Observational Study

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An observational study of the relationship between meaningful use-based electronic health information exchange, interoperability, and medication reconciliation capabilities

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Abstract

Stagnation in hospitals' adoption of data integration functionalities coupled with reduction in the number of operational health information exchanges could become a significant impediment to hospitals' adoption of 3 critical capabilities: electronic health information exchange, interoperability, and medication reconciliation, in which electronic systems are used to assist with resolving medication discrepancies and improving patient safety. Against this backdrop, we assessed the relationships between the 3 capabilities.

We conducted an observational study applying partial least squares-structural equation modeling technique to 27 variables obtained from the 2013 American Hospital Association annual survey Information Technology (IT) supplement, which describes health IT capabilities.

We included 1330 hospitals. In confirmatory factor analysis, out of the 27 variables, 15 achieved loading values greater than 0.548 at $P < .001$, as such were validated as the building blocks of the 3 capabilities. Subsequent path analysis showed a significant, positive, and cyclic relationship between the capabilities, in that decreases in the hospitals' adoption of one would lead to decreases in the adoption of the others.

These results show that capability for high quality medication reconciliation may be impeded by lagging adoption of interoperability and health information exchange capabilities. Policies focused on improving one or more of these capabilities may have ancillary benefits.

Abbreviations: AHA = American Hospital Association, AVE = average variance extracted, CFA = confirmatory factor analysis, EHR = electronic health record, GoF = Tenenhaus goodness-of-fit, HL7 = Health Level Seven, IT = Information Technology, MU = meaningful use, NLBCDR = nonlinear bivariate causality direction ratio, PLS = partial least squares, SEM = structural equation modeling, SSR = statistical suppression ratio.

Keywords: clinical information systems, factor analysis, health policy, interoperability, medication reconciliation, research methodology, structural equation modeling

1. Introduction

As a result of financial incentives offered by the government through the Health Information Technology (IT) for Economic and Clinical Health Act of 2009 and Medicare Access and Children's Health Insurance Program Reauthorization Act of 2015,[1–3] substantial progress has been made with hospitals' adoption of health IT capabilities[4]; however, significant challenges remain.[5–8]

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Simply replacing paper with an electronic format is unlikely to achieve meaningful patient safety benefits. Two foundational functionalities for advanced electronic health records (EHRs) are health information exchange (the ability to electronically share patient-level information among unaffiliated providers across organizational boundaries) and interoperability (the ability to produce standardized patient-level health information that can be integrated into unaffiliated provider EHRs). Neither is yet widespread. The number of operational health information exchanges has in fact decreased by 11% (from 119 in 2012 to 106 in 2014), according to a recent study by Adler-Milstein et al.[8] In addition, planning efforts for new exchanges have been reduced by 60% during same period.[8]

As of 2013, less than half of hospitals had the ability to exchange[5,6] and integrate[7] clinical care summaries into the workflow of unaffiliated recipients: a key aspect of interoperability. Although self-sustainability and unavailability of funding were cited among the reasons for the decline in operational health information exchanges,[8] lack of specificity in standards, which hinders data integration into recipient workflow, was also found to be a key barrier to interoperability.[9]

The above challenges are concerning because, without these foundational capabilities, EHRs may produce fewer benefits for patient safety and clinical efficiency.[10] In particular, we hypothesize that medication reconciliation, the process of creating the most accurate possible medication list, would be hindered in the absence of functional health information exchange and interoperability, including from pharmacies.[11–19] Data from other settings are critical to resolve unintended errors in medication histories, including drug omission, and incorrect dosage and frequency,[20–23] which affect up to 67% of hospitalized patients.[24,25]

In order to provide a better understanding of the underlying relationships between the 3 capabilities, it is worth describing them as follows: Interoperability capability as the *Producer* of standardized and integrable, thus useful clinical information; (2) Electronic health information exchange capability as the *Exchanger* of such information to make it accessible to providers, ideally nationwide; and Medication reconciliation capability as the *Demander* of such information.

In the context of the health IT challenges discussed above, if produced clinical information is exchanged without being integrated into patients' EHRs through the use of appropriate standards for content and vocabulary,[26,27] its utility to busy clinicians is limited. Electronic exchange without interoperability may even create opportunities for errors if nonstandardized information is interpreted differently at different institutions (eg, "Allergies: N/A" may be interpreted either as not available or as no allergies).[26,28] As a result, less demand for such clinical information is expected.

Despite these theoretical concerns, little is known about the association of medication reconciliation with health information exchange and interoperability. This study seeks to empirically examine how the 3 capabilities influence one another so that the appropriate policy can be applied where it can have the greatest impact. To clarify the hypothesized relationships, we drew on information processing theory to develop a research model and used data from the 2013 American Hospital Association (AHA) annual survey IT supplement[29] to test this model and help answer the following questions:

(1) What are the building blocks of the 3 capabilities?
(2) How do decreases in hospitals' adoption of any one of the capabilities affect the adoption of the others?
(3) How do increases in hospitals' adoption of any one of the capabilities affect the adoption of the others?
(4) What is the best policy prescription the study results point to, which can help broaden the adoption of the 3 capabilities?

2. Methods

2.1. Research model

In Fig. 1 below is the research model, hypothesizing a significant, positive, and cyclic relationship between the (3) capabilities displayed as both independent and dependent variables.

2.2. Hypotheses

According to information processing theory, as hospitals begin to receive electronic summary of care documents though electronic exchange, clinicians' capabilities alone will not be sufficient to properly process such a high volume of information.[30,31] Hospitals will accordingly seek to increase interoperability capability in order to facilitate the integration of clinical information into recipient workflow. As a result, more integrable and useful information will be widely available, even from hospitals that are unaffiliated using different vendor certified EHRs technology platforms.

As rational systems,[32] hospitals will then increase their adoption of electronic medication reconciliation capability to give them higher information processing capacity to reduce cognitive overload in the performance of medication reconciliation, and to also maintain timeliness, accuracy, and completeness when they pass that processed information to other providers for follow-up care. Increases in the adoption of medication reconciliation capability will in turn foster demand for broader sharing of interoperable information. We therefore propose that:

Hypothesis 1: As hospitals' adoption of electronic health information exchange capability increases, so will the adoption of medication reconciliation capability.

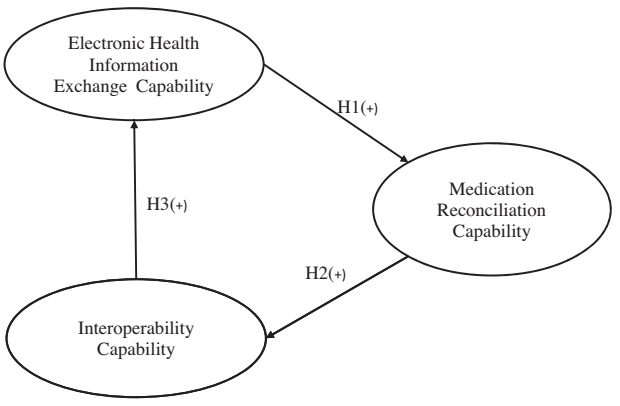

Figure 1. Research model with latent factors. H1(+) denotes hypothesis 1 suggesting a positive relationship between electronic health information exchange capability and medication reconciliation capability. H2(+) denotes hypothesis 2 suggesting a positive relationship between medication reconciliation capability and interoperability. H3(+) denotes hypothesis 3 suggesting a positive relationship between interoperability capability and electronic health information exchange capability.

Hypothesis 2: As hospitals' adoption of medication reconciliation capability increases, so will the adoption of interoperability capability.

Hypothesis 3: As hospitals' adoption of interoperability capability increases, so will the adoption of electronic health information exchange capability.

2.3. Data source and sample

As this study does not involve human subjects, institutional review board approval is not required. We used the 2013 AHA Annual Survey IT Supplement database[33] to obtain a nationally representative sample of nonfederal acute care hospitals[7] that: (1) include acute care general medical and surgical, general children's, and cancer hospitals; and (2) use any type of electronic exchange or sharing of care summaries with other providers, as demonstrated by their responses to question 3B in the AHA IT supplement survey[29]: "If you exchange or share clinical/summary care records with other providers, what is the primary mechanism used?" The above nonfederal acute care hospitals shared a common quality in that they would be eligible for incentives under the Health IT for Economic and Clinical Health Act.

The overall AHA sample had 6295 hospitals. Of these, a total of 3283 hospitals responded to the AHA IT supplement survey, representing a response rate of 52%. However, 4 were excluded as nonrespondents as they did not provide any response to the 27 questions of interest in this study. Nonresponse bias is not an issue in this study because not only is the AHA IT survey response rate high, the *t* tests performed comparing respondents and nonrespondents revealed no significant difference between them in terms of their geographic area and system affiliation, ownership, and size (measured by number of beds).

Of the remaining 3279 hospitals, a sample of 1863 (56.8%) hospitals was drawn by sequentially removing the hospitals that did not meet the above (1) and (2) inclusion criteria. Of these, 28% provided Do Not Know answers, while 1% had Not Applicable answers, and 27.4% had missing data (empty cells). The Do Not Know and Not Applicable answers are considered noncommittal responses from hospitals unsure whether subject functionality exists in their organization. Because of this, we excluded them in this study as they could distort the results. This exclusion left a final sample size of 1330 hospitals, including 276 with missing data that need to be statistically accounted for using appropriate imputation method.

2.4. Variable identification

In accordance with relevant guidelines suggested by Kock and Verville,[34] we examined the meaning of each of the questions and statements in the survey.[29] This examination led to the identification of 27 questions that correspond to the three health IT factors in the research model (Fig. 1). The questions identified for the "Interoperability Capability" factor were extracted from the "Discharge Instructions and Care Summary Documents," and "Health Information Exchange Functionalities" sections of the survey.[29] The ones for the "Electronic Health Information Exchange Capability" factor were from the "Health Information Exchange Functionalities" section, and those for the "Medication Reconciliation Capability" factor from the "Medication Management" section.[29] In total, we identified 27 variables for the analysis.

2.5. Statistical analysis

The 27 variables are dichotomous, and also nonnormal, as confirmed by the Jarque–Bera normality tests.[35] Following Chin et al[36] and Kock,[37] partial least squares-structural equation modeling (PLS-SEM) analysis is the most appropriate statistical technique to use because it does not make normality assumptions about the data. PLS-SEM can examine multiple relationships simultaneously and also allow for nonparametric approaches to calculate *P* values when normality conditions are not met, such as in this case.

The final sample size of 1330 hospitals, including 276 with missing data, is well above the widely cited minimum requirement of 100 for PLS-SEM analysis.[38] Before we conducted the PLS-SEM analysis, we evaluated the pattern of the missing data to determine the best method with which to treat them. First, we examined the frequency and percentages of missing values for each variable listed in Table 1. This examination revealed that the missing values in some of the variables can be predicted by those missing in the other variables, suggesting that the pattern of missingness is monotone or nonrandom, per Soley-Bori.[39](p6) Unlike random or arbitrarily missing data, monotone pattern can impact generalizability of the results, according to Tabachnick and Fidell.[40](p62) For example, the variables associated with the exchange or sharing clinical care summaries and medication history questions appear to have similar number of missing data that occur simultaneously. This relationship confirms that a monotone pattern of missingness exists, which points to the use of imputation methods to statistically account for the data that are missing.

2.6. Selection of PLS-SEM procedures

Because too many missing data can distort the results, Kock[37](p37) suggests that, before selecting a data imputation procedure from the WarpPLS 5.0 software, hospitals with any variable that has 10%, 20%, as high as 30% of its value missing should be deleted. A review of the percentages of missing data for each of the 27 variables showed that no further deletion of hospitals is needed, as no hospitals in the final sample had missing values that exceeded 10% in any of the variables (Table 1). As a result, we selected the multiple regression imputation procedure, which was evaluated by Kock[41](p12) using the WarpPLS 5.0 software, and found to have the least biased path coefficient results. It enabled missing data to be predicted based on the cases or hospitals with complete data, which helped prevent loss of important data that can lead to biased results,[41](p3) unlike the traditional casewise or listwise deletion.

Kock[37](p22) described 2 models associated with PLS-SEM: the measurement or outer model, with which to assess the relationship between a latent or unobserved variable and its observed reflective indicators; and the structural or inner model, with which to measure the relationship between the latent or unobserved variables. In addition to the above missing data imputation method, for the parameter estimation procedure from the WarpPLS 5.0 software we selected the Factor-Based PLS Type PTH1 algorithm to assess the measurement model, Warp3 to evaluate the structural or inner model, and Jackknifing resampling method to assess statistical significance.

The Factor-Based PLS Type PTH1 algorithm is appropriate because the measurement or outer model is reflective, thus factor-based. Additionally, this algorithm includes the measurement error in its estimation, thus is expected to yield more accurate results. It used variance sharing as well as robust path analysis, enabling *P* values to be estimated using nonparametric resampling methods such as Jackknifing and stable methods such as Stable3.[37](p24) For the structural or inner model, we

Table 1

Percentages of missing values for each variable (N = 1330 hospitals).

Variable	Frequency	Percent
V1. Record and maintain medication allergy lists	7	0.53%
V2. Identify and provide patient specific education resources	7	0.53%
V3. Compare a patient's inpatient and preadmission medication list	9	0.68%
V4. Provide updated medication list at the time of discharge	6	0.45%
V5. Check inpatient prescriptions against internal formulary	5	0.38%
V6. Automatically track medications with an eMAR	4	0.30%
V7. Prescribe discharge medication orders electronically	18	1.35%
V8. Generate summary of care record for relevant transitions of care	7	0.53%
V9. Include care teams and plan of care in care summary record	10	0.75%
V10. Send transition of care summaries to unaffiliated org using different certified EHR vendor	10	0.75%
V11. Exchange/share medication history electronically with hospitals in your system	123	9.25%
V12. Exchange/share medication history electronically with hospitals outside your system	123	9.25%
V13. Exchange/share medication history electronically with ambulatory providers inside of your system	123	9.25%
V14. Exchange/share medication history electronically with ambulatory providers outside of your system	123	9.25%
V15. Exchange/share clinical/Summary care record in any format electronically with hospitals in your system	127	9.55%
V16. Exchange/share clinical/Summary care record in any format electronically with hospitals outside of your system	127	9.55%
V17. Exchange/share clinical/summary care record in any format electronically with ambulatory providers inside of your system	127	9.55%
V18. Exchange/share clinical/Summary care record in any format electronically with ambulatory providers outside of your system	127	9.55%
V19. Send clinical/summary of care records in CCR, CDA, or CCD format	19	1.43%
V20. Current arrangements exist in your area to share electronic patient-level clinical data through an electronic HIE or an RHIO	19	1.43%
V21. Your level of participation in a regional HIE or RHIO	31	2.33%
V22. Routinely provide electronic notification to the patient's primary care physician, when he/she visits your ED	20	1.50%
V23. Query electronically for a patient's health information from sources outside of your system	21	1.58%
V24. Send and receive secure electronic messages containing patient's health information with sources outside of your hospital system	38	2.86%
V25. Patients able to view information from their health/medical record online	23	1.73%
V26. Patients able to download information from their health/medical record	21	1.58%
V27. Patients able to electronically send transmission of care/referral summaries to a third party	52	3.91%

CCD = continuous care documentation, CCR = continuous care record, CDA = clinical document architecture, EHR = electronic health records, eMAR = electronic medication administration record, HIE = health information exchange, organization, ED = emergency department, RHIO = regional health information.

found Warp3 to be suitable because it assumes nonlinearity or warping that may be produced by data nonnormality demonstrated in Table 2 by the Jarque–Bera tests.

Jackknifing, Blindfolding, Bootstrapping, and Stable3 are among the various resampling methods available in the WarpPLS 5.0 data analysis software program. As recommended by Kock,[37](p27) separate SEM analyses were conducted using the above resampling methods. Given that our sample is not small, there is no significant difference in the results between the 4 methods tested. Thus, over the others, we retained the Jackknifing resampling method, which used 100 resamples and 9 iterations to assess statistical significance of the study model's structural paths.

2.7. PLS-SEM analysis

Once the above procedure selections were established, the PLS-SEM analysis was performed in 3 stages: confirmatory factor analysis (CFA), model fit and explanatory power analysis, and path analysis. In the 1st stage, CFA was conducted to confirm researchers' selection of variables as "belonging" to the same factor by estimating the reliability, convergent validity, and discriminant validity of the individual factors, full collinearity variance inflation factors (VIFs) for model's multicollinearity, and Stone–Geisser Q-squared coefficients for predictive validity.[34,37,42] In this study, factors refer to latent variables or unobserved variables or capabilities, which are measured by multiple observed variables or indicators.[42] We identified all indicators and measurement model as reflective in order to obtain the indicator-latent variable loadings, via the CFA, with which to answer the research question related to the building blocks of the 3 capabilities (see, Appendix, Supplemental Digital Content, http://links.lww.com/MD/B902, which displays the initial CFA results showing variables' initial combined loadings and cross-loadings by factors). The final CFA results are discussed below.

In the 2nd stage, we comprehensively evaluated the relevancy, and explanatory power of the model, using the following measures[37]: average path coefficient, average R-squared, Tenenhaus goodness-of-fit (GoF), Sympson paradox ratio, R-squared contribution ratio, statistical suppression ratio (SSR), and nonlinear bivariate causality direction ratio (NLBCDR). In the 3rd stage, we performed path analysis using retained variables to measure the paths' coefficients (β) representing the strengths of the relationships between the 3 capabilities, and the R^2 statistics reflecting how much the variance of 1 capability is explained by the other(s). We examined the values of the paths' coefficients (β) and the R^2 statistics to determine whether their effects are small, medium, or large.[37] All statistical analyses were conducted using WarpPLS version 5.0 (ScriptWarp Systems, Laredo, TX), except for the *t* tests which were conducted using Microsoft Office Excel 2007.

3. Results

3.1. Final confirmatory factor analysis and validation results

Of the 27 variables, CFA identified 15 that loaded successfully as expected on the 3 factors: electronic health information exchange capability, and interoperability and medication

Table 2

Factors' reliability, validity, and multicollinearity assessment.

Parameter	Factors		
	Electronic health information exchange capability	Interoperability capability	Medication reconciliation capability
Normality: Jarque–Bera	No	No	No
Normality: Robust Jarque–Bera	No	No	No
Composite reliability	0.878	0.802	0.832
Cronbach alpha	0.833	0.684	0.753
Full collinearity VIFs	1.192	2.232	1.979
Stone–Geisser Q-squared coefficients	0.234	0.566	0.047
AVEs	0.547	0.504	0.497

AVE = average variance extracted, VIF = variance inflation factor.

reconciliation capabilities. The 15 variables have acceptable convergent validity since they met the threshold of 0.548 and also were statistically significant at the $P < .001$ level (Fig. 2).[37] There were no cross-loadings since the variables had high loadings only with their respective factors, and not with the others.

The survey is reliable since all 3 factors achieved scores above the commonly recognized 0.70 threshold (Table 2) for composite

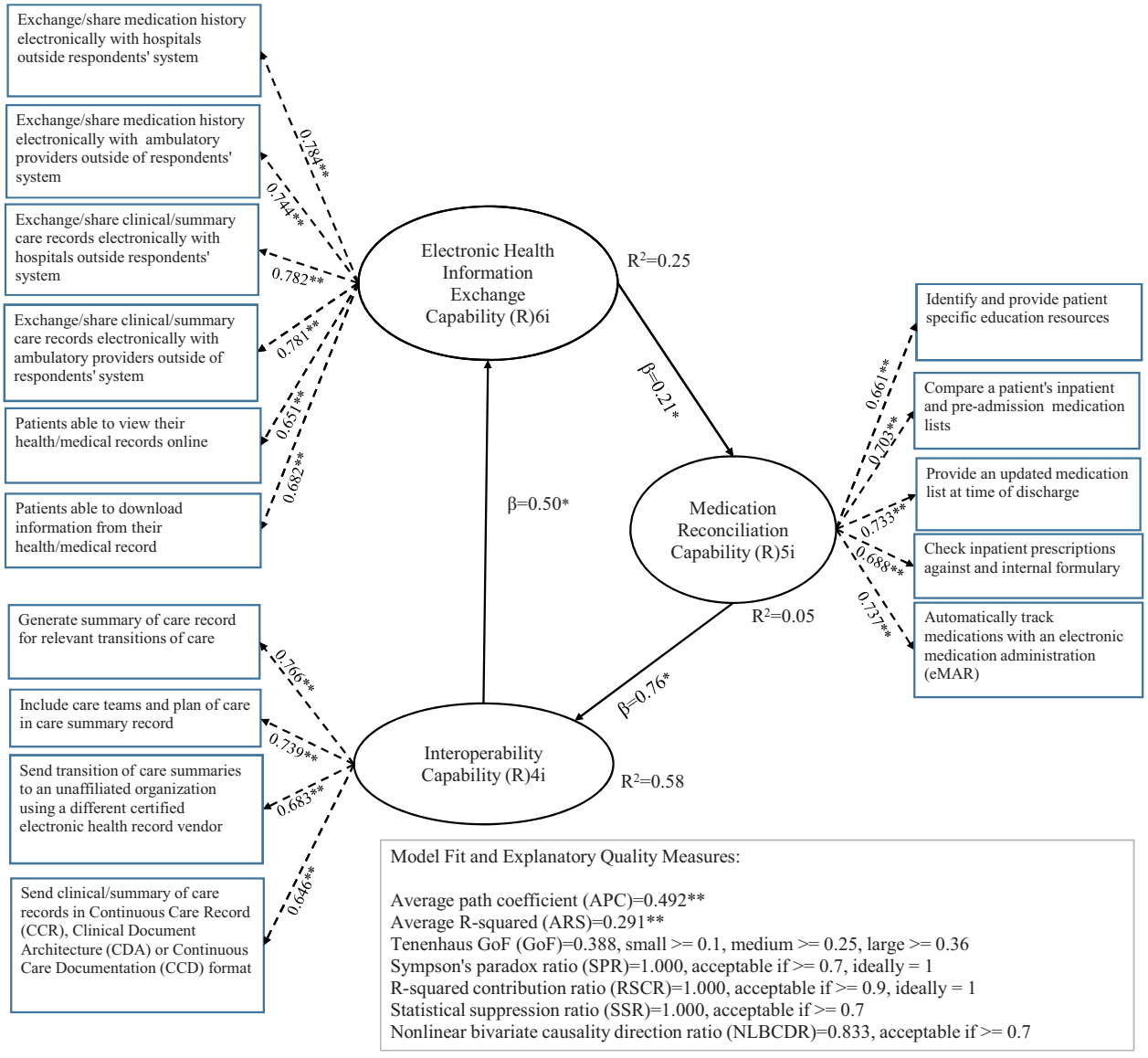

Figure 2. Final results of confirmatory factor and path analyses. Variable names adapted from the 2013 American Hospital Association (AHA) annual survey Information Technology supplement.[29,33] Dashed arrows display loading values and significance levels for retained variables. $^{*}P < .01$; $^{**}P < .001$.

Table 3

Correlations between individual factors with square roots of average variances extracted (AVEs).

Factors	Electronic health information exchange capability	Interoperability capability	Medication reconciliation capability
Electronic health information exchange capability	**0.739**	0.392	0.213
Interoperability capability	0.392	**0.710**	0.700
Medication reconciliation capability	0.213	0.700	**0.705**

Square roots of AVEs are shown on diagonal and in bold.

reliability, which is a more acceptable measure than Cronbach alpha, according to Kock[37] and Wong.[38] Multicollinearity is not an issue in this research model because, as shown in Table 2, full collinearity variance inflation factors (VIFs) is less than 3.3, demonstrating absence of multicollinearity, per the rule of thumb recommended by Kock.[37](p66) Also, as displayed in Table 2, the values of the Stone–Geisser Q-squared coefficients for the 3 latent variables are greater than 0, thus meet the threshold suggested by Kock[37](p67) for acceptable model's predictive validity. However, for discriminant validity, while interoperability capability and electronic health information exchange capability exceeded the generally cited 0.50 average variance extracted (AVE) threshold,[31] medication reconciliation capability, on the other hand, achieved AVE of 0.497 (Table 2). We determined it was close enough to the AVE cut-off point of 0.50, thus constitute a satisfactory level of discriminant validity, particularly, as required by Kock,[37] the square root of AVE for medication reconciliation capability (0.705) was higher than its correlation with electronic health information exchange capability (0.213), and medication reconciliation capability (0.700) (Table 3).

3.2. Variable retention for path analysis

The aforementioned CFA showed that, of the 27 variables, 15 achieved acceptable variable and factor reliability and validity results. Because of this, they were retained for the analysis of the path relations between the factors. The 15 variables are shown in Fig. 2 with dashed arrows pointing at them, and displaying their loading values and significance levels. Six of them define the 1st factor, electronic health information exchange capability. Four of them comprise the 2nd factor, interoperability capability. And, 5 of them define the 3rd factor, medication reconciliation capability. The next stage of the PLS-SEM analysis included the assessment of the model fit and explanatory quality measures.

3.3. Model fit and explanatory quality measures

Before we proceeded with path analysis, a number of fit and quality measures[37] were evaluated, and all found to be within acceptable thresholds (Fig. 2). The model, consisting of 15 variables and the respective 3 factors, is relevant since the values for the average path coefficient and average R-squared shown in Fig. 2 are well above the minimum effect size of 0.02 suggested Kock.[37](pp56,66)

Model explanatory power was assessed based on our examination of the GoF. The GoF score was 0.38, well above the 0.1 threshold recommended by Kock,[37](p51) indicating adequate explanatory power. Consistent with Kock guidelines,[37](p52) the model also had no negative R-squared contributions and no Simpson paradox,[37] since the R-squared contribution ratio and the Simpson paradox ratio were greater than the acceptable thresholds of 0.9 and 0.7 (Fig. 2), respectively, suggesting the absence of a causality problem. To ensure that, at a minimum, 70% of the paths in the model do not have causality problem, an examination of the SSR and the NLBCDR was conducted. Both ratios exceeded the 0.7 threshold, demonstrating that, not only the model does not have causality problem, but there is also support for the "hypothesized direction of causality."[37](p53) It should be noted that, in 2015, Kock indicated that the 2 causality direction tests, SSR and NLBCDR, were still at the experimental stage.[37](p53)

Overall, the above measures provided strong evidence of a reasonable model fit with adequate relevancy, explanatory power, and support for the "hypothesized direction of causality."[37](p53) Next, we assessed the relationships between the 3 factors or Health IT capabilities by analyzing the model's path coefficients (β) or the structural model results.

3.4. Path analysis results

The path analysis revealed that electronic health information exchange capability ($\beta = 0.21$, $P < .01$) is positively and significantly associated with medication reconciliation capability ($\beta = 0.76$, $P < .01$), which is positively and significantly associated with interoperability capability ($\beta = 0.50$, $P < .01$), which is positively and significantly associated with electronic health information exchange capability (Fig. 2), confirming a cyclic relationship between the capabilities.

To determine whether the effects of the above paths' coefficients (β) are small, medium, or large, we used the thresholds typically recommended: 0.02, 0.15, and 0.35,[37](p56) respectively. The effects of the paths' coefficients were from medium to large, given that their scores were between 0.21 and 0.76 (Fig. 2). In finishing the last stage of the PLS-SEM analysis, we also evaluated the R^2 statistics, and found interoperability capability to have the largest variance (58%) in the model, followed by electronic health information exchange (25%), while medication reconciliation capability had the smallest (5%) (Fig. 2).

4. Discussion

This study provides empirical evidence supporting our hypotheses that the relationships between hospitals' adoption of electronic health information exchange, interoperability, and medication reconciliation capabilities are significant, positive, and cyclic, in that if any one of them decreases, then the others will decrease as well as a result.

This means that, if left alone, the current stagnation in interoperability adoption and the declining number of operational health information exchanges could create a bottleneck that can adversely impact hospitals' adoption of the 3 capabilities.[43] This would have a detrimental impact on national efforts to increase the flow of information between different

providers across organizational boundaries in order to achieve a health IT system that is truly interoperable,[44] not just intraoperable. Thus, policy intervention is needed to start and maintain a more promising cycle.

Before we discussed the policy implications this study points to, we examined the loading results in Fig. 2 to answer the research question related to the building blocks of the three capabilities. These results revealed that the building blocks of electronic health information exchange capability factor consisted of variables representing health IT functionalities that enable exchange, not only between unaffiliated hospitals and ambulatory facilities, but also with patients.

The interoperability capability factor, on the other hand, comprised variables having to do with hospitals' ability to produce electronic transition of care summary documents that are interoperable, in that, as required by meaningful use (MU) regulations, they must conform to the structure and vocabulary standards specified by Health Level Seven (HL7) Continuity of Care Document, which is a combination of HL7 Clinical Document Architecture and American Society for Testing and Materials American Society for Testing and Materials Continuity of Care Record standards.[45–49] These variables are located in the MU section of the AHA IT survey supplement. In sum, the variables that define the interoperability capability factor represent MU and HL7 transition of care document standards that facilitate the integration of clinical information received into the workflow of unaffiliated providers (Fig. 2). Typically, consensus on the use of specific standards can in time make them rigorous, enabling their implementations to be done the same way with little effort, leading to improvement in interoperability.

For the medication reconciliation capability factor, it should be noted that the first 3 of the variables that defined it, as displayed in Fig. 2, are similar to the ones the Office of the National Coordinator for Health IT used to measure medication reconciliation as an MU functionality.[6] The last variable with loading higher than 0.70 is related to the Institute of Healthcare Improvement recommendation to review medication administration record during patient intrahospital transfers, and, at discharge, as part of the medication reconciliation processes.[50] In MU stage 1, medication reconciliation was an optional menu,[51] but became a required core measure in subsequent stages.[1]

Our study has several strengths. First, it uses multiple variables, as opposed to a single variable, to more comprehensively capture the complexities in the capabilities, and the relationships between them. Second, it enhances our understanding about how the capabilities are influenced by one another. Third, as evidenced by the medium to high effect sizes of the path coefficients, the study has sufficient level of statistical power, suggesting that its results are significant and conclusions meaningful. Another interpretation of the path coefficients is that they represent the resulting variation in the dependent variables influenced by 1 standard deviation variation in the independent variables.[37](p54) For example, the path coefficient ($\beta = 0.21$, $P < .01$) means that a 1 standard deviation variation in electronic health information exchange capability would lead to a 0.21 standard deviation variation in medication reconciliation capability.[37](p54) A similar approach can be applied to interpret the results for the other 2 capabilities. Last, the study provides a framework for future research by developing a new model that established and tested new cyclical associations that have not been tested before.

4.1. Policy implications

The study results have several policy implications. First, our results suggest that policy interventions focused on aspect of high functioning EHRs, such as interoperability, are likely to have widespread effects on other functionalities. With this in mind, policies should encourage maximum adoption of interoperability capability by substantially increasing the incentives for hospitals that implement rigorous standards enabling easy data integration into workflow of providers that are unaffiliated using different vendor platforms. This in turn will increase the availability of data that are more integrable and useful, which will drive demand for information sharing beyond hospitals' internal systems including, not only between unaffiliated hospitals and ambulatory facilities, but also with patients.

Operational health information exchanges can enable that kind of exchange better than others, which will help improve their self-sustainability. This new dynamic will in turn lead to the need to increase usage of interoperable electronic summary of care documents in medication reconciliations. Because of the cyclical associations, increases in the adoption of the other 2 capabilities will lead to similar outcomes. Policies should also incentivize maximum usage of interoperable electronic summary of care documents in medication reconciliation processes.

4.2. Limitations and recommendations for future research

The 1st limitation of this study is that it is observational – we cannot draw firm causal inferences from the results. Furthermore, our data source is a survey, and no effort has been undertaken to validate the responses directly. However, the CFA we conducted revealed that all reliability, convergent validity, predictive validity, and discriminant validity measures are within acceptable thresholds, except for medication reconciliation capability, which achieved an AVE of 0.497 (Table 2). Since it is close enough to the cut-off point of 0.50, it is considered a satisfactory level of discriminant validity. Furthermore, because the square root of its AVE score was larger than its correlations with the other factors in the model (Table 3), it means that the medication reconciliation capability factor was better determined by its variables than other factors' variables, suggesting that it has an acceptable level of discriminant validity. Future studies should use qualitative data collection methods such as documentation reviews, observations, and interviews of hospitals' chief information officers (CIOs) and other responsible executives to explore the results of this quantitative research in more depth.

The 2nd limitation is that the data used were collected in 2013,[33] a time in which adoption of most health IT functionalities was still nascent. Future quantitative research should use more recent data to take into account the lagged effects of health IT and the rapid pace of technological advances to determine whether the influence of the capabilities on one another decreases or increases over time.

The 3rd limitation is that the R^2 statistics of 58%, 25%, and 5% provide an indication that there are other factors acting on the system that the model did not capture. One reason why the model accounts for only 5% of the variance in medication reconciliation capability might be that hospitals with reconciliation capability limited their exchange of electronic summaries and medication history,[5] either because of concerns that they might not be interoperable or integrable or because providers lacked confidence in the process. Some of the external environmental factors unaccounted for in the model are the

adequacy of policy intervention and alignment of innovative integration technologies with health data standards that can help address these concerns. Also unaccounted for are organizational factors such as strategic information systems planning, culture, top management support, health information systems budget and capabilities, and leadership. Future studies should attempt to improve the model by incorporating these and other organizational and environmental factors to examine how they can influence the relationships studied here.

The 4th limitation is that generalizability of the study findings is restricted to the target population, consisting of nonfederal acute care hospitals that used any kind of electronic exchange or sharing of care summaries with other providers.

Additionally, as this study revealed provider–patient health information exchange functionalities among the dimensions that defined the electronic health information exchange capability, in future studies, researchers should reconceptualize this capability as consisting of provider–provider, provider–government, and provider–patient exchange categories that individually or in combination with interoperability and medication reconciliation capabilities can impact clinical outcomes such as readmissions, patient satisfaction, and mortality from chronic conditions. Additional research should be conducted to determine if the relationships among the 3 capabilities are also positive, significant, and cyclic in ambulatory settings, and the degree to which they are different from the inpatient settings, and at the state-, regional-, and institutional-level.

In conclusion, we find that electronic health information exchange, interoperability, and medication reconciliation capabilities are all positively associated, setting the stage for either a virtuous or a vicious feedback loop as hospitals adopt EHRs and make decisions about which functionalities to support. Policies focused on improving one or more of these capabilities may have ancillary benefits.

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