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## An Exploratory Study of User Resistance in Healthcare IT

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## An exploratory study of user resistance in healthcare IT

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**Abstract:** The US healthcare system is clearly experiencing a major transition. By 2015, the healthcare sector is expected to have migrated from a paper record system to a completely electronic health record (EHR) system. The adoption and use of these systems are expected to increase legibility, reduce costs, limit medical errors and improve the overall quality of healthcare. Hence, the US government is investing \$70 billion over a 10-year period to facilitate the transition to an electronic system. However, early reports show that physicians and nurses among other health professionals continue to resist the full use of the system. This paper uses the *theory of cognitive dissonance* to investigate user resistance in HIT. It builds on a Lapointe and Rivard (2005) framework to offer an explanation as to *why* people resist HITs. A conceptual model is developed and tested. The findings, implications, and limitations of the study are also discussed.

**Keywords:** HIT; health information technology; EHRs; electronic health records; electronic medical records; IT user resistance; change management; healthcare technology.

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## 1 Introduction

“Why do people resist evidence that challenges the validity of long-held beliefs? And why do they persist in maladaptive behaviour even when persuasive information or personal experience recommends change?” (Sherman and Cohen, 2002)

The migration from paper to EHRs in the USA has already begun: signalling a wave of change in the health sector that has also met resistance. The Meaningful Use mandate of the Department of Health and Human Services means that all healthcare organisations must adopt and use EHR ‘meaningfully’. It has now been over two years since this initiative was launched, and early reports show that the benefits are palpable, but changing the way business has been done in the healthcare system is still a challenge for physicians and other practitioners (Buntin et al., 2011).

In a recent study of 20 information technology (IT) and IT-related journals over the past 25 years, Lapointe and Rivard (2005) found that 43 articles identified resistance as a key implementation issue. Although these works acknowledged the importance of resistance, most did not delve into the nature of resistance. Furthermore, Lapointe and Rivard (2005) point out that only as little as four of these articles attempt to address the how and why of resistance. Additionally, while many theoretical models have been proposed so far (see Joshi, 1991; Piderit, 2000; Martinko et al., 1996; Markus, 1983), there is still a dearth of literature on the subject. There is almost a lack of empirically tested frameworks. Notable exceptions include Bhattacharjee and Hikmet (2007) and Kim and Kankanhalli (2009). There is however no doubt that the understanding of *how* and *why* resistance takes place is both important to information system (IS) researchers, and organisational scientists and managers. From a more practical standpoint, a shared understanding of the resistance phenomenon among researchers and managers should help to mitigate resistance to- and increase acceptance of information technology (Martinko et al., 1996). It is worth mentioning that in this paper, we use the term ‘IT’ in a narrow sense to refer to just technology, while the term ‘IS’ is used in a broader sense to refer to the interaction of people, the organisation structure and technology.

Furthermore, earlier research on IS introduction in the workplace has also blamed system implementation failures on factors that go beyond a mere worker-technology relationship (Martinko et al., 1996). When workers either avoid, walk-around or overtly resist the use of a system, implementation goals are undermined and failure of implementation is possible. As Martinko et al. (1996) have also pointed out, huge losses in financial investments are often associated with these implementation failures. It is the view of many researchers that understanding and managing resistance to information technology in a larger context of organisational change is very critical if IS must support organisations in achieving desired outcomes (Kim and Kankanhalli, 2009; Coetsee, 1999).

This research focuses on understanding *why* healthcare IT users resist information technology. We examine the user resistance phenomenon through the lens of the cognitive dissonance theory literature. A conceptual model, exploring the antecedents of user resistance is developed based on a generic resistance model earlier proposed by Lapointe and Rivard (2005). The proposed model is further tested empirically. The role and relationship of the key antecedents, namely: *perceived loss of control*, *perceived dissatisfaction*, *technology self-efficacy* and *social enabling effect* are especially highlighted, in the context of this sector-wide organisational change.

In the following section, we review the IT resistance literature: making a special emphasis on the theory of cognitive dissonance and the IT resistance framework developed by Lapointe and Rivard (2005). Next, we develop and test the research model using preliminary data. The findings are then presented while the implications, limitations and conclusions of the research are discussed in the end.

## 2 Literature review

Information technology resistance has been defined as behaviours intended to prevent the implementation or use of a system or to prevent system designers from achieving their objectives (Markus, 1983). In the context of this research, user resistance is defined as healthcare IT users' behaviours intended to oppose and prevent the use of health IT systems to achieve desired organisational healthcare outcomes following the implementation of a new health IT system. According to these formulations of the concept of resistance, three important points are noteworthy:

- resistance is first and foremost a behaviour
- it can be overt or covert
- its effects can hinder system outcomes.

An often common concept that underlies resistance is the quest of whether it is negative or positive. Some have viewed resistance as negative – especially from the perspective of management – however, resistance has also been thought of as a positive feedback mechanism in which, the user can communicate with the implementer (Waddell and Sohal, 1998; Piderit, 2000).

Very few researchers have conceptualised resistance; fewer still have attempted to test their models empirically (Kim and Kankanhalli, 2009; Bhattacharjee and Hikmet, 2007; Lapointe and Rivard, 2005; Joshi, 1991). Generally, four major theories have been proposed to explain resistance. Joshi (1991) proposed a model based on the equity theory

called the equity-implementation model. This model attempted to explain resistance to change. In it, Joshi (1991) proposed that individuals attempt to evaluate most changes: both favourable and unfavourable in order to make decisions. Favourable changes like increased wages and promotions are easily and quickly accepted while changes considered as unfavourable are resisted. The equity theory is therefore presented as the evaluative framework through which individuals evaluate options and make their choices. Markus (1983) also proposed a set of three theories drawn from Kling (1980) in which he elaborated that resistance theories fall into one of three perspectives namely: factors completely internal to them, factors inherent in the technology or the interaction of people and system factors. Of these three theories, Markus (1983) built her interaction model on the third. Martinko et al. (1996) also proposed the attributional model in which they posit that an individual's attributions influence the individual's expectation with regard to performance outcomes that in turn drive behavioural behaviours towards technology. Lastly, Kim and Kankanhalli (2009) use the status quo bias theory to explain why people may prefer to maintain their current status or situation over change. Most of these resistance theories have been based on social psychological variables which link the realms of cognition, affect and behaviour (Piderit, 2000).

A summary of key research in IT resistance is presented in Table 1. Evidently, case studies and literature reviews have dominated the major approaches to the investigation of resistance. While both conceptual and empirical frameworks have been proposed, these frameworks have largely been untested. The current research is similar to extant studies in that it: builds on Lapointe and Rivard (2005) framework, considers resistance as an attitudinal outcome, examines the individual resistance to IT, and adopts a post-implementation perspective. Nevertheless, it departs from previous studies in that it uses the theory of cognitive dissonance which, so far, has not been leveraged in resistance literature. Additionally, the study not only proposes a theory-based model of resistance, but actually tests it too. Previous research has done little or no testing, as can be seen on Table 1. Lastly, this current study shows that perceived threats, which hitherto has been considered as a single construct, is in fact two related, but completely unique phenomena.

**Table 1** A summary of key research and models in IT resistance

|                              | <i>Theoretical perspective/view</i>             | <i>Type of study/technology type</i>                             | <i>Type of model</i> |
|------------------------------|---|--|----------------------|
| Markus (1983)                | Interaction theory                              | Case study/Group analysis  | Theoretical          |
|                              | Power and politics dynamics                     |  | Untested             |
|                              | Neither good nor bad                            | Financial information systems                                    |                      |
| Hirschheim and Newman (1988) | Resistance as aggression, projection, avoidance | Case study/Group analysis<br>Insurance policy processing systems | Conceptual           |

**Table 1** A summary of key research and models in IT resistance (continued)

|                                 | <i>Theoretical perspective/view</i>                                      | <i>Type of study/technology type</i>  | <i>Type of model</i>          |
|---------------------------------|--|---|-------------------------------|
| Joshi (1991)                    | Equity theory<br>Resistance as a result of gain or loss of equity status | Case study/Individual level<br>Clinical laboratory system; banking system; fourth generation programming language | Theoretical model<br>Untested |
| Martinko et al. (1996)          | Attribution theory<br>Learned helplessness                               | Literature review/<br>Individual level  | Conceptual<br>Untested        |
| Lapointe and Rivard (2005)      | Combination of extant theories<br>Process model                          | Case study/multi-level – group level<br>Electronic medical records  | Theoretical<br>Untested       |
| Bhattacharjee and Hikmet (2007) | Dual factor model<br>Technology acceptance model                         | Empirical study<br>Post-implementation of a clinical system   | Theoretical<br>Empirical test |
| Kim and Kankanhalli (2009)      | Integration of technology acceptance and status quo bias perspective     | Empirical study<br>Pre-implementation of an IT enterprise system  | Theoretical<br>Empirical test |

### 2.1 *The Lapointe and Rivard (2005) framework*

Lapointe and Rivard (2005) proposed a multilevel longitudinal approach to explain the evolutionary nature of IT user resistance. This process model, based on prior literature, suggested that people resist IT primarily because of certain *threats* that they perceive. According to the Lapointe and Rivard (2005), users of an information technology constantly make projections about the consequences of the use of a given technology. If the expected conditions following its use are threatening, they will resist. These threats could be due to perceived inequities, loss of power, stress or fear (Joshi, 1991; Markus, 1983; Marakas and Hornik, 1996). Their model further suggested that *perceived threats* were preceded by certain *initial conditions*. Initial conditions, according to Lapointe and Rivard (2005), include habits, routines, social values, and workplace interrelationships (e.g. distribution of power) within an organisation.

### 2.2 *The theory of cognitive dissonance*

The theory of cognitive dissonance was first proposed by Festinger (1957) and has been used for over 50 years to explain change behaviours. The original theory holds that “when an individual holds two or more elements of knowledge that are relevant to each other but inconsistent with one other, a state of discomfort is created” (Harmon-Jones et al., 2010). The resulting discomforting state is called ‘dissonance’. Because dissonance originates from the conflicting “things a person knows about himself, about his behaviour, and about surroundings” (Festinger 1957, p.9), the concept is collectively known as cognitive dissonance.

Generally, there exists some consistency between what a person knows and what he does. For example, if an individual believes that getting an education is a good idea, they are likely to encourage their children to get an education. This example captures the idea of ‘consistency’ in belief and action; and is generally a norm in life. However, there are exceptions to this rule. An individual may know that stealing is wrong and that it might constitute an offense against the law; and yet, be involved in a theft. According to the dissonance theory, this inconsistency or ‘lack-of-fit’ of cognitions motivates the individual to be involved in a psychological effort to reduce the inconsistency between the cognitions. Hence, if an individual who holds the belief that stealing is wrong steals, he would likely be in a state of dissonance. Once this happens, the theory predicts that the individual is likely to do one of two things. He may either justify his action (“I only stole because I was hungry”) or could change his initial belief that stealing is wrong (“Stealing is not that bad, as long as it’s the only option available”), to reduce dissonance. On the other hand, if his initial beliefs are strong enough, he may decide to hold on to his primary cognition and discontinue stealing – the dissonant behaviour; thereby reducing dissonance. Researchers often measure dissonance reduction as attitude change (Harmon-Jones et al., 2010). Hence, attitude change in response to a dissonant condition is expected to be in the direction of the cognition that is most resistant to change.

Questions as to *why* people experience dissonance and why they are motivated to reduce it have spun several streams of research in social-psychology and has given birth to several mini-theories in the area of cognitive dissonance. Among these, the most popular are: the self-consistency theory (Aronson, 1969); self-affirmation theory (Steele, 1988); self-standards model (Stone and Cooper, 2003); aversive consequences perspective (Cooper and Fazio, 1984) and the action-based model (Harmon-Jones et al., 2010). The difference in these theories rests essentially in the attribution of the role of ‘self’ in the cognitive dissonance process. As has been argued by Harmon-Jones and Harmon-Jones (2002), Festinger (1957) theory stopped short of explaining why individuals find cognitive inconsistency aversive.

Each approach, therefore, makes different predictions regarding the role of cognitions in the dissonance process by assuming that different types of information are regularly brought to the mind when people assess their behaviour and then attempt to cope with their discomfort (Stone and Cooper, 2001).

Having discussed the different perspectives of the dissonance theory, it would be necessary to summarise the fundamental claims of the theory. This theory simply holds that:

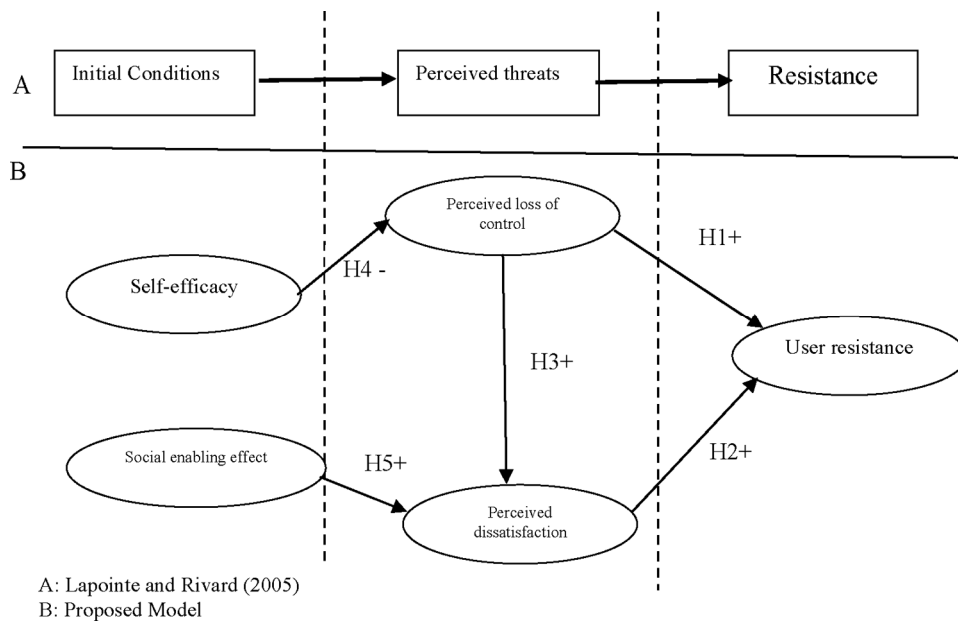
- discrepancies may exist between cognitions, leading to dissonance
- the existence of dissonance leads to motivations within the individual to reduce or even avoid this increase in dissonance
- the manifestation of these pressures include changes in behaviour, cognition, and a cautious exposure to new information and opinions.

### **3 Model development and hypotheses**

In this study, resistance and its antecedents are considered in the light of the Lapointe and Rivard (2005) process framework. As shown in Figure 1, each of the model constructs,

derived from the cognitive dissonance theory (CDT), was mapped to the Lapointe and Rivard (2005) *initial conditions – perceived threats – resistance* framework. Summarily, the *initial conditions* constructs considered in this model were *technology self-efficacy* and *social enabling effect*; the *perceived threats* constructs were *perceived loss of control* and *perceived dissatisfaction*; while the *user resistance* construct was maintained as such. Hence, this model posits that IT user resistance is predicted by *perceived loss of control* and *perceived dissatisfaction* which are each further predicted by *technology self-efficacy* and *social enabling effect* respectively. The research model is illustrated in Figure 1.

**Figure 1** Research model



### 3.1 IT user resistance

Human attitudes have often been thought of to be best conceptualised in terms of cognitions, emotions and behavioural intentions (Ajzen, 1984). It is therefore not strange that a behaviour like resistance – to information technology, in our case – would be perceived in like manner (Piderit, 2000). Resistance in information systems literature has often been characterised as an adverse reaction that is detrimental to the organisation (see Kim and Kankanhalli, 2009). This view sees resistance as a negative reaction that needs to be dealt with. Very often, it pitches employer vs. employee, or administration vs. the staff. In other words, the employees are perceived as those resisting the changes from the employer or the administration. This view seems to be popular given the fact that the introduction of technology is generally considered as an enabler of positive outcomes in the workplace. Hence, resisting a technology is generally perceived to be negative in nature given the fact that it prevents the ‘positive’ outcomes intended by the administration or employer.



It is argued that in the healthcare sector, HIT in general and EHRs in particular will lead to lowered costs, increased legibility, reduced errors, and improved healthcare quality delivery (Jha et al., 2009; Blumenthal and Tavenner, 2010). Actions and behaviours deterrent to the achievement of this purpose may therefore be considered as resistant behaviours. Consistent with the cognitive dissonance theory described above, user resistance in this study is defined as follows. When an individual's intention or action to reduce dissonance or inconsistency is to rationalise or support his present state of cognition or belief: such that a 'new knowledge' is considered as dissonant or inconsistent to with the individual's present cognition or beliefs, the consequent behaviour can be described as resistance. Simply put, resistance is an implicit or explicit intension that results in a behaviour that opposes change towards a particular 'new' attitude or behaviour. Consequently, this research maintains that user resistance of an information system is a covert or overt intension that opposes change towards the use of an information system. This definition has three implications:

- resistance is first and foremost a behaviour
- it can be overt or covert
- its goal is to hinder system outcomes.

In summary, user is the subject; the object is the information technology (EHR); and the attitude is resistance.

In the sections following, we develop the research model and the hypothesised relationships based on the Festinger (1957) cognitive dissonance theory while using the Lapointe and Rivard (2005) generic model as a basis.

### *3.2 Perceived loss of control*

Festinger (1957) questioned: "what... are the circumstances that make it difficult for the person to change his actions" (p.25)? In response to his own question, Festinger (1957) provides insight to the resistance concept in many ways. First, he suggests that people resist change because, it is 'painful', or may 'involve loss'. Furthermore, he asserts "the magnitude of this resistance to change will be determined by the extent of pain or loss which must be endured" (p.25). *Perceived loss of control* refers to an individual's perception that carrying out a particular behaviour will cost them their control over the situation.

Shine (2002) had argued that the elimination of written clinical notes by 2010 is a reachable objective; but cautioned that health professionals would need to move from a 20th-century paradigm to a 21st-century one. This paradigm, noted Shine (2002), constituted among other things a shift from physician autonomy to teamwork and systems, solo practice to group practice, continuous learning to continuous improvement, and infallibility to multi-disciplinary problem-solving and from knowledge to change.

This change of paradigm has far reaching consequences on the health professional's work environment. It means that their autonomy, power and workflow will be impacted. The move from 'knowledge' to 'change' means that the professional's world will never be a calm, predictable and stable one. Consequently, it leads to a sense of loss of control in power, autonomy and the flow of work. Mrayyan (2004) also noted that autonomy

plays an important part in nurses' job satisfaction and retention. He argues that nurses are often dissatisfied with the lack of autonomy and constantly demand for greater autonomy in decision-making (Mrayyan, 2004). Furthermore, Warren et al. (1998) commented that: "[P]hysicians have lost control over who become their patients, the terms and content of their work, the equipment and facilities needed for their work, and the amount and rate of remuneration for their labour stemming from federal control and managed healthcare".

It is evident that some of the changes in the healthcare system are likely to generate resistance due to the loss of control in autonomy and power of the health professional. This loss of control is further exacerbated by the constraints placed on medical professionals by governmental control and management of healthcare (Warren et al., 1998). Since these changes do not originate from healthcare professionals, but rather from policy makers, physicians and other professionals are likely to resist such changes. Hence, it is hypothesised:

*Hypothesis 1: Perceived loss of control due to EHR introduction will positively affect user resistance to the system.*

### 3.3 *Perceived dissatisfaction*

Perceived dissatisfaction is defined as an individual's belief that carrying out a particular behaviour will not be a gratifying thing. Festinger (1957) states: "[t]he resistance to change would be a function of the satisfaction obtained from the present behaviour" (p.26). Poon et al. (2006) observed that the use of non-interoperable HIT systems was likely to negatively impact workflow and productivity.

Furthermore, Poon et al. (2006) also asserted that the income of healthcare providers was directly tied to their productivity but not to their quality. Consequently, dissatisfaction with productivity and workflows is likely to cause resistance to change especially in an era of decreasing reimbursement (Poon et al., 2006). These productivity and workflow challenges are then likely to contribute to the clinician's dissatisfaction with the system due to its threat on productivity and workflows.

Summarily, dissatisfaction due to the introduction of an information system in the healthcare workplace can result in the alteration of reward systems, and impact productivity and workflow. This means that health professionals whose productivity, workflow and rewards are affected by electronic records introduction are likely to be dissatisfied and hence, resist the technology. The more dissatisfied an individual is, vis-à-vis a system, the more they are likely to resist it. It is therefore hypothesised:

*Hypothesis 2: Perceived dissatisfaction with EHRs will positively affect user resistance to the systems.*

The *perceived loss of control* due to the introduction of an information system in the workplace can also be a source of dissatisfaction in itself. For instance, Mrayyan (2004) has stated that autonomy plays an important part in nurses' job satisfaction and retention. Hence, nurses are often dissatisfied with the lack of authority and demand better working conditions and greater autonomy in decision-making. If this autonomy of practice in the profession is not granted, dissatisfaction ensues. In this study's context,

when IT is introduced into the healthcare workplace, the disruption of routines may dictate and impose new ways of doing things, making professionals to feel unsafe and insecure. This perceived loss of control is likely to cause dissatisfaction with the introduced system. Research findings suggest that autonomy (lack of control) is the strongest predictor of physician and nurses' job satisfaction (Mrayyan, 2004; Warren et al., 1998). In fact, in one particular study, nursing autonomy was positively correlated with better perceptions of the quality of care delivered and higher levels of job satisfaction (Rafferty et al., 2001). Evidently, the sense of *loss of control* in autonomy and/or workflows due to systems introduction are also likely to increase the professionals' dissatisfaction with the given information system. It is therefore hypothesised:

*Hypothesis 3: Perceived loss of control due to EHR introduction will positively affect perceived dissatisfaction with the system.*

### 3.4 Self-efficacy

The theory of cognitive dissonance also argues that the belief about 'self' is key to the reducing dissonance and thus, changing behaviours. Compeau and Higgins (1995) defined *computer self-efficacy* as "individuals' beliefs about their abilities to competently use computers". Applied to technology, *technological self-efficacy* therefore refers to an individual's beliefs about their ability to competently use a technology. As has been shown in previous research, and based on Bandura (1986), this belief is positively associated with expectations of future use of technology (Compeau and Higgins 1995). One reason for resistance of new technology lies in the unpredictable outcome on the use of the technology, sometimes based on the lack of exposure to similar technology in the past.

Simply put, individuals, who have used computers in the past, are likely to be more favourable to use them in the future compared to non-users. Bandura's (1977) *theory of self-efficacy* hypothesises that "expectations of personal efficacy determine whether coping behaviour will be initiated, how much effort will be expended, and how long it will be sustained in the face of obstacles and aversive experiences". Furthermore, Bandura (1977) adds: "[p]ersistence in activities that are subjectively threatening but in fact relatively safe produces, through experiences of mastery, further enhancement of self-efficacy and corresponding reductions in defensive behaviour" (p.191). In other words, past experiences of mastery of a particular behaviour are likely to reduce 'defensive behaviour' – or a sense of loss of control, in this case – even though the new activity may be subjectively threatening. In the light of health IT, previous exposure to similar technologies is likely to lessen the sense of loss of control due to the introduction of a given technology. Hence, the greater the *technological self-efficacy*, the more less likely an individual will feel threatened or have a sense of a loss of control over the new technology. It is therefore hypothesised:

*Hypothesis 4: Technology self-efficacy will negatively impact perceived loss of control over the EHR system.*

### 3.5 *Social enabling effect*

Festinger (1957) also postulated that “when it is established by agreement with other people, the resistance to change would be determined by the difficulty of finding persons to support the new cognition” (p.27). In other words, when individuals do not find support for ‘change ideas’ with significant or referent others around them, they tend to feel a social nudge that encourages them to perform a particular contrary behaviour. For example, if the prevailing belief within a healthcare facility or practice is not in favour of a particular change, and individual within that social unit is likely to resist the change behaviour in question. He or she does so, based on the perception that the behaviour in question is somehow consistent with those of significant others around him or her.

Social psychology research is conclusive on the potential influence of significant others on an individual’s attitudes and behaviours. The subjective norm, described as “a person’s perception that most people who are important to him think he should or should not perform the behaviour in question” (Fishbein and Ajzen, 1975).

*Social enabling effect* is the perception by an individual that his or her behaviour is consistent with significant others’ beliefs about the given behaviour. For example, if an individual’s perception within a healthcare practice community is that significant others are dissatisfied with a particular change behaviour, the individual is equally likely to be dissatisfied. Hence, it is hypothesised:

*Hypothesis 5: Social enabling effect will positively impact perceived dissatisfaction with EHRs such that, if the perception about referent others towards the system is dissatisfactory, then the behaviour of the subject in question will also be that of dissatisfaction with the system.*

## 4 **Methodology**

### 4.1 *Sampling procedure*

This exploratory study was conducted in the College of Health Sciences and Human Services of a large southwestern university. This college houses among other academic departments nursing, physician assistants, and rehabilitation departments. It also offers degrees, both undergraduate and graduate professional degrees, in these disciplines. The physician and nursing graduate programs specifically train professionals who use EHRs in their routine work.

The sample was drawn from a class of final year students in the physician assistant studies and a graduate nursing practitioner course. The subjects were handed the surveys following a study recruitment notification and encouraged to participate voluntarily and anonymously in the study. They were informed that their participation would help the scientific community in understanding healthcare professionals’ behaviours towards HIT usage. Of the 80 surveys that were distributed, 64 were found usable (80% response rate), and the rest were incomplete with missing data. Given our sampling population, and response rate, we did not find any non-response bias issues. Of the total surveyed, 43 were physician assistants and 21 were nurse practitioners. The general sample had an average daily computer usage of 6 hrs. It must be noted that this survey excluded all individuals who had no experience with both paper and electronic records.

A summary of the descriptive statistics of the sample is presented in Table 2a and Table 2b. As can be seen from Tables 1a and 1b, 40 of the total number of respondents were females, while the remaining 24 were males. Particularly over nearly 60% of all respondents had an EHR experience of less than a year, while a third had an experience exceeding two years. Additionally, a majority of respondents (nearly 60%) had a practice experience of less than two years while about a quarter (about 27%) had practiced for more than five years.

**Table 2a** Sample EHR experience

| <i>EHR experience</i>      | <i>Count</i> | <i>Percentage</i> |
|----------------------------|--------------|-------------------|
| <i>Below one year</i>      | 38           | 59.38             |
| Male                       | 16           | 25.00             |
| Female                     | 22           | 34.38             |
| <i>1–2 years</i>           | 6            | 9.38              |
| Male                       | 4            | 6.25              |
| Female                     | 2            | 3.13              |
| <i>More than two years</i> | 20           | 31.25             |
| Male                       | 4            | 6.25              |
| Female                     | 16           | 25.00             |

**Table 2b** Sample years of practice

| <i>Years of practice</i>    | <i>Count</i> | <i>Percentage</i> |
|-----------------------------|--------------|-------------------|
| <i>Less than two years</i>  | 38           | 59.38             |
| Male                        | 18           | 28.13             |
| Female                      | 20           | 31.25             |
| <i>2–5 years</i>            | 9            | 14.06             |
| Male                        | 3            | 4.69              |
| Female                      | 6            | 9.38              |
| <i>More than five years</i> | 17           | 26.56             |
| Male                        | 3            | 4.69              |
| Female                      | 14           | 21.88             |

## 4.2 Measures

The five constructs used in the study were either adapted from previous studies. Each of these constructs was measured on a five-point Likert scale depicting the respondent's level of agreement with a particular item. The range was from *strongly disagree* to *strongly agree*. Items on *User resistance* were adapted from Bhattacharjee and Hikmet (2007) who also investigated physician resistance of HIT. Items of *perceived loss of control*, *perceived dissatisfaction* and *social enabling effect* were adapted from Ngafeeson (2013). Lastly, items on *technology self-efficacy* were adapted from Compeau and Higgins (1995). A summary of the original instrument:

including construct definitions and sample items used are included in the summarisation on Table 3.

**Table 3** Construct definition and derivation

| <i>Construct</i>                | <i>Definition</i>   | <i>Sample Item</i>  | <i>Source</i>                  |
|---------------------------------|---|---|--------------------------------|
| User resistance (UR)            | A covert or overt intention that opposes change towards the use of an information system                        | I don't want the EHR system to change the way I order patient tests   | Bhatacherjee and Hikmet (2007) |
| Perceived loss of control (PLC) | An individual's belief that carrying out a particular behaviour will cost them their control over the situation | The EHR system makes me lose my sense of autonomy as a professional   | Ngafeeson (2013)               |
| Perceived dissatisfaction (PD)  | An individual's belief that carrying out a particular behaviour will not be a gratifying thing                  | I am not satisfied with the way the EHR system interferes with my professional autonomy   | Ngafeeson (2013)               |
| Technology self-efficacy (TSE)  | An individual's belief that they are able to competently use technology   | I feel confident that I could complete my job using the EHR with productivity as a professional if I had never used a system like that before | Compeau and Higgins (1995)     |
| Social enabling effect (SEE)    | An individual's belief that his/her beliefs are consistent with those of referent others around them            | My peers would agree with me that the EHR system has flaws that prevent usage   | Ngafeeson (2013)               |

## 5 Data analysis and results

### 5.1 Data analysis

To test the research hypotheses, partial least squares (PLS) was used. PLS is a component-based algorithm for structural equation modelling (SEM), that is quite similar to the covariance-based SEM technique but with some unique differences. Unlike the latter, PLS does not make assumptions that observations must follow a specific distributional pattern and that each observation is independently distributed (Chin, 2010, p.659). This characteristic of PLS makes it suitable for exploratory studies, which have a limited sample sizes and where claims of multivariate normality of distribution may not be made. Nevertheless, Fornell and Bookstein (1982) have shown that PLS can generate similar loadings and structural path values comparable to other SEM techniques without requiring these distributional assumptions.

The minimum sample size consideration for this study was determined using two criteria suggested by Hair et al. (2014). First, the general rule of thumb is to use a sample size that is 10 times the largest number of structural paths directed at a particular construct in the structural model. Since the largest number of arrowheads pointing to a latent variable in the proposed model was 2, the 10 times arrowhead rule required a sample size of at least 20. However, like Hair et al. (2011) have noted, PLS-SEM like

every other statistical technique must also consider the background of model and data characteristics. Specifically, power analyses have been highly recommended. Given the characteristics of the proposed model (i.e., with a maximum of 2 arrowheads to a latent variable); it will require a least sample size of 52 to yield a statistical power of 80% at 95% confidence level for a minimum  $R^2$  of 0.25 (see Hair et al., 2014, p.21). The sample size of 64 satisfied both the rule-of-thumb and the more stringent power analysis calculations; and hence, proving adequacy for use in this study.

PLS allows for a combined principal component factor analysis as well as regression analysis. Hence, PLS is clearly superior to the traditional regression analysis as it assesses the measurement model is assessed within structural model context (Thompson et al., 1991). Consequently, PLS is a clearly useful tool for exploratory research (Chin, 2010, p.660) capable of handling complex models using smaller samples. SmartPLS version 2.0 was particularly used in the analysis of this data.

After coding of sample research data, seven missing values were found for different observations. The missing values were treated in a two-step process. First, missing data cells were replaced with a sentinel value in each cell (in this case -99) and resaved. Second, the data were then imported to SmartPLS and the missing values settings corrected to reflect the sentinel value before proceeding with validation of data. In order to estimate the model, a case-wise replacement algorithm was chosen. This process forces PLS to not discard useful information for the non-missing values cells. The model was then estimated using both the PLS algorithm and bootstrapping techniques. The PLS algorithm helps us the determine path coefficients while bootstrapping enables us to determine the significance of these paths and to finally test the proposed hypotheses. Table 4 presents the descriptive statistics of all the constructs – their mean and standard deviation values, as well as the number of items that were used of represent the construct.

**Table 4** Descriptive statistics of constructs

| <i>Construct</i>                | <i>Number of items</i> | <i>Mean</i> | <i>Standard deviation</i> |
|---------------------------------|------------------------|-------------|---------------------------|
| User resistance (UR)            | 4                      | 3.336       | 1.005                     |
| Perceived loss of control (PLC) | 5                      | 2.391       | 0.833                     |
| Perceived dissatisfaction (PD)  | 3                      | 2.406       | 0.909                     |
| Social enabling effect (SEE)    | 3                      | 3.448       | 0.871                     |
| Self-efficacy (SEF)             | 3                      | 1.823       | 0.576                     |

## 5.2 Model evaluation: measurement model results

Generally, first part of model evaluation is to present the measurement model results. This portion focuses on ascertaining how accurate or reliable the measures are as well as assessing the convergent and discriminant validities of the proposed model. The measurement model was assessed for internal consistency by computing both the Cronbach's alphas and composite reliability values. Composite reliability measures the internal consistency of a construct, but unlike Cronbach's alpha, it does not assume equal indicator loadings (Hair et al., 2014). Composite reliability measure is therefore a suitable measure for use in lieu of Cronbach's alpha in this study. Hair et al. (2014) suggest a threshold of 0.70 in exploratory research or a range of 0.06–0.07 to be considered acceptable (p.115). The Cronbach's alpha values for the measurement were

all adequate: ranging from 0.71 (for technology self-efficacy) to 0.92 (for social enabling effect). The composite reliabilities measures also confirmed reliability given that these measures are all greater than the recommended 0.7 threshold level (see Table 5). The inter-construct correlations and reliabilities are also included in Table 5. It should be noted here that these measurements represent the final values after inter-item cross-loadings were identified and some items dropped from the analysis. According to these results, the reliability measures were considered to be adequate given that all were greater than the recommended 0.70 level (Nunnally, 1978). An additional check on reliability was also done by measuring the average variance extracted (AVE) and the composite reliability measures. The AVE serves to further support the reliability of these measures as recommended by Fornell and Larcker (1981). AVEs are expected to be greater than the squared inter-construct correlations to establish discriminant validity. Results reveal that the AVEs are all above the 0.5 threshold level, meaning that more than 50% of the variance in the indicators is accounted for; and that all AVEs were greater than the squared inter-construct correlations, establishing discriminant validity.

**Table 5** Inter-construct and reliability measures

| <i>Squared correlations among constructs</i> |                              |            |           |            |            |           |           |
|--|------------------------------|------------|-----------|------------|------------|-----------|-----------|
| <i>Construct</i>                             | <i>Composite reliability</i> | <i>AVE</i> | <i>PD</i> | <i>PLC</i> | <i>SEE</i> | <i>EF</i> | <i>UR</i> |
| PD   | 0.9225                       | 0.7990     | 1         |            |            |           |           |
| PLC  | 0.8602                       | 0.6070     | 0.5849    | 1          |            |           |           |
| SEE  | 0.9501                       | 0.8640     | 0.1614    | 0.0754     | 1          |           |           |
| SEF  | 0.8342                       | 0.6277     | 0.0004    | 0.0001     | 0.0005     | 1         |           |
| UR   | 0.8926                       | 0.6754     | 0.1335    | 0.3207     | 0.0766     | 0.0133    | 1         |

Convergent validity was also assessed. Convergent validity refers to the extent to which blocks of items strongly agree or ‘converge’ in their representation of the underlying construct they were created to measure Chin (2010). It answers the question as to *how high* each of the loadings is and whether they are more similar or dissimilar. Though there is no generally accepted rule of thumb, Chin (2010) recommends that loadings be high enough and to have about a difference in range of about 0.02. Except for the self-efficacy item – SEF4 – which loaded highly but had a wider range of 0.58–0.86 all of the rest of the items both loaded highly and within an acceptable narrow range. We therefore see evidence of convergent validity from the data. Table 6 reveals the squared factor cross-loadings for a more intuitive assessment of the convergent validity.

**Table 6** Squared factor cross-loadings between constructs

|      | <i>PD</i> | <i>PLC</i> | <i>SEE</i> | <i>SEF</i> | <i>UR</i> |
|------|-----------|------------|------------|------------|-----------|
| PD1  | 0.8838    | 0.5483     | 0.1451     | 0.0009     | 0.1350    |
| PD2  | 0.8017    | 0.5108     | 0.0715     | 0.0015     | 0.1356    |
| PD4  | 0.7117    | 0.3398     | 0.1972     | 0.0028     | 0.0527    |
| PLC1 | 0.3966    | 0.6942     | 0.0581     | 0.0001     | 0.2366    |
| PLC2 | 0.3846    | 0.6631     | 0.0214     | 0.0051     | 0.1590    |
| PLC4 | 0.3026    | 0.5109     | 0.0277     | 0.0055     | 0.1897    |



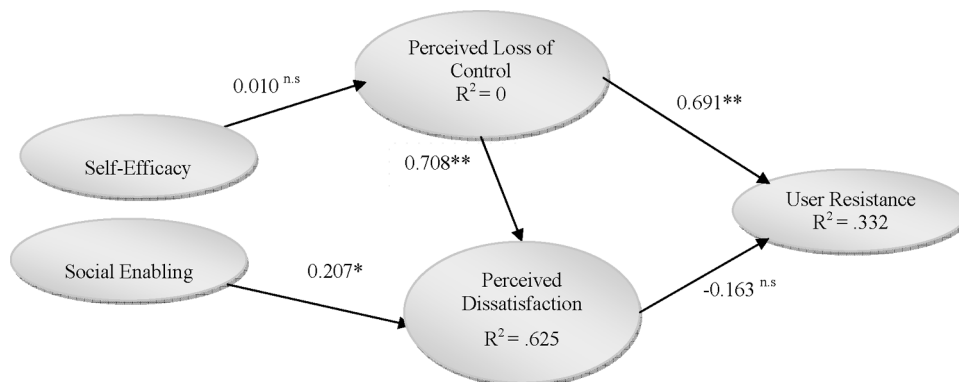
**Table 6** Squared factor cross-loadings between constructs (continued)

|      | <i>PD</i> | <i>PLC</i> | <i>SEE</i> | <i>SEF</i> | <i>UR</i> |
|------|-----------|------------|------------|------------|-----------|
| PLC5 | 0.3361    | 0.5600     | 0.0895     | 0.0103     | 0.1947    |
| SEE1 | 0.2270    | 0.1080     | 0.8844     | 0.0030     | 0.0620    |
| SEE2 | 0.0978    | 0.0483     | 0.8586     | 0.0102     | 0.0761    |
| SEE3 | 0.0686    | 0.0276     | 0.8490     | 0.0044     | 0.0637    |
| SEF3 | 0.0045    | 0.0001     | 0.0107     | 0.5909     | 0.0150    |
| SEF4 | 0.0003    | 0.0001     | 0.0013     | 0.7526     | 0.0137    |
| SEF6 | 0.0000    | 0.0000     | 0.0130     | 0.5395     | 0.0003    |
| UR1  | 0.0212    | 0.1915     | 0.0050     | 0.0144     | 0.6392    |
| UR2  | 0.0795    | 0.1974     | 0.0419     | 0.0043     | 0.6876    |
| UR3  | 0.1708    | 0.2317     | 0.1478     | 0.0583     | 0.6187    |
| UR4  | 0.1319    | 0.2470     | 0.0654     | 0.0065     | 0.7560    |

5.3 Model evaluation: structural model results

The results of the structural model are summarised in Figure 2. These results show the path coefficients, R-square values as well as the significance levels. The *t*-statistics for significance levels were obtained from the bootstrapping procedure of PLS. Bootstrapping is a non-parametric technique that does not require the normality assumptions associated with regression models. In order to obtain reliable structural path results and their *t*-values a bootstrapping procedure of 5000 samples and 64 cases was run. Results for the structural model show that the hypotheses were only partially supported for the proposed *cognitive dissonance model of resistance*. Specifically, three hypotheses were supported while two were not. Examining the path coefficients as well as the directionality, we can see that Hypotheses 1, 3 and 5 were supported while Hypotheses 2 and 5 were not ( $P < 0.05$ ).

**Figure 2** Structural model showing path coefficients



n.s.: not significant; \*significant at 0.05 level; \*\*significant at 0.01 level.

*User resistance* was predicted positively by *perceived loss of control* ( $\beta = 0.69$ ;  $P < 0.01$ ), but not by *perceived dissatisfaction* as originally hypothesised. *Perceived dissatisfaction*, on the other hand, was positively predicted by *perceived loss of control* ( $\beta = 0.71$ ;  $P < 0.01$ ) and *social enabling effect* ( $\beta = 0.21$ ;  $P < 0.05$ ). *Technology self-efficacy's* influence on *perceived loss of control* turned out to be non-significant. The total variance in *user resistance* that was explained by *perceived loss of control* and *perceived dissatisfaction* was 33.2%, while the total variance in *perceived loss of control* and *perceived dissatisfaction* were 0% and 62.5% respectively.

## 6 Findings, implications and limitations

### 6.1 Findings

The purpose of this study was to understand *why* user resistance to IT happens. The goal was to develop a theory-based model that could be empirically tested and to make sense of these exploratory findings. The study utilised the *theory of cognitive dissonance* and built on the Lapointe and Rivard (2005) generic framework to propose an empirically testable model.

This study found that user resistance originates from *perceived threats* that may come from two sources, namely: *perceived loss of control* and *perceived dissatisfaction*. Earlier research (e.g., Bhattacharjee and Hikmet, 2007; Lapointe and Rivard, 2005) had looked at perceived threat as a singular construct. This research suggests that there are two possible types of threats that can generate user resistance (UR), namely *perceived loss of control* (PLC) and *perceived dissatisfaction* (PD). However, while the PLC-UR relationship was clearly strong and positive, the PD-UR was non-significant. It is possible that the limited sample size for the study was a contributing factor to this non-significant relationship, given that previous studies show that dissatisfaction with technology outcomes may cause users to resist its use (see Mrayyan, 2004).

The relationship between perceived loss of control and perceived dissatisfaction was also strong and positive. This means that threats of loss of control can also trigger dissatisfaction with outcomes. This finding is very important because it shows that *perceived loss of control* and *perceived dissatisfaction* should not be considered under the umbrella term of *perceived threats* because not only are there at least two distinct types of threats, but that one of them (*perceived loss of control*), could actually lead to the other (*perceived dissatisfaction*).

*Perceived dissatisfaction*, on the other hand, was found to be influenced by *social enabling effect*. As discussed earlier, when an individual belief about the introduction of a system in the workplace is that this technology will cause significant others to be dissatisfied with it, they are likely to be equally dissatisfied with the technology. This finding is consistent with normative behavioural theories which suggest that individuals' important others can directly or indirectly influence their behaviours (see Ajzen, 1991). In fact this model showed that up to 62.5% of perceived dissatisfaction was jointly predicted by *perceived loss of control* and *social enabling effect*.

No support was found for the relationship between *technology self-efficacy* and *perceived loss of control*. It is possible that the small sample size would have impacted this relationship by providing very small variability in the sample. Additionally, it is possible that if items were adapted to be more specific in capturing technological

self-efficacy in general, but healthcare technology self-efficacy, better results could be yielded.

## 6.2 *Implications*

The study offers both theoretical and practical implications. Theoretically, this research extends the body of knowledge in IT user resistance by leveraging a social psychological theory (cognitive dissonance) to explain the concept of resistance. As Piderit (2000) has cautioned, user resistance is a complex phenomenon that requires a multidimensional approach examining it. This research therefore introduces a relevant body of literature from which resistance studies can be viewed from. Second, this study introduces the concept of two distinct but identical types of perceived threats which heretofore has only regarded as one and the same thing. Because each threat is different, the strategy to combat each threat will be different and would improve our knowledge perspectives on the subject.

Practically, change managers will find this research helpful for two major reasons. First, it attempts the answer as to why people resist technology. From the standpoint of the two major ways that perceived threats are manifested, managers may design strategies for combating or at least mitigating user resistance. By proactively dealing with issues of *perceived loss of control* due to power imbalances or autonomy concerns resulting from the introduction of a system, managers can organise programs or campaigns to deal with the threats. Additionally, the items used in this study could be utilised pre-implementation to identify potential threat areas. For instance, if a manager finds out that employees are afraid to lose the power vested in their positions, campaigns to assure threatened employees may be in order. By the same token, if the managers notice a general perception of dissatisfaction with the outcomes of the systems, they may equally work out strategies designed to target this concern. Knowles and Linn (2004) have noted that theoretical understanding of resistance, can lead to the right application of persuasion – its antithesis. Lastly, Vendors of EHR software will find this research useful in that, elements of the system that conflict flagrantly with workflows and autonomy leading to threats could be minimised so as to mitigate user resistance due to the system.

## 6.3 *Limitations and future research*

These findings and implications must, however, be interpreted within the confines of the limitations of this study. First, the resistance model proposed was based on the theory of cognitive dissonance. Different perspectives are also needed to study a complex concept as user resistance. Second, the sample data was small and could present issues of generalisability of results. Lastly, the lack of pre-validated scales for resistance and the perceived threats constructs means that further testing would be required in the future. Nevertheless, this research has its merits, as it can serve as a departure point for future empirical research in user resistance: by leveraging the cognitive dissonance theory with IT user resistance and testing it empirically. Additionally, though a small sample size is used, it still met the minimum requirements for SEM using the PLS technique.

Future research could consider the use of more theoretical paradigms that lend an understanding of the concept of IT user resistance for greater insights. It might be that more theories lead to the discovery of new types of threats as Bhattacharjee and Hikmet (2007) have noted. Furthermore, future studies might test the validity of the study's new

scales here-developed and by using new paradigms arrive at a testable comprehensive model.

## 7 Conclusion

Understanding user resistance is crucial in the current US healthcare transition. *Why* people resist the use of health technology must be sufficiently answered if the promise of quality outcomes would be realised. This preliminary research shows that the theory of cognitive dissonance can be a useful lens through which an understanding the role of user resistance to IT can be gained. It also revealed that *perceived loss of control*, *social enabling effect* and *perceived dissatisfaction* are important antecedents of IT user resistance.

If change managers would be successful in managing the current healthcare transition, they must convince healthcare professionals that the benefits of the system far outweigh the inconveniences of change. While change is never static, the challenge of managers of change must seek for a way to ‘normalise’ the inevitable change.

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