



The impact of service level on the acceptance of application service oriented medical records

Liping Liu^{a,*}, Qingxiong Ma^b

^a College of Business Administration, University of Akron, Akron, OH 44325-4801, USA

^b Harmon College of Business Administration, Central Missouri State University, Warrensburg, MO 64093, USA

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Abstract

Service level is considered to be the most important criterion in evaluating application services. In our study we empirically investigated how perceived service level (PSL) influenced healthcare workers' willingness to use application service oriented medical records. In particular, we extended the technology acceptance model (TAM) by embedding PSL as a causal antecedent. We found that PSL explained 61% of the variation in ease of use, which is twice as much as our current understanding. We also found that TAM was validated when tested in isolation but failed within the larger nomological network. We provided an explanation based on the notion of conditional independence. We further applied TETRAD III to explore the phenomenon and discovered two spurious associations in TAM, successfully confirming the explanation.

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1. Introduction

Outsourcing has recently become a strategic alternative in information technology (IT) related decisions [43,53]. At the same time, with the advent of emerging e-business technologies, the software industry has undergone a revolutionary transition from software as products to software as services [68]. These streams of development are now converging,

breeding the next generation outsourcing model based on providing and consuming e-services, including application, web, and grid services.

Application services aim at providing packaged applications over the Internet as an alternative to hosting them in house [22]. Sharing a similar vision, web services aim at providing modular software components to achieve collaborative computing via Internet protocols [23]. Grid services seek even larger-scale sharing of computational and informational resources across platforms, devices, and institutional boundaries [26]. Although the grid was positioned to be independent of the Internet, it is now rapidly converging with web

* Corresponding author. Tel.: +1 330 972 5947; fax: +1 330 972 6588.

E-mail address: liu@acm.org (L. Liu).

services to form a single set of standards [27] and has conveniently served as a marketplace for exchanging web services [51], as an environment to organize web services [82], or as a framework for architecting next generation information systems [34].

While emerging e-service models are being explored for potential applications in healthcare [50], *application service provision* (ASP) has grown into an industry and sparked a great interest in management of electronic medical records (EMR). Besides the usual factors, such as demand for sharing patient records and reducing healthcare costs, compliance with the US Health Insurance Portability and Accountability Act of 1996 has been a force that increases the popularity of application services in this sector [55]. Organizations that are unable or unwilling to allocate resources necessary to become compliant with the law have chosen instead to outsource their business processes.

Essentially, the ASP model allows organizations to hand over the responsibility for IT deployment or its execution to an outside vendor while still satisfying its own information needs. When this is applied to EMR, a vendor hosts and maintains medical records on its own facilities, publishes the user interface over the Internet, and provides clinics with shared access to the interface. A clinic, on the other hand, uses the records on an “as needed” basis as an alternative to hosting the records in house. By doing so, a vendor can amortize expenditures over its client base, enabling it to improve its quality of service, enhance security, and reduce risks that individual clinics may find cost-prohibitive. Clinics, on the other hand, can save IT deployment and maintenance costs while focusing on their core business [19,56].

Despite many benefits, the growth of the ASP industry has been slow. Some researchers have attributed the problem to limited user satisfaction [71]. However, the medical informatics community has tended to blame medical workers for not being ready for change [77], and has attributed the problem to limited end-user acceptance.

Anecdotal evidence suggests that the low usage of installed systems is a key explanation to the “productivity paradox” [44,64]. Any decision that changes work behavior should consider user willingness to accept the change. Studies have shown that technology that has won user acceptance is more successful [10,48]. Furthermore, end-user acceptance

is necessary for long-term continuous adoption [8], and this is particularly crucial to an ASP, because most vendors operate on short-term renewable contracts and therefore find it more effective to retain existing clients than recruit new ones [21].

Here we investigated end-user acceptance of application service oriented medical records. Drawing on existing studies, we identify ease of use and usefulness as two ensuring factors, not only because they are the two key beliefs mediating the impact of external variables on technology acceptance [17], but also because lack of them has been mooted as an obstacle to EMR adoption [78]. Drawing on the literature, we found that service level was the most important criterion in evaluating application services [70]. Accordingly, we extended TAM into a nomological network with perceived service level as a causal antecedent and examined how this construct, along with perceived ease of use and perceived usefulness, predicted user acceptance of EMR.

2. Research hypotheses

The technology acceptance model (TAM) was constructed from the theory of reasoned action [24]. It stipulates that, while mediating the effect of external variables, perceived ease of use (PEU) and perceived usefulness (PU) are the two direct causal antecedents to behavioral intention (BI). Also, as it impacts PU, PEU impacts BI indirectly. Since its inception [16], TAM has received extensive empirical support [47,54] in meta analyses. It has been confirmed with subjects across cultures [69] and different technologies, including email, word processors, spreadsheets, groupware, telemedicine [9], and web commerce systems [45,57]. Except for occasional weak findings, studies supported TAM. Therefore, we expected that it would also be applicable to application service oriented medical records, leading to the following hypotheses:

Hypothesis 1. The perceived ease of use of application service oriented medical records has a direct positive impact on the perceived usefulness of the records.

Hypothesis 2. The perceived ease of use of application service oriented medical records has a direct

positive impact on the end-user's behavioral intention to use the records.

Hypothesis 3. The perceived usefulness of application service oriented medical records has a direct positive impact on the end-user's behavioral intention to use the records.

TAM is believed to be more parsimonious, predicative, and robust than other models [75]. While Occam's razor prefers parsimony, TAM has been criticized for being less informative in understanding usage behavior or prescribing interventions [72]. As Gefen and Keil [28] noted, without a better understanding of the antecedents to PU and PEU, managers cannot know which methods can affect these beliefs and, through them, technology usage.

Realizing the limitation, recent studies have attempted to understand what determines PEU. The factors that have been explored include management support [37], self-efficacy [76], gender [30], and trust [11]. Thus we proposed that perceived service level (PSL) was yet another determinant and defined it to be *the end-user's perception of how well an application service performs during the normal course of operations in terms of its reliability and responsiveness*.

Service level is the performance benchmark that a vendor usually agrees to provide contractually in the form of a service level agreement (SLA). This details the contractual obligations, including applications, training, support, updates, termination, and other important service and business issues. From a vendor's perspective, an SLA demonstrates a promise whereas, from a client's perspective, it represents an expectation. A well-documented SLA addresses availability, response time, reliability, and accuracy [3] as well as other non-performance related issues, such as security, recoverability, and affordability.

Conceptually, the notion of PSL is similar to service quality in dimensions like system accessibility, flexibility, reliability, and response time [4]. In a sense, PSL measures the perceived level of service quality that a vendor offers. Here we used PSL instead of service quality because service level is a more frequently used term than service quality in the ASP industry. Also, service quality is a more complex construct that includes many sub-dimensions that may be irrelevant to end-users.

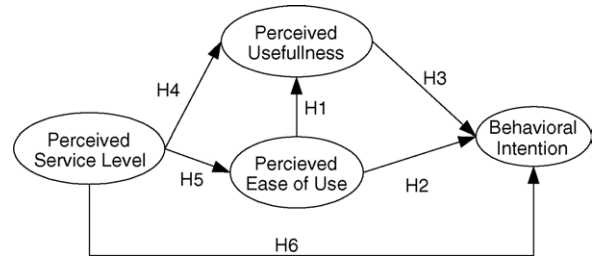


Fig. 1. Research model.

Incorporating PSL into TAM, we obtained an extended nomological network, as shown in Fig. 1. Generally, the more responsive and reliable an application service, the less effort it takes and the more useful it is. When service level is below the user's expectation, frustration arises, and this will inevitably negate his or her perception of usefulness and ease of use. Therefore, we hypothesized that PSL directly influenced PEU and PU, which in turn influenced BI. We also hypothesized that PSL directly influenced BI.

To formally justify the causal links $PSL \rightarrow PEU$ and $PSL \rightarrow PU$, we interpreted PEU and PU from the perspective of user satisfaction. The notion of satisfaction refers to an affective state related to and resulting from a cognitive appraisal [52,59]. By definition, PEU is *the degree to which a person believes that using a particular system would be free of effort*. It reflects a cognitive appraisal of reduced personal investments and frustrations involved with a system. Similarly, PU is *the degree to which a person believes that using a particular system would enhance his or her job performance, reflecting a cognitive appraisal of increased job performance due to using the system*. Therefore, both PEU and PU represent certain aspects of user satisfaction. Other scholars hold a similar view; e.g., in their classic instrument for end-user computing satisfaction [20], Doll and Torkzadeh proposed five component measures, including ease of use and four other components related to usefulness.

Since PSL measures service performance, the new perspective renders a justification for the causal links $PSL \rightarrow PEU$ and $PSL \rightarrow PU$ from the performance-customer satisfaction contingency; these have been well studied in the marketing literature [13,35,60,74]. The positive relationship between performance and

customer satisfaction follows from the notion of a value-percept diversity; customers are likely to be more satisfied with an offering as the ability of the offering to provide consumers what they need, want, or desire increases relative to the costs incurred [39]. The end user is likely to be more satisfied with a service if it has better performance. Therefore, we have the following hypotheses:

Hypothesis 4. The perceived service level of application service oriented medical records positively influences the perceived usefulness of the records.

Hypothesis 5. The perceived service level of application service oriented medical records positively influences the perceived ease of use of the records.

To justify the causal link PSL \rightarrow BI, we noted that service quality had a direct impact on the success of IT outsourcing [33], and perceived behavior control — beliefs about having necessary resources and opportunities — directly determined the end user's intention to use a system. Facilitating conditions are a most important type of behavior control, since behavior cannot occur if objective conditions in the environment prevent it [73]. Triandis defined facilitating conditions as “objective factors” that several observers can agree make an act easy to perform. In our context, the responsiveness, reliability, and availability of an application service may be a type of facilitating conditions. Therefore, we made the following hypothesis:

Hypothesis 6. The perceived service level of application service oriented medical records positively influences the end-user's behavioral intention to use the records.

3. Research design

3.1. Representative users

The population under study consisted of healthcare workers responsible for managing patient records. Since they are typically support staff, their contact information is not accessible to outsiders and mail surveys were therefore difficult to use. Therefore, we identified senior students from a Medical School as

surrogate subjects. The students were either majoring in dental hygiene, as physician assistants, or in radiology; these are four-year degree programs designed to prepare graduates for work in healthcare organizations. Their curricula included intense problem-based learning modules combined with clinical experience. Through formal contacts with the School, we recruited the students on a volunteer basis, and screened them to ensure that they were familiar with the daily operations of hospitals and clinics and had extensive experience in managing patient records through their internships and externships.

Among 90 selected participants, 79 made experiments and returned completed usable questionnaire responses. The response rate was 88%. After the survey, we were informed that extra credits were given as an incentive for participation. Almost all of the respondents were female and over 85% of them were 20–25 years of age. 13% of them reported awareness of EMR systems and only 8% had experience with application services. The rest used traditional paper-based systems. Using a 5-point Likert scale from very negative to very positive, 69% of the participants reported a neutral attitude to their current paper-based systems. 84% had over three years of Internet experience and 69% had positive feelings toward surfing on it. In terms of online shopping, 26% had a negative attitude, 28% were neutral, and 46% were positive.

3.2. Representative systems

Hundreds of vendors claimed to provide EMR applications. To select a representative system for the study, we imposed three critical requirements as follows:

1. To avoid maintenance issues, the target system had to be truly web-based and delivered over the Internet; the user needed a web browser to load the system and perform the task.
2. To mimic a real usage setting, we required a commercial vendor, who had a large client base and allowed participants to use its production system for an extended period of time.
3. To be a representative EMR application, the target system had to have the features and functions of a typical EMR system. This required: creation,

updating, deletion, and retrieval of patient records, including prescriptions and medications; support for electronic communication with labs, pharmacies, hospitals, and other service providers, and integration with phone and fax systems; support of multiple file types including sound and video so that the user could add quick notes to a record, and store and maintain dictation files on the server; and compliance with insurance and regulatory guidelines—thus, all data communication had to be encrypted to ensure security and access to patient charts through an authorized permission-based interface.

These requirements posted some challenges. For example, we found no vendors who were willing to give free access to their production systems. Instead, they distribute video demonstrations to non-subscribers. To meet the challenges, we went through a long process of searching and negotiating. We first read vendor white papers to develop a list of those who satisfied our requirements. We then wrote to salesmen and managers to explain our research purpose. After a long negotiation, HyperCharts™ stood out and was selected. Like all other vendors, it was reluctant to give out full-fledged test accounts. However, after we agreed to help promote their products by offering seminars to local medical service providers, they granted our participants the right to use their production system as regular subscribers.

3.3. Measurement scales

There were four constructs in the research model. Table 1 lists their operational definitions and sources. We adapted most scale items from the literature, because they have been widely tested and validated. To develop the scale for PSL, we followed the advice of Churchill [14] and utilized an expert panel to participate in a pre-test and a pilot test. Eventually we

ended up with 21 items, and the entire survey, including additional questions on demographics, could fit on one standard printed page. We randomized all questions to minimize potential order effects and measured each item using a 7-point Likert scale ranging from “strongly disagree” to “strongly agree.” The demographic data include gender, age, work experience, attitude toward current medical record systems, Internet experience, EMR awareness, and attitude toward Internet surfing and online shopping.

The scale items for measuring PU and PEU are adapted from those by Davis and successively validated by other studies. For PU, we selected all the original six items from Davis. For PEU, we selected three with no modification: *Clear and Understandable*, *Easy to Become Skillful*, and *Easy to Use*. Then we considered the unique usability dimensions of application services and had one item emphasizing navigation, as in Levi and Conrad [49] and Lederer et al. [45], and one emphasizing ease in performing functions (see Table 2). The items for BI were adapted from Davis et al. [18] and the operationalization guideline of Ajzen and Fishbein [2]. For example, the questions on BI were worded to refer to a specific target, a specific behavior, and a specific context. We developed three items that reflected sub-dimensions of BI: intention to use, intention to make an effort, and intention to use in future (see Table 2).

To assess service level, the prevailing method has been to gauge reliability and responsiveness over a period of time using a system management tool. Of course, this type of assessments was not available (and probably irrelevant) to the end-user. Instead, his or her perception of how a system performed and of being willing to use a system was based on subjective measures [6]. Therefore, we used user perceptions and focused on its reliability and performance dimensions where we had items tied to specific tasks.

Table 1
Construct definitions

Construct	Definitions
PU	The degree to which a person believes that a particular information system would enhance his or her job performance [17]
PEU	The degree to which a person believes that using a particular information system would be free of effort [17]
BI	A measure of the strength of the user's behavior intention to use an information system [18]
PSL	The degree to which a person believes that an information system is reliable, stable, and responsive

Table 2
Scale items

PEU1	My interaction with this system was clear and understandable
PEU2	I found it was easy to do whatever I want
PEU3	The navigation on the site is easy
PEU4	Learning to operate this system is easy for me
PEU5	It would be easy for me to become skillful at using this system
PU1	Using this system would improve my job performance
PU2	Using this system would enhance my effectiveness on the job
PU3	Using this system in my job would increase my productivity
PU4	Using this system in my job would enable me to accomplish tasks more quickly
PU5	Using this system would make it easier to do my job
PU6	This system is useful in my job
BI1	I am willing to use the system for my work
BI2	I do not mind spending some time to learn how to use this system for my work
BI3	I would like to come back to this site for a second look
PSL1	It is fast to search for a patient record on this site
PSL2	I was able to retrieve data quickly
PSL3	The system loads quickly
PSL4	It is fast to create a patient record on this site
PSL5	The system reliably handled my queries
PSL6	It is fast to use on this site
PSL7	I found the system performed as well as I expected

3.4. Experimental task

We distributed a questionnaire and a cover letter with instructions to each selected participant through their school advisors. In the cover letter, the participants were informed that the experiment was voluntary and that they could refuse to participate or quit at any time. In the instructions, each participant was provided with a link to HyperChartsTM, a user account for login, and a quick user guide about the functionalities of the system under test.

We asked each participant to accomplish the following tasks: (1) log into the system; (2) create, update, and delete a patient record, search for a patient record, and add quick notes to it; (3) search for prescriptions for a patient, add and sign off new ones, and add and modify medications on one; and (4) upload and download a dictation audio file. Also, along with these tasks, the participants could explore any other of the HyperChartsTM functions.

4. Data analysis

Hypotheses 1–3 essentially ask for a replicated test of TAM in the health care industry. To this end, we first conducted a factor analysis involving items for PEU, PU, and BI. Using the Kaiser eigenvalue criterion, we extracted three factors that collectively explained 73.9% of the variance in all responses. We found that item PU6, “Overall Usefulness”, did not load clearly. Thus, we eliminated it from the further study. The final rotated factor matrix (Table 3) shows that all the items cleanly loaded to the correct latent constructs, supporting the factorial validity of PEU, PU, and BI.

After PU6 was removed, we conducted reliability analysis for each construct and found that the item correlations ranged from 0.48–0.68 for PEU items, 0.57–0.87 for PU items, and 0.54–0.67 for BI items. The Cronbach alpha values were 0.88 for PEU, 0.92 for PU, and 0.81 for BI; all these were above the acceptable threshold of 0.70 [58], supporting the reliability or convergent validity of the scales.

We employed multivariate linear regressions as the primary method for data analysis. Table 4 shows the regression models. The significant regression coefficients clearly supported the validity of TAM and Hypotheses 1–3. In particular, we confirmed that both PU and PEU had significant positive impacts on BI, and that PEU positively influenced PU and then BI indirectly. Overall PEU and PU explained 45% of the variance in BI, and PEU explained 26% of the variance

Table 3
Factor loadings

	Components		
	1	2	3
PU1	0.72	0.44	0.01
PU2	0.77	0.25	0.25
PU3	0.83	0.23	0.35
PU4	0.83	0.15	0.37
PU5	0.80	0.06	0.37
BI1	0.22	0.17	0.80
BI1	0.33	0.22	0.80
BI3	0.34	0.15	0.72
PEU1	0.07	0.84	0.07
PEU2	0.23	0.78	0.36
PEU3	0.20	0.79	0.12
PEU4	0.22	0.82	0.11
PEU5	0.22	0.60	0.44

Table 4
Regression analyses for Hypotheses 1–3

Relationship	Adj. R-square	Beta	Sigma	F
BI = PU + PEU	0.45			32.526***
PU		0.55	0.000***	
PEU		0.21	0.036**	
PU = PEU	0.26	0.52	0.000***	28.539***

** $p < 0.05$.
*** $p < 0.001$.

in PU. We also found that the effect of PU on BI was much stronger than that of PEU, suggesting that much of the impact of PEU on BI came indirectly from the mediating effect of PU. All these findings were consistent with other studies [31].

The replicated test showed that, when tested in isolation, TAM in general and Hypotheses 1–3 in particular were well supported. Therefore, it set a target for a comparison with successive tests against the extended research model.

4.1. A test of the extended model

Besides factor and reliability analysis, we invoked the PURIFY subroutine of Tetrad III to detect potential impure scale items in the measurement model. The subroutine detected that PSL5 was cross-construct impure. Thus, we eliminated it from further study. The remaining six items for PSL had a Cronbach alpha 0.83, which was greater than the acceptable threshold.

To test Hypotheses 4–6, we conducted multiple regressions. First, we regressed BI against three predictors PSL, PEU, and PU. Table 5 shows that both PSL and PU were significant to BI but that PEU was not. Removing PEU from the regression model, we regressed BI against PSL and PU. The second row of Table 5 showed a stronger model fit, as indicated by the increased F value compared to the three-predictor model. It also showed that PSL and PU were strongly significant to BI at level $\alpha = 0.001$ and jointly explained 50% of the variance in BI. Then we regressed PU against PSL and PEU. We found that PEU was significant to PU as hypothesized but PSL was not, although it had a modest positive coefficient. Removing PSL from the regression model produced a better model fit. Finally, we regressed PEU against PSL. The coefficient was positive and significant at

Table 5
Regression analyses for Hypotheses 4–6

Relationship	Adj. R-square	Beta	Sigma	F
BI = PU + PEU + PSL				
PU	0.50	0.51	0.000***	26.857***
PEU		(0.07)	0.587	
PSL		0.39	0.004**	
BI = PU + PSL				
PU	0.50	0.49	0.000***	40.510***
PSL		0.34	0.000***	
PU = PEU + PSL				
PEU	0.26	0.38	0.018**	14.995***
PSL		0.18	0.253	
PEU = PSL	0.61	0.78	0.000***	122.835***

** $p < 0.05$.
*** $p < 0.001$.

$\alpha = 0.001$. As a sole predictor, PSL explained 61% of the variance in PEU.

4.2. Discussion

The test result confirmed the causal link $PSL \rightarrow PEU$ but rejected $PSL \rightarrow PU$. This finding was unexpected and led us to re-examine our interpretation of PEU and PU from the perspective of user satisfaction. We realized that the measure of PEU and PU might affect this. According to Table 2, all questions on PEU tapped past user experience in interacting with a system, whereas those on PU were merely the anticipations of its future usefulness. In contrast, the questions on usefulness in the user satisfaction instrument emphasized current rather than future use. Thus, our finding did not constitute evidence against our theory. Rather it suggested a need for an alternative way of measuring PU. Of course, this would have involve a radical change to a widely tested instrument, on which TAM was validated.

Our second finding was also unexpected but interesting. When TAM was the frame of reference, we obtained a strong support to Hypotheses 1–3. However, when the extended model was the frame of reference, the previously significant relationship between PEU and BI vanished. In the literature, PU has been consistently found to be a significant antecedent to BI, whereas the significance of PEU remained controversial [29,40] and did not pass the fail-safe test across studies. However, we wondered

why PEU significantly influenced BI in TAM but not in the extended model, even for the same sample.

To understand the phenomenon, we examined the large body of literature on statistical and philosophical accounts of causality and found a possible resolution to the paradox by using the notion of *conditional independence*. Conceptually, two variables are conditionally independent given a third variable X if their correlation vanishes when X is controlled [80]. The phenomenon we observed matched this concept. When PSL was absent, we observed a significant correlation between PEU and BI. However, when PSL acted as a covariate, the correlation disappeared. This meant that BI was independent of PEU given PSL. Logically, there are only two causal structures that manifest such phenomenon [61]:

- (1) That PSL was a common causal antecedent to PEU and BI; and
- (2) That PSL mediated the relationship between PEU and BI.

In either case, the correlation between PEU and BI was spurious and would not lend support to the causality hypothesized by Davis [17].

4.3. Causal discovery using TETRAD

“To test whether a correlation between two variables is genuine or spurious, additional variables and equations must be introduced, and sufficient assumptions must be made to identify the parameters of this wider system. If the two original variables are causally related in the wider system, the correlation is genuine” ([65], pp. 467). Our procedure for testing TAM and its extension followed this approach. Our next task was to apply the proposed test systematically in order to infer which correlation was genuine and which was spurious and thus to find a genuine causal structure that best explained the data.

There were three broad classes of statistical techniques that could be applied to induce causal models from data, including independence maps [79], Bayesian networks [15], and TETRAD [32]. Since the first two require prior knowledge of either the causal ordering of variables or a prior probability distribution over the set of causal models, TETRAD was less demanding when such knowledge was absent and thus

it was more appealing to us. Like other statistical techniques, TETRAD assumes that a linear model holds for the data, and this allows the program to check for conditional independence based on vanishing partial correlations or *tetrads*. The advantage of TETRAD therefore lies in its use of artificial intelligence techniques to test all possible alternative models and search for the one that best fits the data.

TETRAD is publicly available for download from Carnegie Mellon University in three different versions. The newest, TETRAD IV, has a better graphical user interface but appears to still have bugs. TETRAD II limited the number of variables to 17 for DOS and 100 for UNIX. In our study, we therefore used TETRAD III and two of its subroutines [62]: PURIFY for finding unidimensional (or pure) measurement models and MIMBUILD for discovering causal relationships among latent variables.

4.3.1. PURIFY

The goal of this subroutine is to obtain a pure measurement model, in which each scale item measures the construct that it intends to measure. This occurs if each item is a direct effect of exactly one latent variable and one error term but not the cause of other variables. Also, no two-error terms may be correlated [66]. Impure items violate this causal structure. They fall into one of four categories: latent-measured, intra-construct, cross-construct, and common cause impure. Fig. 2 shows an impure measurement model, because Item PSL5 is the effect of two latent variables.

The input to PURIFY includes an initial measurement model and the observed correlation matrix. The system searches for vanishing tetrads that validate the initial measurement model. If the model does not fit the data, then PURIFY systematically eliminates items from the initial model until the model becomes pure [63]. Fig. 3 shows the input for the current study, where a portion of the observed correlation matrix was omitted. The input data included sample size, a list of observed variables, and a covariance matrix under the /covariance heading. The initial model was specified by a list of variable pairs under the /graph heading representing causal links. For example, the pair [PSL PSL1] represented the link $PSL \rightarrow PSL1$.

PURIFY detects both intra-construct and cross-construct impure items using Bonferroni tests. For

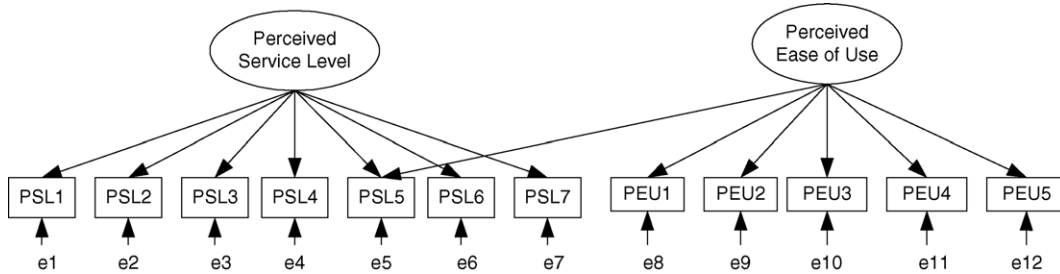


Fig. 2. An impure measurement model.

cross-construct impurity, it checks both 2×2 and 3×1 foursomes for vanishing tetrads, where an $n \times m$ foursome means taking n scale items from one latent construct and m items from a second construct to test for vanishing tetrads. It then suggests a pure measurement model. The output is listed in Fig. 4, where all scale items are intra-construct pure. However, one of 2316 tetrads involving PSL5 failed the Bonferroni test at the 3×1 foursome phase. Dropping this item made the model cross-construct

pure. Thus, the program suggested removing PSL5 as a scale item for PSL. Following this suggestion, we re-initialized the measurement model and re-executed the PURIFY subroutine. The new model passed all unidimensional tests. The default level of significance for each test was set at 0.05. However, to accommodate small sample size, we also performed the tests at level 0.10 and 0.15, as suggested in [67], and obtained the same result.

4.3.2. MIMBUILD

The goal of this routine is to discover causal models among latent variables, each of which was measured by multiple indicators. Since a unidimensional measurement model implies a variety of vanishing tetrad constraints on the observed correlations no matter what the structural model may be, PURIFY could be executed before specifying a structural equation model among latent variables [62].

The input to the MIMBUILD subroutine included a unidimensional measurement model, as suggested by PURIFY, and the data for observed variables, such as a covariance matrix. In fact, the input to the PURIFY subroutine, after removing the variable pair [PSL PSL5], was used as the input to MIMBUILD. During its execution, MIMBUILD asked whether it should mark uncertain adjacencies. We ran the program in both ways and obtained exactly the same result, implying that the program did not detect any uncertain causal links. The output file was listed in Fig. 5. As it showed, MIMBUILD concluded that both PSL and PEU were direct causal antecedents to BI as we hypothesized (Hypotheses 3 and 6). It also concluded that PSL and PEU were causally adjacent, although here the direction of causation could not be

```

/covariance
79
psl1 psl2 psl3 psl4 psl5 psl6 psl7 peu1 peu2
peu3 peu4 peu5 pu1 pu2 pu3 pu4 pu5 bi1 bi2 bi3

0.810
0.511 1.253
0.526 0.433 1.689
0.571 0.533 0.464 1.137
.....

/graph
PSL psl1
PSL psl2
PSL psl3
PSL psl4
PSL psl5
PSL psl6
PSL psl7
PEU peu1
PEU peu2
PEU peu3
PEU peu4
PEU peu5
PU pu1
PU pu2
PU pu3
PU pu4
PU pu5
BI bi1
BI bi2
BI bi3
    
```

Fig. 3. The input to the PURIFY subroutine.

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INTRA-CONSTRUCT PHASE.
-----
PSL -- Original Status: Needs NO pruning.
      0 of 105 tetrads fail the Bonferroni test.

PEU -- Original Status: Needs NO pruning.
      0 of 15  tetrads fail the Bonferroni test.

  PU -- Original Status: Needs NO pruning.
      0 of 15  tetrads fail the Bonferroni test.

BI -- Original Status: Has LESS THAN 4 variables.

CROSS-CONSTRUCT PHASE.
-----

3x1 Phase
-----
Iteration 1: 1 of 2316 tetrads fail the Bonferroni test.
Dropped ps15. Without it, 0 of 1668 tetrads fail the
Bonferroni test.

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Output Measurement Model

Indicators of PSL: [ps11 ps12 ps13 ps14 ps16 ps17]
Indicators of PEU: [peu1  peu2  peu3  peu4  peu5]
Indicators of PU:  [pu1   pu2   pu3   pu4   pu5]
Indicators of BI: [bi1   bi2   bi3]

ALL tetrad equations implied by this measurement model
pass the Bonferroni test.
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```

Fig. 4. The output of the PURIFY subroutine.

distinguished. This means that there is insufficient evidence to determine the direction of the causal link. The corresponding inferred causal model is shown in Fig. 6.

Of course, according to the theory of user satisfaction, we believe the correctness of $PSL \rightarrow PEU$ (as stated in Hypothesis 5). However, one should realize that TETRAD reached its conclusion without any theory or prior knowledge. Instead, it was purely based on the three vanishing tetrads identified from the sample correlations: $\rho(PSL, PU|PEU) = 0$, $\rho(PEU, PU|PSL) = 0$, and $\rho(PEU, BI|PSL) = 0$. Also, its conclusion did not depend on how a causal model may be parameterized using regression, LISREL, EQS, etc.

Statistically, each vanishing tetrad implied independence or conditional independence. For example,

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MIMBUILD:
A Program to Build Linear Latent Variable
Models

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Statistical conclusions about the structural
model

Edge          (Partial)
Removed       Correlation
-----
PSL -- PU     rho(PSL PU . PEU) = 0
PEU -- PU     rho(PEU PU . PSL) = 0
PEU -- BI     rho(PEU BI . PSL) = 0

-----
---
Pattern for the Structural Model

PSL -- PEU
PSL -> BI
PU -> BI
    
```

Fig. 5. The output of MIMBUILD.

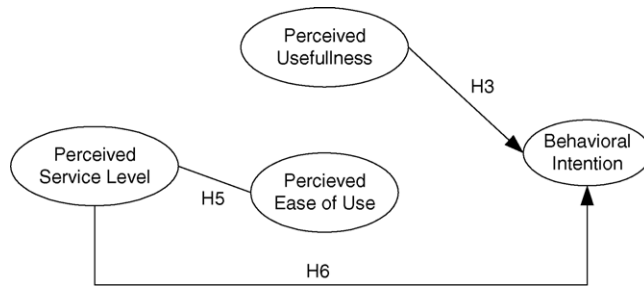


Fig. 6. Inferred causal model.

$\rho(\text{PEU}, \text{BI}|\text{PSL}) = 0$ implied that BI was conditionally independent of PEU given PSL. Thus, there was no causal adjacency between PEU and BI in either direction. Rather, PSL was either a common causal antecedent to both PU and BI, or PSL mediated the causal impact between PU and BI. Note that this was exactly the same conclusion as that previously made.

Besides confirming our explanation, TETRAD also identified two additional conditional independencies: (1) PSL was conditionally independent of PU given PEU; and (2) PEU was conditionally independent of PU given PSL. The first independency was consistent with the regression result in Table 2 (Row 3). We failed to notice it because the research model did not warrant exploratory trial and error. The second independency was more interesting; it constituted another piece of evidence against TAM: the correlation between PEU and PU was judged to be spurious. Again, regression analysis failed to detect this independency.

Table 6 summarizes the support for all the hypotheses. Since regression analysis was performed with respect to both TAM and its extension, we had two sets of test results for Hypotheses 1–3. Of course, TETRAD applied only to the extended model. For each hypothesis, we showed the corresponding path and whether it was supported by regressions and TETRAD. In sum, TETRAD confirmed the significance of PSL in predicting both PEU and BI. However, it rejected two of three hypotheses made by TAM based on vanishing tetrads.

4.4. Behavioral explanation

There could be some behavior explanations to these findings. First, one may emphasize the shortcomings of the current web platform [1,42,81] and their negative impacts on end-user perceptions and intentions.¹ From this perspective, one may argue that TAM may not be applicable to the context of adopting and using web-based systems.

Table 6
The summary of support

Reference	Path	Hypothesis	Supported by regressions?	Supported by TETRAD?
TAM	PEU to PU	H1	Yes	
	PEU to BI	H2	Yes	
	PU to BI	H3	Yes	
Extension	PEU to PU	H1	Yes	No
	PEU to BI	H2	No	No
	PU to BI	H3	Yes	Yes
	PSL to PU	H4	No	No
	PSL to PEU	H5	Yes	Yes
	PSL to BI	H6	Yes	Yes

The second explanation draws on other studies [9,12,36,38] and attributes the failure of TAM to the use of healthcare professionals as the test bed. For example, Chau and Hu found that PEU had no significant effect on either PU or BI for physicians. Jayasuriya had a similar finding with nurses. These authors argued that, because of the high user competence or strong staff support, ease of use may be of less concern to them than typical end users. As a result, physicians may place less weight on PEU and thus do not consider it a factor in low usefulness. Thus, PEU becomes less relevant to PU and BI.

These explanations, although plausible, do not address the fundamental issue of why TAM is valid when tested in isolation but not in the extended model. A third explanation challenges the theoretical basis of TAM. One may argue that,² instead of mediating the effect of external variables on BI, PEU is actually an antecedent to PSL. If the user believes that use of a system was not free of effort, it would negatively affect the perception of its performance. For instance, if navigation was not easy and the user could not therefore perform properly (PEU2 and PEU4), then the response would be low for “I was able to retrieve data quickly” and “I found the system performed as well as I expected” (PSL2 and PSL7). This, along with others possible explanations, implies that PSL mediates both PEU-PU and PEU-BI relationships. Of course, this argument rationalizes only one of the two causal structures that manifest the observed phenomenon. The other causal structure has PSL as a common cause between PEU and PU and between PU and BI. The behavioral argument could also be drawn from our justifications for the research model, except that TAM cannot be taken for granted.

5. Conclusion

Service level is the most important factor concerning the adoption of application services. Drawing on TAM we empirically examined how medical workers' perception of service level impacts their willingness to

use application service oriented medical records. Using healthcare participants and commercial application services as the test bed, we obtained some interesting results. First, we found that perceived service level explained 61% of the variation in perceived ease of use, which is twice as much as our current understanding about ease of use. This result is significant given the recent surge of interests in understanding ease of use. We achieved a good level of understanding using only one predictor.

Second, we found that TAM passed the confirmatory test in isolation but failed when embedded in a larger nomological network. For example, we found a strong correlation between ease of use and behavioral intention but the correlation vanished when service level was introduced.

Third, to infer a most likely causal model with no reference to any theory, we applied TETRAD III and detected three conditional independencies among the constructs. The discovery successfully confirmed our explanation of a spurious correlation between ease of use and behavioral intention. It also suggested a similar association between ease of use and usefulness, which regression analysis failed to detect. These findings are important because the detected spurious correlations were previously believed to be genuine or at least hypothesized to be so. Our result challenges the validity of TAM and shatters the foundation of hundreds of other studies.

Lack of theories is the unique problem in empirical MIS research. Thus, there is a call for attention to exploratory studies [41]. However, conventional exploratory tools have some statistical pitfalls, allowing violation of causal assumptions to pass undetected to the confirmatory phase [46]. To mitigate such pitfalls, Lee et al. proposed using TETRAD as an alternative. Unfortunately, since their proposal in 1997, there has been no study in MIS that actually applied TETRAD. We have filled the void. As the result shows, TETRAD has much to offer.

The phenomenon of spurious association is prevalent in empirical studies. As in his criticism of epidemiological literature on smoking and lung cancer, Fisher [25] stated that the correlation between two variables could not distinguish a direct effect from an unmeasured common cause. Our study echoed this criticism and provided a lesson on theory development. That is, it is imperative to embed the variables in

¹ We thank an anonymous referee who brought up this argument.

² We thank an anonymous referee who provided this behavioral explanation and an alternative logic to arrive at the same conclusion using Baron and Kenny's test for mediation [5].

question into a nomological network of other antecedents and/or consequences. Although Simon was the first in examining the issue, his suggestion has been largely unnoticed in MIS studies.

With respect to the primary research goal, we found that perceived service level was a strong determinant of behavioral intention. Along with perceived usefulness, it accounted for 50% of the variance in medical workers' willingness to use e-service oriented medical records. This finding provides a prescription to improve the acceptance of application service oriented medical records. Since perceived service level and usefulness predicted user acceptance whereas perceived ease of use did not, interventions should target at enhancing belief of service level and usefulness. For example, system developers could emphasize the service features toward improving users' perception of job performance, effectiveness, and productivity, whereas service vendors could focus on service delivery by improving the perception of responsiveness, reliability, availability, etc. Since ease of use is not important, much of the effort on usability engineering could be de-emphasized.

Finally, we acknowledge the limitations of our study with respect to the sample. Although the subjects well represented entry-level healthcare workers, they may not be representative of the population, especially older workers. Also, due to lack of availability of potential subjects, our sample size was small. This limitation restricted us from applying techniques such as confirmatory factor analysis [7]. Fortunately, the sample was sufficient for linear regressions and TETRAD.

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Liping Liu was born in Auhui, China in 1962. He received his BS in Applied Mathematics from Huazhong University of Science and Technology, China, in 1986, BE in River Dynamics from Wuhan University, China, 1987, Master of Engineering in Systems Engineering from Huazhong University of Science and Technology, in 1991, and his Ph.D. in Business from University of Kansas,

USA, in 1995. He is currently an Associate Professor of Management and Information Systems at the University of Akron. His research interests have been in the areas of Uncertainty Reasoning and Decision Making in Artificial Intelligence, Electronic Business, and Systems Design. His articles have appeared in *Decision Support Systems*, *European Journal of Operational Research*, *IEEE Transactions*, *Journal of Risk and Uncertainty*, and others. He has served as a guest editor for *International Journal of Intelligent Systems*, and a co-editor for *Classic Works on the Dempster-Shafer Theory of Belief Functions*. Dr. Liu is a member of American Association for the Advancement of Science, *Association for Computing Machinery*, *Association for Information Systems*, and *Institute for Operations Research and Management Sciences*. He has won numerous teaching and research awards.



Qingxiang Ma is an assistant professor of Computer Information Systems at Central Missouri State University. He received his Ph.D. in Management Information Systems in Southern Illinois University at Carbondale, and MBA from Eastern Illinois University, Charleston, IL. His research interests include information technology adoption/diffusion, electronic commerce, and information security management. His articles have appeared in *International Journal of Healthcare Technology and Management*, *Journal of Organizational and End User Computing*, and *Information & Management*. He presented numerous papers at the America's Conference on Information Systems and Decision Sciences Institute Annual Meetings. His teaching interests include Systems Analysis and Design, Data Communication and Networks, Management of Information Systems, Database Management Systems, and Client/server Application Development.