Physicians' Resistance toward Healthcare Information Technologies: A Dual-Factor Model

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Abstract

This paper proposes and validates a theory of physician resistance toward IT usage by drawing on prior research in the resistance to change literature and a recent dual-factor model of IT usage. This theory elaborates the interdependent and asymmetric effects of resistance vis-à-vis current usage predictors such as behavioral intention. Additionally, we propose perceived threats as a salient determinant of user resistance in the IT usage context. The resulting model is empirically supported via a survey of practicing physicians at a large acute-care hospital in the southeastern United States. Implications of this research for IT research and practice are discussed.

1. Introduction

Healthcare information technologies (HIT) such as computerized physician order entry (CPOE) systems, electronic medical records (EMR), and electronic prescriptions are widely expected to reduce medical error rates, improve healthcare delivery quality, and increase staff productivity [1]. However, these technologies are often strongly resisted by the same professionals who are expected to benefit from its use. For instance, in 2003, doctors at the prestigious Cedars-Sinai Medical Center at Los Angeles rebelled against their newly installed CPOE system, complaining that the system was too great a distraction from their medical duties and forcing its withdrawal after the system was already online in two-thirds of the 870-bed hospital [2]. Similar patterns of resistance were also encountered at other facilities [3] and for other healthcare innovations [4]. This apparent resistance, given the expected benefits of such systems, not only runs counter much of our current understanding of information technology (IT) adoption and usage research, but may also seriously undermine the potential benefits of HIT systems.

Why are seemingly useful technologies sometimes resisted by potential adopters? This is the central problem of interest to this study. More specifically, we examine two related research questions: (1) what factors cause potential HIT users to resist a new technology, and (2) how does resistance influence potential users' HIT usage behaviors?

Addressing these questions is important for theoretical as well as practical reasons. From a practical standpoint, these questions brings into focus the critical and pervasive problem of HIT resistance, which is often overlooked in HIT implementation initiatives, since resistance hurts the long-term success and sustainability of HIT. Healthcare administrators should also be cognizant of the factors that cause HIT resistance, if they are to devise effective strategies for minimizing user resistance. This is more so because traditional change management practices commonly used to enable HIT usage, such as software demonstration, user training, and help desk staffing, have had limited success in overcoming user resistance. Further, since most technologies are designed with the intent of enabling adopters' work behaviors, rather than minimizing their resistance, resistance considerations are often underemphasized in HIT design efforts. A better understanding of technology resistance may therefore help design better systems that are more easily accepted by their targeted users.

From a theoretical standpoint, though this study specifically examines HIT resistance within healthcare settings, its findings have broader ramifications for understanding information technology (IT) resistance in non-healthcare organizations as well. Prior research on IT resistance has been limited, fragmented, and non-cumulative, while that on IT usage has largely ignored the problem of resistance. Current theories of IT usage do little to explain IT resistance because resistance is not equivalent to non-usage, but a different phenomenon in its own right [5]. While non-usage may imply lack of awareness of a new IT or that potential adopters are still evaluating the IT prior to its adoption, resistance implies that the IT has been considered and rejected by the targeted adopters. Further, resistance is often marked with open hostility toward the change agents or covert behaviors to stall or undermine change, while non-usage does not necessarily engender such subversive behaviors.

Despite the above differences, IT usage and resistance are related in that an IT resistor is likely to be a non-user than a user. Hence, IT usage and resistance must be examined in concert within a common theoretical model. This study attempts to build such a unifying model of IT resistance, by building on recent developments in the dual-factor structure of IT usage [5] and previous studies in the resistance to change literature. Our hypothesized model not only elaborates some of the key drivers of HIT resistance, but also illustrates the complex interplay between resistance and pro-usage perceptions in shaping one's overall IT usage behavior. This theoretical model is empirically validated using survey data collected from practicing physicians at a large acute-care hospital in the southeastern United States.

The rest of the paper proceeds as follows. In the next section, we describe prior research in this area to set the stage for our study. The third section builds a theoretical model of IT resistance. The fourth section describes our research methods, including instrument construction, site selection, and sampling issues. The fifth section describes statistical data analysis techniques and results. The final section discusses the limitations of our study and its implications for future HIT research and practice

2. Prior Research

Prior research in IT resistance has been diverse in terms of the perspectives and methodologies used to study resistance. In a study of personal computer adoption among U.S. households, Venkatesh and Brown [6] observed that: (1) resistors (67%) outnumbered acceptors (33%) by a significant margin, (2) factors that predicted resistance (e.g., fear of technological obsolescence, high cost of technology, and lack of requisite knowledge) were unique and distinct from those that predicted acceptance (e.g., utilitarian outcomes, hedonic outcomes, and social outcomes), and (3) the association between intention and behavior was asymmetric between the two groups, with resistors behaving more closely with their stated intent than acceptors.

Studying individual usage of Internet access service, Parthasarathy and Bhattacherjee [7] noted that end-users who discontinued using Internet service at the end of the promotional trial period (a proxy for resistors) were systematically different from continued users (adopters) in terms of their service utilization, service-related perceptions (usefulness, ease of use, compatibility, and network externality), and communication influences related to initial service trial (mass-media versus interpersonal sources). Likewise, Jiang et al. [8] reported that the reasons for resistance for transaction processing systems among business managers were different from those for decision support systems. Goode [9] found that CIOs tend to resist open source software, due to the IT's unclear relevance to their operations, perceived lack of reliable support, substantial learning costs, and incompatibility with current software.

Among the qualitative studies in this area, Markus [10] observed significant resistance among a firm's divisional accountants toward a new financial accounting system. Based on her observations, Markus inferred that this resistance was caused not by system deficiencies or individual limitations, but by the accountants' loss of control over key accounting data and consequent loss of organizational power. Using a case research approach to study physicians' resistance toward clinical IT in three hospitals, Lapointe and Rivard [11] found that resistance is an emergent process that changes with time across different stages of the implementation process, and that resistance behaviors are triggered or exacerbated by perceived threats among adopter groups such as loss of power and reorganization of work.

Among more theoretical research, Joshi [12] used an equity theory perspective to compare IT resistance in a hospital, a bank, and a software development firm, and found that users resist when they perceive their personal outcomes from the IT to be inequitable or unfair relative to (1) their inputs to the system, (2) outcomes realized by their organizations, and (3) outcomes realized by others in their referent group. Martinko et al. [13] proposed an attributional model suggesting that one's prior experiences with tasks involving similar IT evoke causal attributions toward new IT, which may lead to its resistance. Marakas and Hornik [14] proposed a model to explain resistance as passive-aggressive responses to the fear or stress of an IT intruding into users' previously stable world, though this model was not empirically examined.

These above studies point to a general recognition of the importance and pervasiveness of the problem of IT resistance across a wide variety of situational contexts. However, these studies have also been largely exploratory, isolated from each other, and lacking a cumulative knowledge tradition. Part of the problem may have been the lack of theoretical grounding of resistance research within an established base of research such as IT usage. In the next section, we attempt to build such a theory that connects resistance to usage research and elaborates the key drivers and outcomes of IT resistance.

3. Theory and Hypotheses

3.1. Defining Resistance to Change

Early thoughts on resistance to change in the organizational development literature are credited to Kurt Lewin's [15] pioneering studies on force-field analysis. Lewin [15] suggested that social systems share with biological systems the characteristic of "homeostasis," or the tendency to maintain a status quo by resisting change and reverting back to the original state. This status quo represents a equilibrium between the forces favoring and opposing change. Hence, successful change rests on organizations' ability to first "unfreeze" the equilibrium by altering the dynamics of these forces before change can be enacted.

Among other notable research in this area, Zaltman and Duncan [16] defined resistance to change as "any conduct that serves to maintain the status quo in the face of pressure to alter the status quo" (p. 63). In the IT context, Keen [17] defined resistance as "social inertia," similar to Lewin's [15] notion of homeostasis. These definitions suggest that while usage (or non-usage) refers to a specific IT, resistance is a generalized opposition to change engendered by a new IT based on the expected consequences of such change. Resistance is therefore not simply the lack of or the opposite of usage, but a cognitive force preserving the status quo and preventing change. In other words, resistance is an antecedent of organizational change (such as using IT for organizational tasks), and must be first overcome for successful IT implementation.

3.2. Outcomes of Resistance

Though it appears that resistance precedes IT usage, it is unclear whether this is association is direct or mediated by other constructs. To further explore the relationship between resistance and usage, we draw upon Cenfetelli's [5] dual-factor model of IT usage. The core argument in this model is that IT usage by potential end-users is based on simultaneous considera-tion of enabling and inhibiting factors, similar to Lewin's [15] notion of opposing forces. While enabling factors, such as users' perceived usefulness and ease of use of IT have been extensively studied in the usage literature [18, 19], there has been little if any considera-tion of inhibiting factors. Cenfetelli [5] defined inhibitors as those negative factors that discourage IT usage when present, but have no effect on the outcome when absent. This "one-sided" or asymmetric nature of inhibitors implies that they are not quite the opposite of enablers, but are qualitatively distinct constructs that are independent of but may coexist with enablers. Further, Cenfetelli [5] contended that inhibitors tend to have different antecedent and consequent effects than enablers, and that IT rejection is best predicted by inhibitors rather than enablers.

There is some limited empirical evidence that inhibitors do have a negative and asymmetric effect on IT usage. For example, Speier et al. [20] observed that system interruptions, such as pop-up advertisements on a web site, "you've got mail" announcements in an e-mail system, and animation characters offering help with writing letters in Microsoft Word, hinders users' IT usage and task performance, though the lack of such interruptions does not enhance IT usage.

Though Cenfetelli's [5] dual-factor model did not mention any specific inhibitor of IT usage, resistance to change fits the classic definition of an inhibitor as well as portrays similar idealized behaviors. For instance, resistance hurts IT usage, but lack of resistance does not imply enhanced IT usage, thereby demonstrating asymmetric effects characteristic of inhibitors. Further, the causal independence between enablers and inhibitors in Cenfetelli's [5] model is consistent with prior empirical findings that different motivations drive IT usage and resistance [7, 21]. In other words, the dual-factor model provides a theoretical bridge to link IT usage and resistance with an integrated model.

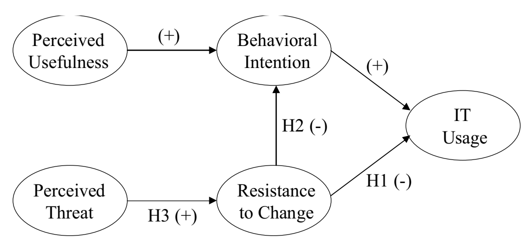

Figure 1. Research Model

Based on Lewin's [15] idea of opposing forces and Cenfetelli's [5] dual-factor structure of IT usage, we propose that one's decision to adopt or a new IT is based on two opposing forces: her behavioral intention to adopt IT and her resistance to change (see Figure

1). Prior theories of IT usage, such as the technology acceptance model [18] and the unified theory of acceptance and usage of technology [19], have viewed IT usage as being predicted by intention in a positive manner. Our addition of resistance as a negative driver of usage is our unique contribution to the IT usage literature. A second conceptual distinction between intention and resistance is that the former is IT-specific, while the latter is a generalized reaction to change resulting from the interaction of IT with the status quo. The expected negative effect of resistance on usage behavior is formally hypothesized as:

H1. Users' resistance to change is negatively related to their subsequent IT usage behaviors.

Cenfetelli [5] contended that inhibitors influence IT usage both directly *and indirectly* via enablers as mediators. There are two plausible reasons for this expectation. First, inhibitors tend to be more diagnostic of IT non-usage than enablers are of IT usage. Theoretical support for this expectation comes from norm theory, which suggests that negative perceptions and acts garner more cognitive attention, are remembered better, and instigates greater information processing than positive ones [22]. For instance, we remember isolated instances of system failure for longer periods of time, than more frequent instance of proper system functioning. In addition, resistance tends to garner a wider range of emotional reactions ranging from overt opposition to covert stalling, than does enablers such as beneficial system features.

Second, the asymmetric effects of inhibitors suggest that inhibitors may have a "biasing effect" on enablers, while the reverse may not occur. Presumably, inhibitors anchor one's overall perception toward attitude objects, subsequently biasing the positive effect of enablers. For instance, a single instance of system failure may lead potential users to view the target IT as being of overall poor quality, despite its having a multitude of positive attributes. Because of these reasons, resistance may also plausibly bias user intentions to use IT, stated as:

H2. Users' resistance to change is negatively related to their intention to use IT.

3.3. Causes of Resistance

Why do people resist? Piderit [23] noted, "Rarely do individuals form resistant attitudes, or express such attitudes in acts of dissent or protest, without considering the potential negative consequences for themselves" (p. 784). In other words, people resist change if they expect it to threaten the status quo, such as a potential loss of power or loss of control over critical organizational resources. A case in point is Markus' [10] seminal study of accountants' resistance toward a new financial accounting system, caused by their expected loss of control over key accounting data and consequent loss of organizational power. Markus concluded that despite the best intentions, new IT implementations can fail unless managers can adequately address power imbalances engendered by the new system.

The notion of perceived threats is reiterated in Lapointe and Rivard's [11] case study of physician resistance, "When a system is introduced, users in a group will first assess it in terms of the interplay between its features and individual and/or organizational-level initial conditions. They then make projections about the consequences of its use. If expected conditions are threatening, resistance behaviors will result." (p. 461). These expectations lead us to hypothesize:

H3. Perceived threat from IT usage is positively related to users' resistance to change.

Perceived threats from IT usage may vary across situational contexts. For instance, the threats faced by financial accountants in Markus' [10] study (i.e., loss of power) may be different from those faced in other IT usage contexts. In order to build a generalized model of IT resistance, we are not providing a specific definition of perceived threat, but rather leaving it for researchers to define based on their empirical context.

Drawing from prior IT usage research [19, 20], we posit perceived usefulness as a positive influence on users' behavioral intentions in our research model. Our inclusion of perceived usefulness is based on extensive empirical validation of this construct in the extant IT usage literature as a dominant predictor of usage intentions across diverse situational, technological, and temporal contexts. Other predictors such as perceived usefulness provide limited explanation of intention for certain types of IT and during later stages of IT usage, and are therefore excluded from our model. The positive associations between perceived usefulness and intention and between intention and IT usage are not stated here as formal hypotheses, because these effects are well-known from prior research and are not unique to or value-added in our proposed model.

Finally, it should be noted that the above model (Figure 1) is our first-cut attempt at building a theory of IT resistance, which may require further refinement and extensions in future research. For instance, there may be additional predictors of resistance not examined in this study, such as lack of knowledge about the change and low tolerance for change [24]. These constructs were excluded from this study in order to keep our model as simple and parsimonious as possible. However, such constructs may be considered in future studies in order to improve overall understanding and prediction of IT resistance.

4. Research Design

4.1. Empirical Setting

Empirical data for testing our hypothesized research model was obtained via a field survey of practicing physicians at one of the largest acute-care hospitals in the southeastern United States. The specific HIT examined was a computerized physician order entry (CPOE) system, used by physicians to order laboratory tests (e.g., blood culture, urine analysis), radiological tests (e.g., X-rays, magnetic resonance imaging, etc.), pharmacy prescriptions, and special procedures (e.g., bronchoscopy, biopsy) for inpatient medical care. The system was recently integrated with an electronic medical record (EMR) system which stores complete medical history of all patients, including admission history, vital signs (e.g., blood pressure, pulse rate) as well as served as a repository of all lab test and radiology results ordered via the CPOE. The system had many value-added features such as adverse drug reporting, which checked all doctor prescriptions against the patient's allergy record for possible unfavorable interactions and provided instant alerts of the same, and workflow management, which tracked when a patient should receive a new dose of medication and alerts the attending physician or nurse of the same. Repetitive ordering of multiple labs, procedures, and medications for a common diagnosis (by ICD code) was automated via "order sets", which could be further customized by physicians based on their personal preferences. The system was voice-activated to accept physicians' dictations, which were then forwarded to transcribing services.

The original CPOE system (without the EMR) was first introduced in one unit of this hospital in 1997. The implementation was however discontinued in 1998 due to ongoing technical and implementation problems, including lack of functionality, network problems, and training setbacks. The revised system, including EMR integration, workflow support, and wireless connecti-vity, was reintroduced in September 2003, after 18 months of process reengineering. System rollout was completed throughout the hospital by late 2005.

Physicians could electronically sign into the system using a password (the system tracked login date and time), and retrieve complete medical data on their own patients. They could track real-time status of their own work orders and retrieve results if available from local or remote locations. Whenever a new order came in, floor nurses were flagged by the system, who could inform or forward a printout to the ordering physician if she was not logged into the system at that time.

At the time of this study, it was estimated that 25-30% of physicians used the CPOE system for entering about 50% of their orders. The high level of non-usage was surprising, given the high level of management priority, technical support, and user support accorded to this project. This hospital was one of the most technological sophisticated facilities in the southeast, with a large IT support staff. Because many physicians were to busy to show up for prescheduled training classes, the administration decided to provide direct one-on-one support to work around busy physician schedules. The CPOE steering committee included physicians from the Physician User Group to ensure that their concerns were heard and addressed.

During our initial site visits to this facility and direct interactions with the physicians involved, the common reasons cited for resistance were "it is new and difficult", "it takes too long to learn", "every patient is different, so a common system won't help," and "there was nothing wrong with the previous state." Some physicians liked the system and used it regularly, such as checking patient charts in the morning from home before arriving at the hospital for rounds. Others hated it and used interesting strategies to avoid its use, such as "smuggling" in old paper-based order sheets, calling in an order to a nurse (who would enter it into the system), requesting work assignments on floors where the system was not yet installed, devising workarounds such as sticking Post-It notes to patient charts, and/or occasional tantrums. Given widespread resistance toward the system despite organizational conditions favoring its use, this hospital was an ideal site for testing our model of IT resistance.

4.2. Measurement of Constructs

The five constructs of interest to this study were perceived usefulness, behavioral intention, perceived threat, resistance to change, and IT usage. Wherever possible, construct measures were adapted from prior research. Perceived usefulness was measured using Davis et al.'s [18] four-item Likert scale that examined subjects' expectations of productivity, performance, and effectiveness gains from CPOE usage, and its overall usefulness. Behavioral intention was measured using a modified version of Taylor and Todd's [25] three-item Likert-scale that examined subjects' intent to use CPOE, more features of the CPOE system, and for more of their job responsibilities.

IT usage was measured using three items similar to Thompson et al. [26] that asked subjects the number of times they currently use the system per week, the number of CPOE modules they use on a regular basis, and the percentage of patient orders that they currently process using the system. We did not have access to actual system-recorded usage data, given the hospital's policies about protecting physicians' privacy, and hence, self-reported usage data was employed as a proxy for actual usage. Since the usage items were in the "circle the answer" format, in contrast to Likert scales for other perceptual constructs, common method bias was expected to be a less significant problem.

Given the absence of pre-validated scales for perceived threat and resistance to change, new multiple-item scales were created for measuring these constructs. Nunnally's [27] domain sampling technique was used for this purpose, where the different domains of physician's work were identified and individual items were created to represent each domain. Based on our initial interviews with physicians, perceived threat of HIT usage was interpreted as physician's loss of control over their work [11], i.e., the way they worked, made clinical decisions, ordered patient tests, and accessed and read lab results. Hence, we created a four-item Likert scale that examined the extent to which physicians feared that they might lose control over the four dimensions of their work listed above if they used the CPOE system. Resistance to change was measured using a similar four-item scale that asked respondents the extent to which they did not want the CPOE system to change the way they ordered clinical tests, made clinical decisions, interacted with other people on their job, and the overall nature of their job.

The survey questionnaire was administered in paper format to all participating physicians at this facility, along with a cover letter from the hospital's Chief Executive Officer, emphasizing the importance of this study, and a postage-prepaid envelope for returning completed responses. Respondent anonymity was guaranteed and no identifying information was recorded. The survey questionnaire was reviewed by the Institutional Review Boards at the researchers' university and the hospital.

Two rounds of survey were conducted in early 2005, spaced 1.5 months apart (earlier respondents were asked to ignore the second round). Comparison of means test for physician age, full-time medical work experience, and length of prior computer use between earlier and later respondents (with later respondents serving as a proxy for non-respondents) found no significant differences between the two groups. This finding assured that non-response bias was not a significant problem in our study.

5. Data Analysis and Results

Following two rounds of survey, 131 responses were obtained from a total of about 700 practicing physicians, for a response rate of about 19%. Two of these responses consisted of mostly missing values, and were discarded. Respondents included physicians from all specialties, including internal medicine, pediatrics, gynecology, pathology, radiology, general surgery, anesthesiology, neurology, oncology, and cardiology. Respondents had a mean age of 49.5 years (SD=10.1 years), medical experience of 20.1 years (SD=11.4 years), general computer usage experience of 14.2 years (SD=6.2 years), and computer usage experience at work for 9.6 years (SD=6.2 years).

5.1. Scale Validation

Confirmatory factor analysis (CFA) was used for assessing the validity for our measurement scales. This was performed using the partial least squares (PLS) technique using Visual PLS 1.04. The variance-based PLS approach was preferred, because unlike covariance-based structural equation modeling approaches such as LISREL, PLS is distribution-free and does not impose sample size restrictions. Raw data was used as input to the PLS program, and path significances were estimated using the bootstrapping resampling technique with 100 sub-samples.

Scale validation proceeded in two phases. In the first phase, convergent validity of scale items was assessed using three criteria suggested by Fornell and Larcker [28]: (1) all item factor loadings should be significant and exceed 0.70, (2) composite reliabilities

(ρ_c) for each construct should exceed 0.80, and (3) average variance extracted (AVE) for each construct should exceed 0.50. Standardized CFA loadings for all scale items in the CFA model were significant at p<0.001 and exceeded the minimum loading criterion of 0.70, with the minimum loading being 0.77 for the fourth perceived threat item (see Table 1). Composite reliabilities of all factors also exceeded the required minimum of 0.80, with the lowest value being 0.90 for IT usage (see Table 2). Further, AVE values for all seven constructs exceeded 0.70, with the lowest values being 0.75 for perceived threat and IT usage (see Table 2). Hence, all three conditions for convergent validity were met.

Discriminant validity between constructs was assessed using Fornell and Larcker's [28] recommendation that the square root of AVE for each construct should exceed the correlations between that and all other constructs. The highest correlation between any pair of constructs in our CFA model was 0.71 between perceived usefulness and behavioral intention (see Table 2). This figure was lower than the lowest square root of AVE among all constructs, which was 0.86 for perceived threat and IT usage. Hence, the discriminant validity criterion was also met for our data sample.

Table 1. CFA Results

Scale Item	Item Mean	Item S.D.	Factor Loading [a]	T-statistic
PU1	4.01	2.12	0.953	151.83
PU2	3.53	2.22	0.965	148.49
PU3	3.80	2.16	0.983	317.88
PU4	4.21	2.13	0.940	66.44
INT1	5.22	1.95	0.932	48.91
INT2	4.92	1.94	0.967	119.05
INT3	4.80	1.86	0.957	107.48
PT1	3.46	1.82	0.883	35.14
PT2	3.40	1.82	0.921	44.21
PT3	3.62	1.85	0.894	39.69
PT4	3.16	1.83	0.769	13.88
RES1	5.18	1.57	0.875	40.26
RES2	5.71	1.44	0.894	30.85
RES3	5.67	1.45	0.874	23.62
RES4	5.22	1.59	0.854	23.87
USE1 [b]	6.74	4.34	0.903	47.63
USE2 [b]	2.43	1.37	0.780	14.20
USE3 [b]	54.4	28.8	0.909	58.40

Item legend: PU: Perceived Usefulness, INT: Intention, PT: Perceived Threat, RES: Resistance to Change, USE: IT usage.

[a] All factor loadings were significant at p<0.001.

[b] USE1 measured as times per week, USE2 measured as a raw count of applications, and USE3 measured as a percentage.

Table 2. Scale Properties

			Inter-Construct Correlations			
	ρ_c	AVE	PU	INT	PT	RES
PU	0.98	0.92	-			
INT	0.97	0.91	0.71	-		
PT	0.92	0.75	-0.50	0.63	-	
RES	0.94	0.76	-0.46	-0.49	0.53	-
USE	0.90	0.75	0.51	-0.50	-0.44	-0.61

Item legend: PU: Perceived Usefulness, INT: Intention, PT: Perceived Threat, RES: Resistance to Change, USE: IT usage.

5.2. Hypotheses Testing

The next step in our data analysis was to statistically test our hypothesized research model (Figure 1) as whole and individual paths in this model. This analysis was also conducted using PLS. Model testing was done by comparing the explanatory power (R^2 value) of our hypothesized model with that of a baseline model that excluded resistance to change and its antecedent perceived threat from the research model. The purpose of this analysis was to isolate the effects of resistance and its antecedents on IT usage. The baseline model (see Figure 2) explained 38% of the variance in IT usage, similar to that reported in previous IT usage studies (e.g., Davis et al. 1989; Venkatesh et al. 2003). However, this explanation increased to 52% in the research model (see Figure 3). A nested model F-test found this R^2 increase to be significant at p<0.001 after adjusting for degrees of freedom, suggesting that our hypothesized model, which included resistance to change as a predictor of IT usage, indeed provided a superior explanation of users' IT usage behaviors.

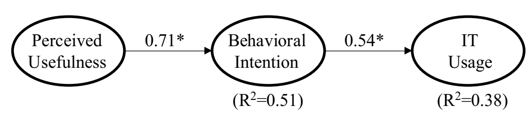

Figure 2. PLS Analysis of Baseline Model

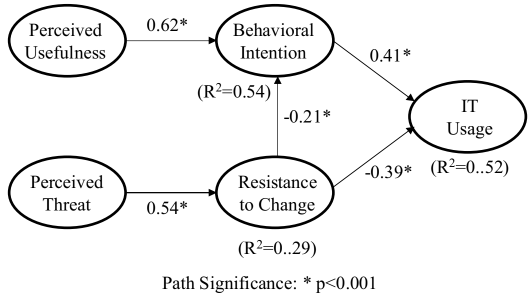

Figure 3. PLS Analysis of Research Model

The variance explained in behavioral intention also increased from 51% in the baseline model to 54% in the research model. This increase is due to the addition of resistance to change as an added predictor of behavioral intention. However, most of the explanation of behavioral intention came from perceived usefulness, confirming that behavioral intention indeed represents the effects of positive perceptions of IT usage, in contrast to resistance, which captures the negative effects.

Examining individual path effects, we find that all hypothesized paths in the two models were significant at $p<0.001$. Resistance to change had a direct negative effect on IT usage (β=-0.39), supporting Hypothesis H1 and confirming its role as a significant inhibitor of usage. The size of this effect was comparable to that of behavioral intention (β=0.41), highlighting the importance of resistance effects, that have been overlooked in prior IT usage research.

Resistance to change also had a significant negative effect on behavioral intention (β=-0.21), providing empirical support for Hypothesis H2 and demonstrating that resistance does indeed have a biasing effect on user intentions. Further, resistance influences IT usage in two ways: a direct effect and an indirect effect mediated by behavioral intention. If the direct and indirect effects are combined, the overall negative effect of resistance on IT usage exceeds the positive effect of behavioral intention.

Perceived threat had a significant positive effect on resistance to change (β=0.54), explaining 29% of the dependent variable. This large effect size is a testament to the importance of perceived threats in shaping one's resistance perceptions. However, 71% of the variance in resistance remained unexplained, suggesting that there may be other salient predictors of resistance that were not examined in this study.

Finally, perceived usefulness had a significant positive effect on behavioral intention, which in turn, significantly influenced IT usage. However, these effects are not discussed in detail, since they were expected from prior research and were not part of our formal hypotheses.

6. Discussion and Conclusions

6.1. Key Findings

Our study theorized the role of resistance to change in influencing individual IT usage in a negative manner, and empirically validated this effect via a study of physicians' reactions to CPOE system at a southeastern hospital. In our study, physicians' resistance to change not only lowered their usage of the CPOE system, but also biased their intention to use the system, which in turn, further hurt their CPOE usage behavior. The joint direct and indirect effect of physician resistance was greater than the effect of behavioral intention, attesting to the importance of resistance as a key inhibitor to CPOE usage.

Our study also confirmed that physician resistance to change was caused by the perceived threat of their loss of control over their work procedures if they used the CPOE system. In particular, physicians viewed the CPOE system as a tool that would make them lose control over the way they ordered patient tests, accessed lab results, made clinical decisions, and worked in general.

While this study was conducted within the specific context of CPOE usage, there is no reason why these results are not generalizable to non-healthcare contexts. Knowledge workers who perceive a threat from a new IT, such as via loss of control over their work, are likely to resist change, and thereby not use the target IT as expected. Of course, there may be other predictors of resistance that were not studied here, that may be the subject of future research.

6.2. Limitations of the Study

The findings of this study should be interpreted in light of its empirical limitations. The first limitation is our measurement of the IT usage construct. Our self-reported usage measure was certainly not as accurate, unbiased, or objective as usage data collected from system logs. Hospital policies regarding physician privacy prevented us from accessing usage logs. However, we urge future research to consider system log based measures of IT usage, if possible.

Second, for the sake of simplicity and parsimony of our preliminary model of resistance, we considered perceived threat as the sole predictor of resistance to change. However, there may be additional predictors of resistance such as low tolerance to change and lack of knowledge. Future research may consider such factors to improve the explanatory power of our model.

Finally, though we viewed resistance as a negative perception, it can conceivably be a positive perception in some contexts, such as where management wants to implement an inferior or sub-optimal system. Exploring such ramifications of the resistance construct was beyond the scope of this study, but could however be the subject of future research.

6.3. Implications for Practice

The findings of this study have interesting implications for IT practitioners. First, this study draws attention to the problem of user resistance, which is often ignored in IT implementation programs. Change management programs in organizations designed to enhance workers' intentions regarding IT usage, through user education and training may be futile if workers possess a strong resistance to change, and hence any change management effort must try to first unfreeze the status quo before enacting change. Managers should therefore understand the concept of resistance and factors causing it, if they are to effectively combat the problem of resistance in their organizations and improve their chances of successful IT implementation.

User resistance may also provide a valuable diagnostic tool for post-mortem analysis of failed IT implementation efforts in organizations. In order to do so, managers need to gauge the current and expected levels of user resistance in their organizations, which they can do using our four-item resistance measure developed in this study.

6.4. Implications for Research

This study was possibly the first to (1) theoretically integrate user resistance within a unified model of IT usage and (2) empirically compare the positive effect of intention and negative effect of resistance on IT usage. Given that current theories of IT usage explain only about 35-40% of IT usage, further exploration of the significant predictors of IT usage is certainly warranted. Toward this end, we incorporated the resistance construct into a unified model of IT usage. Our findings suggest that extant models, based mostly on positive perceptions of usage, provides a partial and limited view of IT usage, and that future research should incorporate the role of negative perceptions, such as perceived threats and resistance to change, and study their effects on usage behaviors.

Second, we demonstrate the asymmetric effects of positive and negative perceptions on IT usage. Specifically, we demonstrate the negative perceptions such as resistance have a biasing effect on positive perceptions such as intention, while the reverse may not occur. Such asymmetric effects further underscore the need to further examine the complex interplay between positive and negative perceptions shaping IT usage behaviors.

Third, we provide evidence of perceived threat as a significant predictor of user resistance, but there may presumably be additional predictors that were not examined in this study. Identifying such predictors, empirically testing their effects, and comparing their effects relative to that of perceived threats are areas that can benefit from future research.

Given the nascent stage of theorizing and cumulative research in IT research, our study anchored this nascent body of resistance research within our substantial body of prior research on IT usage. We hope that this study will motivate future researchers to examine in further depth this interesting but unexplored area of IT research.

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8. Appendix: Questionnaire Items

Perceived Usefulness:

PU1. Using the CPOE system will improve my job performance.
PU2. Using the CPOE system will increase my productivity at work.
PU3. Using the CPOE system will make me more effective in my work.
PU4. Overall, I find the CPOE system to be useful in my job.

Perceived Threat:

PT1. I fear that I may lose control over the way I work if I use the CPOE system.
PT2. I am worried that I may lose control over the way I make clinical decisions if I use CPOE.
PT3. I am worried that I may lose control over the way I order patient tests if I use CPOE.
PT4. I fear that I may lose control over the way I access lab results if I use CPOE.

Intention:

INT1. I intend to use the CPOE system.
INT2. I intend to use more CPOE features/modules.
INT3. I intend to use the CPOE system for more of my job responsibilities.

Resistance to Change:

RES1. I don't want the CPOE system to change the way I order patient tests.
RES2. I don't want the CPOE system to change the way I make clinical decisions.
RES3. I don't want the CPOE system to change the way I interact with other people on my job.
RES4. Overall, I don't want the CPOE system to change the way I currently work

IT Usage:

USE1. Number of times I currently use the CPOE system on average per week:
Less than once | 1-2 times | 3-5 times | 6-9 times | 10-14 times | 15-21 times | 22-35 times | More than 35 times
USE2. CPOE modules that I currently use (circle as many as applicable):
Pharmacy | Lab work | Radiology | Other (please state): ______________________________
USE3. Percentage of patient orders I currently process using the CPOE system:
1-10% | 11-20% | 21-30% | 31-40% | 41-50% | 51-60% | 61-70% | 71-80% | 81-90% | 91-100%