement EMRs within a specified timeframe. Collectively, these policies aim to establish an integrated digital health ecosystem through the SATUSEHAT platform.

At the macro level, Indonesia has made significant progress in digitizing the health sector. The WHO Global Health Monitor ranks Indonesia at digital maturity level 4^[1], indicating that digital technology use is mature and functional. However, achievements in national-level policy are not fully reflected in implementation at the health facility level. Data from the Center for Indonesia's Strategic Development Initiatives (CISDI) reveal that 48.9% (4,807) of community health centers (Pusat Kesehatan Masyarakat—Puskesmas) have yet to adopt electronic medical records (EMRs), with low technological literacy among healthcare workers identified as the primary obstacle^[2].

These findings align with numerous studies confirming that barriers to health technology adoption in developing countries arise not only from limited exposure to technology but also from psychological and structural factors, such as low self-efficacy^[3], intrinsic motivation^[4, 5], and low trust in technology^[6].

Furthermore, digitizing health systems—particularly those requiring interoperability—demands maturity in resources, infrastructure, and governance, which developing countries often lack^[7-9]. Under these conditions, governments tend to rely on mandatory policies to accelerate the adoption of health technologies.

This coercive regulatory approach generates institutional pressure that may shape healthcare workers' technology use. Several studies demonstrate that public policy can affect behavioral intentions both directly and indirectly through attitudes, perceived control, and risk perceptions^[10-12].

However, policy factors are generally not yet systematically incorporated into mainstream health

technology adoption frameworks. In the context of developing countries, regulation functions not merely as a supportive tool but as a coercive mechanism that demands compliance and may induce psychological stress due to the threat of sanctions.

In institutional literature, coercive pressure from regulators is recognized as a major driver of organizational change, particularly during the formal technology adoption phase^[13]. In the health sector, responses to this pressure manifest through coercive, normative, and mimetic mechanisms^[14]. Recent studies indicate that coercive pressure not only promotes compliance but also heightens sanction-based strain, which is likely to influence how individuals interpret and utilize technology^[15].

In line with this, research on health technology adoption heavily relies on the Unified Theory of Acceptance and Use of Technology (UTAUT) as its primary analytical framework^[16]. Various adaptations of UTAUT have incorporated contextual factors, including policy and risk perception^[17-19]. However, most studies treat policy as a form of facility support that enhances trust and reduces risk^[20-22], rather than as coercive pressure that mandates technology adoption.

In addition to regulatory factors, perceived threat is increasingly recognized as a crucial determinant in technology adoption, especially in environments characterized by low digital literacy and limited infrastructure^[23, 24]. Perceived threats—whether technological risks or psychological pressures such as technostress—can shape perceptions of ease of use, behavioral intention, and actual use of digital systems^[25, 26]. In the context of mandatory EMR implementation, there is significant interest in exploring how regulatory pressure and perceived threat interact to shape healthcare workers' behavior.

Studies on EMR adoption in Indonesia have highlighted the benefits of EMR for data security and service monitoring^[27] and identified various obstacles, including regional disparities^[28], infrastructure limitations^[29, 30], and low literacy levels^[31].

However, empirical evidence remains limited regarding the simultaneous influence of coercive regulatory pressure and perceived threat on the cognitive determinants of EMR adoption.

By positioning EMR as a tool for health policy and service system development, this study aimed to provide empirical contributions to strengthening the governance of digital health transformation in developing countries, while offering policy implications to enhance the effectiveness of EMR implementation at the primary care level. This study analyzed EMR adoption in Indonesia using the UTAUT framework, which integrates regulatory pressure and perceived threat as key factors.

Instrument and Methods

This analytical multisite cross-sectional study integrated the UTAUT with two regulatory pressures and perceived threat to examine EMR adoption within the context of health policy in developing countries [16, 32].

UTAUT identifies the core cognitive determinants of EMR adoption, including performance expectancy, effort expectancy, social influence, and facilitating conditions, all of which are explored in relation to behavioral intention and actual use [16]. To capture the context of mandatory EMR implementation, the model is expanded to include regulatory pressure, which represents the coercive influence of government policies and regulations on institutional compliance [33-35].

Additionally, perceived threat is considered a psychological response to the risks, uncertainties, and adaptation burdens associated with mandatory implementation, especially in environments with low digital literacy [36, 37]. This framework guided the analysis of the structural relationships among these factors, which were evaluated using partial least squares structural equation modeling (PLS-SEM; Figure 1).

An instrument was developed to measure EMR adoption by adapting and expanding the UTAUT model to incorporate perceived threat and regulatory influence, with the questionnaire grounded in relevant literature on technology adoption and health information systems and tailored specifically to the context of EMR use by healthcare workers. The initial draft was refined through consultations with experts in digital transformation and healthcare management to ensure both conceptual accuracy and contextual relevance. The questionnaire was organized into sections covering basic information, experience (Exp), core UTAUT constructs (performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), regulatory influence (RI)), behavioral intention (BI), and usage behavior (UB).

(EE), Social influence (SI), Facilitating conditions (FC), Behavioral intention (BI), Usage behavior (UB), Perceived threats (PT), and Regulatory influence (RI). All items were measured using a five-point Likert scale. It was translated into Indonesian through a back-translation procedure and piloted to ensure clarity of wording. Reliability testing produced Cronbach's alpha values exceeding the acceptable threshold for all constructs (Table 1).

The questionnaire was distributed to healthcare workers in Bantul Regency, Indonesia, through both an online survey (Google Forms) and offline printed questionnaires. Of the 748 targeted healthcare workers, 688 completed valid questionnaires, resulting in a response rate of 91.98%. All returned questionnaires met the inclusion criteria, and no data were excluded during screening.

We assessed indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Structural model evaluation involved a bootstrapping procedure to examine the strength and direction of associations among constructs, as well as the model's explanatory power (R^2), predictive relevance (Q^2), and effect size (f^2). The roles of mediation and moderation were also assessed in accordance with the proposed model. To enhance methodological validity, common method bias (CMB) was assessed using the full collinearity variance inflation factor (VIF) and Harman's single-factor test.

Data analysis was conducted using partial least squares structural equation modeling with SmartPLS 4 software. The PLS-SEM approach was chosen because it is well-suited for analyzing complex relationships involving multiple constructs simultaneously [38, 39]. Q^2 values above 0.4 indicate medium-to-high predictive relevance, along with relatively low root mean squared error and mean absolute error [40, 41].

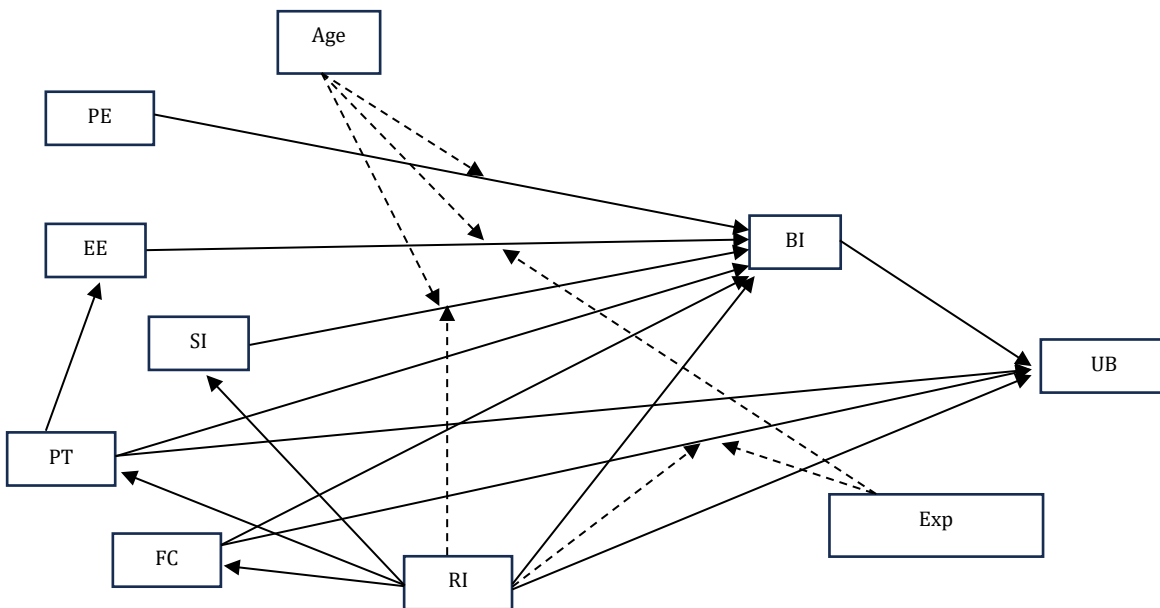


Figure 1. Theoretical framework model

Table 1. The developed instrument

Construct	Code
Basic information	
Gender (select one answer choice): A. Male B. Female	
Age (select one answer choice): A. <25 B. 25-40 C. 41-45 D. 46-55 E. >55	
Education level (select one answer choice): A. High school or less B. Diploma C. Undergraduate D. Postgraduate	
Work experience (select one answer choice): A. <1 year B. 1-5 years C. 6-10 years D. 11-20 years E. >20 years	
Experience (Exp)	
I feel that I have become increasingly familiar with using the EMR system over time	EXP1
I feel that I have become more proficient in using the EMR compared to when I first started using it	EXP2
I have participated in training or mentorship related to the EMR	EXP3
Performance expectancy (PE)	
I believe that implementing or using the electronic medical record (EMR) can improve my performance in documenting patient data	PE1
I believe that using the EMR enables me to complete patient documentation tasks more quickly	PE2
I consider the EMR to be useful in supporting healthcare services	PE3
Effort expectancy (EE)	
I feel that I can easily learn how to use the EMR system	EE1
I feel that I can interact with and understand the EMR system clearly and easily	EE2
I feel that the EMR system will be easy to use for documenting patient data	EE3
Social influence (SI)	
I feel that recommendations from colleagues or supervisors who are important to me encourage me to use the EMR	SI1
Recommendations from people whose opinions I value encourage me to use the EMR	SI2
I feel more motivated to use the EMR when my colleagues or supervisors give personal support or appreciation for using it	SI3
Facilitating conditions (FC)	
With the existing infrastructure, I feel that my environment supports the use of the EMR system for documenting patient data	FC1
I have the resources and knowledge necessary to use the EMR	FC2
With the facilities and resources available in my work environment, I believe I will receive technical assistance if I encounter difficulties using the EMR	FC3
Behavioral intention (BI)	
I intend to use the EMR to document patient data	BI1
I intend to use the EMR to improve my work efficiency as a healthcare worker	BI2
I plan to continue using the EMR in my work	BI3
Usage behavior (UB)	
I use the EMR in most of my patient documentation activities	UB1
I routinely use the EMR to record patient data in my daily work	UB2
I use the EMR whenever I perform patient documentation tasks	UB3
Perceived threats (PT)	
I am worried that I may become stressed when using the EMR system	PT1
I am concerned that using the EMR may threaten patient data privacy and security	PT2
I am worried that I may not be able to use the EMR without assistance from others	PT3
Regulatory influence (RI)	
Internal rules and standard operating procedures in my unit strongly require the use of the EMR	RI1
I use the EMR because not complying with EMR policies in my workplace may have consequences	RI2
Government regulations play a decisive role in driving EMR adoption in our unit	RI3

Findings

A total of 603 respondents (88%) were female, and 85 (12%) were male. Also, 11 cases (2%) were under 25 years, 371 cases (54%) were aged 25-40 years, 129 cases (19%) were aged 41-45 years, 135 cases (20%) were aged 46-55 years, and 42 cases (6%) were over 55 years. Regarding work experience, most respondents had 11-20 years (31%), followed by more than 20 years (24%), 6-10 years (23%), 1-5 years (19%), and less than 1 year (4%).

The model showed the reliability of the indicators through outer loadings, with all indicators exceeding the 0.70 threshold (ranging from 0.828 to 0.961). Internal consistency and convergent validity were confirmed, with average variance extracted (AVE) values ranging from 0.726 to 0.914, indicating that each construct adequately explained the variance in its respective indicators (Table 2). Furthermore, discriminant validity was assessed to assess the conceptual distinctiveness of the parameters; all Heterotrait-Monotrait (HTMT) values were below the required threshold (<0.90), confirming that each

construct was empirically distinct and did not overlap with others. Consequently, the correlation matrix and the ratio of shared variance demonstrate that the measures for each parameter specifically capture their intended concepts, establishing the validity and independence of the framework's components (Table 2).

Structural analysis explored the relationships between the constructs using a bootstrapping procedure. Behavioral intention played a positive role in shaping usage behavior. Among the primary factors, effort expectancy, facilitating conditions, and performance expectancy emerged as contributors to behavioral intention, while social influence showed a minimal role.

Regulatory influence emerged as a central determinant within the framework and showed a strong association with facilitating conditions, perceived threat, and social influence, and it also directly related to behavioral intention. Perceived threat demonstrated a positive connection with effort expectancy and usage behavior (Table 3).

Table 2. Summary of the measurement model results

Construct	Indicator	Factor loading	Cronbach's alpha	Composite reliability	Average variance extracted
Usage behavior (UB)	UB1	0.875	0.892	0.933	0.822
	UB2	0.909			
	UB3	0.935			
Behavioral intention (BI)	BI1	0.961	0.953	0.970	0.914
	BI2	0.950			
	BI3	0.957			
Effort expectancy (EE)	EE1	0.923	0.904	0.940	0.840
	EE2	0.941			
	EE3	0.885			
Facilitating conditions (FC)	FC1	0.912	0.901	0.938	0.835
	FC2	0.914			
	FC3	0.915			
Performance expectancy (PE)	PE1	0.912	0.903	0.939	0.838
	PE2	0.913			
	PE3	0.922			
Perceived threats (PT)	PT1	0.897	0.819	0.893	0.735
	PT2	0.828			
	PT3	0.846			
Regulatory influence (RI)	RI1	0.832	0.811	0.888	0.726
	RI2	0.833			
	RI3	0.889			
Social influence (SI)	SI1	0.930	0.900	0.937	0.833
	SI2	0.939			
	SI3	0.868			

Table 3. Summary of structural relationships

Path	Path coefficients (β)	Association
Performance expectancy \rightarrow Behavioral intention	0.081	Positive
Effort expectancy \rightarrow Behavioral intention	0.198	Positive
Social influence \rightarrow Behavioral intention	-0.002	Not clear
Facilitating conditions \rightarrow Behavioral intention	0.329	Positive
Facilitating conditions \rightarrow Usage behavior	0.124	Positive
Behavioral intention \rightarrow Usage behavior	0.299	Positive
Perceived threats \rightarrow Effort expectancy	0.657	Positive
Perceived threats \rightarrow Behavioral intention	0.138	Positive
Perceived threats \rightarrow Usage behavior	0.386	Positive
Regulatory influence \rightarrow Perceived threats	0.681	Very strong
Regulatory influence \rightarrow Social influence	0.717	Very strong
Regulatory influence \rightarrow Facilitating conditions	0.736	Very strong
Regulatory influence \rightarrow Behavioral intention	0.203	Positive
Regulatory influence \rightarrow Usage behavior	0.081	Not clear
Age \times Performance expectancy \rightarrow Behavioral intention	0.040	Not clear
Age \times Effort expectancy \rightarrow Behavioral intention	-0.033	Not clear
Age \times Social influence \rightarrow Behavioral intention	0.040	Not clear
Experience \times Effort expectancy \rightarrow Behavioral intention	-0.033	Not clear
Experience \times Facilitating conditions \rightarrow Behavioral intention	-0.017	Not clear
Regulatory influence \times Social influence \rightarrow Behavioral intention	0.006	Not clear
Regulatory influence \times Facilitating conditions \rightarrow Usage behavior	0.032	Positive

Table 4. Predictive power and effect size results

Construct	Explanatory power (R^2)	Key predictor	Effect size (f^2)	Effect magnitude
Effort expectancy (EE)	0.431	Perceived threat (PT)	0.759	Large
Social influence (SI)	0.514	Regulatory influence (RI)	1.059	Very large
Facilitating conditions (FC)	0.542	Regulatory influence (RI)	1.185	Very large
Perceived threat (PT)	0.464	Regulatory influence (RI)	0.865	Large
Behavioral intention (BI)	0.698	Facilitating condition (FC)	0.329	Medium
Usage behavior (UB)	0.660	Perceived threat (PT)	0.189	Medium

Demographic parameters, such as age and work experience, did not substantially alter the primary relationships within the model. However, a notable interaction was observed between regulatory influence and facilitating conditions regarding usage behavior ($\beta=0.032$).

The model demonstrated substantial explanatory power, with R^2 values of 0.698 for behavioral intention and 0.66 for use behavior. Regulatory pressure significantly shaped the mediating of the digital constructs, confirming its dominant role in the

transformation process within this context. Predictive relevance analysis (Q^2) further supported the model's robustness, showing that regulatory influence had a large effect size on facilitating conditions and perceived threat. Effect size (f^2) analysis revealed that regulatory influence had large-to-very-large effects on facilitating conditions, social influence, and perceived threat. In contrast, traditional UTAUT constructs and moderator parameters contributed only modestly to the primary endogenous parameters (Table 4).

To ensure data integrity, potential biases were monitored using multiple diagnostic approaches, including collinearity assessment and factor analysis, and the data were free of substantial bias, supporting the reliability and consistency of the findings.

Discussion

This study analyzed EMR adoption in Indonesia using the UTAUT framework, which integrates regulatory pressure and perceived threat as key factors. EMR adoption in primary healthcare services in Indonesia cannot be explained solely by individual cognitive determinants but must be understood in the context of coercive health policies and systemic inequalities in developing countries. Thus, digital health transformation in such settings is driven more by structural and institutional factors than by the individual preferences of healthcare workers [33, 34].

The primary elements of the UTAUT framework—performance expectancy, effort expectancy, and facilitating conditions—showed a positive role in shaping behavioral intention. These findings align with existing literature, which demonstrates that perceptions of benefits and ease of use remain crucial in shaping technology adoption intentions, even under mandatory conditions [16, 42, 43]. However, the pronounced role of facilitating conditions highlights that infrastructure readiness and organizational support are essential prerequisites in resource-constrained primary healthcare settings burdened by high administrative demands [44, 45].

The limited role of social influence on behavioral intention suggests that interpersonal pressure becomes less relevant when system use is mandated by policy. In top-down managed healthcare systems, compliance with regulations and institutional standards often replaces informal social norms [46, 47]. This indicates that social influence is highly contextual and diminishes in professional, mandated environments [48, 49].

The positive role of perceived threat was observed, which contributed to effort expectancy, behavioral intention, and usage behavior. This contrasts with the dominant technostress literature, which views technological threats as inhibitors of adoption [50, 51]. In Indonesian health services, threat perceptions—arising from regulatory compliance demands, administrative risks, and professional pressures—trigger adaptive responses. Healthcare workers respond by increasing learning efforts and making adjustments to their work to meet institutional demands, thereby accelerating system use [52-54].

The predominance of regulatory pressure over other factors confirms that EMR adoption in Indonesia is primarily driven by institutional forces. Regulations not only mandate usage but also shape compliance norms and perceptions of facility readiness. The direct link between regulatory pressure and behavioral intention suggests that technology

acceptance in the public health sector is more policy-driven than based on individual evaluations of usefulness [33].

However, regulatory pressure did not automatically lead to actual use. The gap between policy mandates and actual usage behavior highlights a common challenge in implementing health technologies in developing countries [55-57]. This confirms that mandatory policies, without accompanying infrastructure support, system stability, and capacity building, may result in administrative compliance rather than sustainable use. Policy effectiveness is maximized when regulatory pressure works in tandem with facility readiness, as demonstrated by its moderating role in promoting actual EMR use [58, 59].

Theoretically, this study extends the analytical framework by demonstrating that, in developing countries subject to coercive health policies, external factors—particularly regulatory pressure and technostress—can overshadow individual cognitive constructs. Integrating technology acceptance models with institutional theory provides a more comprehensive understanding of how health policies influence technology acceptance and use [60, 61]. Furthermore, the positive role of perceived threat supports the concept of techno-eustress, where stress triggers adaptive responses and improves performance [51, 62].

From a public health policy perspective, successful EMR implementation cannot rely solely on regulation. Digital transformation in primary health care requires sustained investments in infrastructure, technical support, and organizational readiness. Policies must also address the psychological impacts of regulations on health workers through training, technical assistance, and supervision to manage technostress constructively [3, 63]. In this way, EMR adoption moves beyond administrative compliance to strengthen the health system and improve the quality of public health services.

Our findings have significant implications for strengthening the public health system and advancing health development, particularly in primary healthcare within developing countries. Based on the observed relationships between institutional pressure and practitioner behavior, three recommendations are proposed. First, in the context of primary and community health care, EMR implementation should be viewed as a tool for enhancing services rather than simply an administrative requirement. Governments and primary healthcare managers must ensure that EMRs support service continuity, patient monitoring, and the integration of community health data. Essential prerequisites include basic infrastructure, system stability, and technical support to enable the effective functioning of EMRs in community health services. Second, in health policy and management,

institutional and regulatory factors are the primary drivers of EMR adoption. Therefore, health digitalization policies should be supported by managerial mechanisms to ensure facility readiness and system sustainability. EMR regulations should be integrated with resource planning, budget allocation, and health facility performance evaluation systems to maximize their impact on the quality of public services. Third, from the perspective of environmental and occupational health, EMR implementation policies should consider digital workload, the psychosocial impact of rapid adoption, and the psychosocial well-being of health workers. Promoting a supportive work environment that encourages healthy technology use is essential for the sustainability of digital transformation in the public health sector.

Conclusion

The interplay among institutional pressure, organizational readiness, and the psychological adaptation of healthcare workers forms the foundation of EMR adoption and use.

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