Modeling End-users' Acceptance of a Knowledge Authoring Tool

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Summary

Objectives: Knowledge bases comprise a vital component in the classic medical expert system model, yet the knowledge acquisition process by which they are created has been characterized as highly iterative and labor-intensive. The difficulty of this process underscores the importance of knowledge authoring tools that satisfy the demands of end-users. The authors hypothesize that the acceptability of a knowledge authoring tool for the creation of medical knowledge base content can be predicted by an accepted model in the information technology (IT) field, specifically the Technology Acceptance Model (TAM).

Methods: An online survey was conducted amongst knowledge base authors who had previously established experience with the authoring tool software. The Likert-based questions in the survey were patterned directly after accepted TAM constructs with minor modifications to particularize them to the software being used. The results were analyzed using structural equation modeling.

Results: The TAM performed well in predicting end-users' behavioral intentions to use the knowledge authoring tool. Five out of seven goodness-of-fit statistics indicate that the model represents the behavioral intentions of the authors well. All but one of the hypothesized relationships specified by the TAM were significant with p values less than 0.05.

Conclusions: The TAM provides an adequate means by which development teams can anticipate and better understand what aspects of a knowledge authoring tool are most important to their target audience. Further research involving other behavioral models and an expanded user base will be necessary to better understand the scope of issues that factor into acceptability.

Keywords

Knowledge acquisition, knowledge bases, software acceptance, clinical information systems, Technology Acceptance Model

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Background

One of the core components of the classic medical expert system model is the knowledge base, a specialized repository designed to house structured, coded medical knowledge. Knowledge bases have been critical components of notable clinical decision support systems (CDSS) for several decades, including landmark systems such as MYCIN, DXplain, QMR, and Iliad [1-4]. The importance of the knowledge bases in developing clinical decision support systems has been well established [5-10]. Yet the knowledge acquisition process by which these knowledge bases are created has been characterized as highly iterative and labor-intensive [11]. Much research has been focused toward developing methods that facilitate easier methods of knowledge acquisition, including Compton's 'ripple-down rules'[12]. The difficulties associated with the knowledge acquisition process underscore the importance of good software that is acceptable to the knowledge base authors charged with creating and maintaining these knowledge bases. The authors hypothesize that the acceptability of a knowledge authoring tool for the creation of medical knowledge base content can be accurately predicted by software acceptance models in the information technology (IT) field.

The development of clinical knowledge bases typically requires heavy involvement from both clinical domain experts and knowledge engineers [13]. This joint effort facilitates mutual cooperation in refining and capturing medical knowledge, so that the clinical manifestations, relationships, and subtleties associated therewith can be represented in a consistent, computable fashion. Extensive literature review is necessary throughout this process in order to extract valid, relevant findings and frequencies associated with specific medical knowledge concepts. Heuristics typically used in medical problem-solving must be recreated in a computable format. An exhaustive validation process is also required, so that the medical knowledge content behaves as desired within the context of a CDSS. It is estimated that over 100,000 person-hours were expended in creating the knowledge base for QMR, and nearly 150,000 in developing Iliad's knowledge base [14].

Knowledge base maintenance is also vital in sustaining the validity of any clinical decision support system, yet it poses a difficult challenge. Miller et al. demonstrated that updates to QMR's knowledge base comprise a substantial portion of the total knowledge base life cycle [11]. Many CDSS knowledge bases are created initially under academic research grants, and often lack funding to provide sustained maintenance [15]. Clinical collaborators in such projects are typically paid for their efforts in treating patients and promoting academic research. Their ability to assist in knowledge base development efforts in the long-term is often complicated [13, 16]. Ongoing literature review and classification of the knowledge content it contains are also time-consuming requisites in this process [17]. Other difficult issues such as when a given piece of medical knowledge should be established as 'fact' further complicate the effort.

Given that both the development and maintenance of clinical knowledge bases pose substantial challenges, the need for powerful knowledge authoring tools is increasingly important [7, 18-21]. Many CDSS-specific authoring tools have been designed to accelerate the knowledge acquisition process by supporting flexible, quick authoring through user-friendly interfaces. QMR-KAT (QMR Knowledge Ac-

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quisition Tool) was created to facilitate disease profile composition and updates within the QMR system [22, 23], and KESS (Knowledge Engineering Support System) was designed to facilitate knowledge engineering within Iliad [13]. OPAL was created at Stanford to accelerate the encoding of medical knowledge concepts for use within ONCOCIN, a cancer-specific CDSS [24]. Researchers at Columbia University developed EzMLM in order to speed the creation of Arden Syntax Medical Logic Modules [25]. Shiffman et al. recently recognized the need for powerful knowledge authoring environments to facilitate the encoding of GEM-based (Guideline Elements Model) clinical guidelines [26]. Protégé (developed at Stanford University) has been used in a variety of different projects, to provide an ontology-based approach to knowledge base development [27, 28]. Although many of these authoring tools are specific to the domain and knowledge representation paradigm for which they were created, they clearly demonstrate the need for software tools that support knowledge authoring, including acquisition and maintenance.

At Intermountain Healthcare (Intermountain), we are currently developing applications to systematically generate clinical knowledge for an enterprise-wide knowledge base [29]. The breadth and depth of the knowledge base content must meet the needs of the various clinician groups across the entire corporation. Intermountain is a non-profit integrated delivery network with 21 hospitals, several outpatient clinics, over 450 employed physicians, and a comprehensive insurance plan [30].

The authors currently developing medical knowledge base content at Intermountain can be categorized into three main groups. The first group corresponds to a series of specialty-focused "Clinical Programs". Each program is an authoritative clinician-led initiative whose directives are primarily to develop and promote 'best-practice' standards throughout Intermountain's delivery network [31]. A second authoritative group, led by an interdisciplinary group of knowledge engineers, has been developing what is termed the Intermountain 'Collaborative Practice Guidelines' or 'CPGs' [32]. The intent of this second group is to help reduce care practice variability throughout the enterprise, focusing specifically on nursing actions and interventions. The third group includes individual clinicians with special informatics interests that have been invited to contribute as knowledge base authors. This third group is involved with several localized initiatives that fulfill the needs of specific hospitals or clinical services.

Given the various needs that this authoring strategy and author base presented, we proceeded to develop the Knowledge Authoring Tool (KAT) [29, 33]. KAT is a web-based knowledge editor that interacts with a centralized knowledge repository (KR) through a service layer. It is a flexible tool that facilitates knowledge base editing by allowing authors to create and update XML documents within Microsoft's Internet Explorer web browser. These individual XML documents comprise 'units of knowledge' within our knowledge base and each is assigned a unique numeric identifier. The authoring tool supports modular content production, as each document can be linked to related content by inserting references to these unique identifiers. At runtime, the knowledge can be compiled into an integrated whole via these linked identifiers through a service layer. KAT supports the au thoring of any XML document, provided that an XML schema and the requisite accompanying template forms have been created and stored in the centralized KR. These XML documents are used as knowledge content inside various applications within IHC, including a physician order entry system, an online clinical guidelines reference, and an information retrieval application.

Since its initial release in July of 2003, a total of 6170 unique documents have been created with the tool. A monitoring log was added to the program in May 2004; users have spent over 2180 hours logged into the system to date. One hundred and three unique users have logged into the system, and approximately 40 unique authors use KAT on a monthly basis. Two developers are working to develop the tool, and two other knowledge engineers are working with domain experts to develop knowledge content models for use within KAT and training them about how to use the tool.

In order for KAT or any knowledge base authoring tool to be truly successful, it must adequately meet the needs of those who will create and maintain the knowledge base content. Developers of these software tools need to be able to anticipate what aspects are most important to knowledge content authors. By understanding a priori what factors are important in determining end-users' intentions to use (or not use) a software application, they can focus their development efforts on the most important elements first. Following this approach allows software developers to create 'acceptable' applications in the short-term.

Many IT projects have been rejected because software developers did not attend to key factors underlying user acceptance. User acceptance of information technology (IT) has been the subject of much scrutiny. In recent years, Fred Davis and Robert Bagozzi developed a prominent model in the study of IT acceptance known as the "Technology Acceptance Model" (TAM) [34, 35]. By many accounts, the TAM is one of the most influential extensions of Ajzen and Fishbein's theory of reasoned action in the information systems literature [36].

The TAM predicts that a number of factors are key to users in deciding whether or not they will utilize a new software application. The TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) are key underlying factors that model users' intentions to use (ITU) a particular technology. This intention, in turn, directly predicts the actual use (AU) of that particular technology. Davis defined "perceived usefulness" as 'the degree to which a person believes that using a particular system would enhance his or her job performance'[34]. He also defined "perceived ease of use" as 'the degree to which a person believes that using a particular system would be free from effort' [34]. The model and the relationships between these factors are depicted in Figure 1.

A limited number of studies have been conducted to test the validity of the TAM in healthcare. Hu et al. found that the TAM was applicable to physicians' acceptance of telemedicine technology [37]. Another study conducted amongst physicians in Hawaii found that an extended version of the TAM

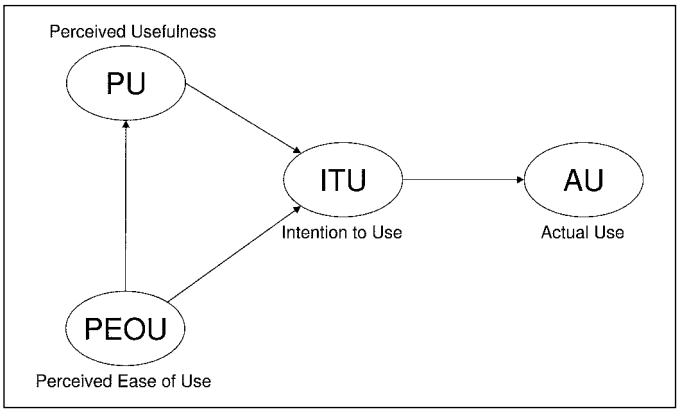

Fig. 1
The Technology Acceptance Model. The technology acceptance model with its four main constructs as proposed by Davis and Bagozzi.

only partially modeled pediatric physicians' acceptance of Internet health applications [38]. Yet another recent study found that the TAM modeled patients' acceptance of e-health applications particularly well [39]. Researchers have also studied variants of the TAM with regards to knowledge sharing within knowledge communities [40]. To date, no studies have been conducted regarding the extent to which TAM models the acceptance of clinical knowledge base authoring tools.

In order to better understand our users' motivations for accepting or rejecting our software, we propose the following hypotheses, testing the applicability of the TAM as it pertains to KAT:

- Hypothesis 1: Perceived Ease Of Use will have significant influence upon Intention To Use amongst KAT users.
- Hypothesis 2: Perceived Usefulness will have significant influence upon Intention To Use amongst KAT users.
- Hypothesis 3: Perceived Ease Of Use will have significant influence upon Perceived Usefulness amongst KAT users.
- Hypothesis 4: Intention To Use will have significant influence upon Actual Use amongst KAT users.
- Hypothesis 5: The Technology Acceptance Model will exhibit significant goodness of fit amongst KAT users.

Methods

We designed a survey to test these hypotheses by patterning questions directly after the original and validated TAM constructs. These questions have been analyzed repeatedly for validity and reliability, and have consistently been found to be psychometrically stable [41, 42]. The questions were customized to be specific to the software under study, in this case, KAT. The survey was then given to an internal survey development group and a focus group for refinement and suggestions. As per their suggestions, the Likert-based scales were reduced from a seven-point scale to a five-point scale. We also negated several questions in an effort to prevent block answering, and to induce the survey-takers to pay close attention to the questions being asked. The questions used for this particular study are a subset of the total questions asked in the survey, and they are included in the appendix.

The survey was then re-created in electronic format on our local intranet. This was done to make responding to the survey easier, as per the review of our survey refinement groups. Access to the survey was secured by requiring a login and password (generated at random and distributed to end users through e-mail). Tables were created in a database to house the individual survey results. These results were de-identified prior to loading the data into the tables.

We then established a set of eligibility criteria for access to the survey. Since KAT requires that end-users input a local LDAP-based login and password, it is able to log which users have used the application and how often. We determined that users who met at least one of the following two criteria would be included as potential survey participants:

- logged into KAT within the past three months;
- created actual clinical knowledge base content using KAT.

In addition, we excluded IS support staff members and software developers. These criteria would help us sample the impressions of actual knowledge base authors with real intentions to use the software for its designed purpose, as opposed to occasional clinical users or non-clinical users.

Using these criteria, 70 potential respondents were identified. Each was contacted via e-mail about the survey. This message contained a brief summary of the intent of the survey, as well as a hyperlink that users could use to access the survey directly. It also contained the login and password necessary to access the online survey. Finally, the e-mail also indicated that five of the actual respondents would receive a gift certificate to local restaurants as a reward for answering the survey.

Users were given six weeks to respond to the survey. Those who had not completed the survey at four weeks were sent a follow-up e-mail, almost identical to the first, as a reminder of the survey. Of the 70 potential respondents, 40 completed the survey, a response rate of 57%. A closer analysis of the responses showed that one respondent had only answered two or three questions in the survey, and two others had omitted substantial sections of the survey. These results were discarded, leaving a final response rate of approximately 53%.

The resultant data set was analyzed for reliability amongst the questions measuring the latent constructs (PU, PEOU, ITU, AU). We tested the reliability of the questions in the survey instrument by calculating Cronbach's alpha measurements for each construct. We also tested the validity of the TAM amongst our end-users by conducting factor analysis and also by using structural equation modeling (SEM). SEM is an extension of linear regression that allows a researcher to test a set of regression equations simultaneously [43]. SPSS Amos 5.0 software was used to conduct our analysis [44].

Results

Survey Reliability

All but one of the four constructs in the TAM exhibit reliability in excess of 0.90 (Cronbach's alpha). The ITU construct had a Cronbach's alpha measurement of 0.841, still well within recommended ranges cited by the literature [45]. The reliability scores for each of the TAM constructs can be found in Table 1.

Survey Validity

We accounted for the validity of the survey instrument itself by assessing the convergent and discriminant validity of the survey questions. We proceeded to do so by conducting principal component factor analysis with varimax rotation (to enhance the interpretability of the variables). The Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's Test of Sphericity were conducted to ensure that our data sample would be adequate to conduct factor analysis research. Both measurements (see Table 2) indicate that the sample is comfortably 'adequate' for use in factor analysis research.

As summarized in Table 3, four factors were extracted (since the model was defined with these four constructs a priori) whose eigenvalues were greater than one following rotation. These four factors account for roughly 92% of the variance within the sample. As shown by the rotated component matrix in Table 4, in almost every case, the questions load highly and discriminately upon their own construct. This is indicative of good convergent and discriminant validity within the sample. These data, in parallel with the reliability data indicate that the measurements used in the survey are adequate for use in the study

Effectiveness of TAM

In order to test the hypotheses described by the TAM as pertaining to KAT, we conducted SEM to assess the predicted relationships among the constructs. All predicted relationships were significant at $p < 0.05$, except for the relationship between PEOU and ITU. These data support Hypotheses 2-4 and fails to support Hypothesis 1. The results of these analyses are summarized in Figure 2 and Table 5.

In assessing a model using SEM analysis, no single model fit criterion completely addresses the different aspects of goodness-of-fit; namely parsimony, independence from sample size, and penalties for the inclusion of additional parameters. As a result, a series of different metrics are recommended for use in conjunction with each other [46]. Seven of the major accepted metrics are presented for the data set as applied to the TAM. These are summarized in Table 5. The following fit metrics were used [43]:

- **χ^2/df:** The ratio of the minimum sample discrepancy (also known as chi-squared) divided by the degrees of freedom. A non-significant χ^2 value with respect to its degrees of freedom indicates that the observed and predicted variance-covariance matrices aren't significantly different. In other words, the implied theoretical model significantly reproduces the samples variance-covariance relationships in the matrix. Ratios less than 3:1 indicate acceptable model fit.
- **GFI/AGFI:** The goodness of fit index (GFI) is a measurement that quantifies the amount of variance and covariance in the sample that is predicted by the model-implied variance-covariance matrix. The adjusted goodness of fit index (AGFI) is a variant of GFI that uses mean squares instead of total sums of squares in the numerator and denominator of 1 – GFI. GFI scores > 0.90 and AGFI scores >0.80 are considered indicators of good fit.
- **NFI:** The normalized fit index (NFI) rescales the chi-squared score into a 0.0-1.0 range. It compares a badly-fit-

Table 1 Construct reliability, mean, and standard deviation scores (5-point Likert Scale)

Construct/question	Mean	SD	Cronbach's alpha
Perceived Ease of Use (PEOU)			0.907
PEOU1	3.38	0.86	
PEOU2	3.43	0.80	
PEOU3	3.30	0.91	
Perceived Usefulness (PU)			0.953
PU1	3.59	0.98	
PU2	3.57	1.01	
PU3	3.51	0.93	
Actual Use (AU)			0.956
AU1	2.84	1.40	
AU2	2.32	1.55	
Intention To Use (ITU)			0.841
ITU1	2.54	1.71	
ITU2	3.62	1.19	

Table 2 KMO and Bartlett's Test

Kaiser-Meyer-Olkin measure of sampling adequacy		.881
Bartlett's test of sphericity	approx. chi-square	418.850
	Df	45
	Sig.	.000

Table 3 Total variance explained[a]

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	7.096	70.964	70.964	7.096	70.964	70.964	3.244	32.436	32.436
2	1.187	11.871	82.835	1.187	11.871	82.835	2.571	25.707	58.143
3	.496	4.957	87.792	.496	4.957	87.792	2.140	21.398	79.541
4	.429	4.288	92.079	.429	4.288	92.079	1.254	12.538	92.079
5	.288	2.881	94.961						
6	.186	1.856	96.816						
7	.137	1.366	98.183						
8	.107	1.070	99.253						
9	.041	.414	99.667						
10	.033	.333	100.000						

Extraction method: Principal Component Analysis. Rotation method: Varimax with Kaiser Normalization.
[a]Rotation converged in five iterations.

ting baseline model to the predicted model. Scores near 1.0 indicate good fit.

- **CFI:** The comparative fit index (CFI) modifies the NFI metric by accounting for non-centrality in the sample. Scores close to 1.0 indicate reasonable fit.
- **TLI:** The Tucker-Lewis index (TLI) was originally created for factor analysis and later adapted for use in SEM. It compares the proposed model against a null model. Values close to 1.0 indicate good fit.
- **RMSEA:** The root mean square error of approximation (RMSEA) measures the distance between the observed covariance matrix and the theoretical covariance matrix. It is generally recognized that RMSEA scores lower than 0.08 indicate acceptable fit.

The TAM exhibited significant goodness-of-fit for five of the seven metrics, excluding the GFI and AGFI scores. Even the AGFI score is very near the desired range of 0.8. Although the model does not perfectly satisfy each goodness-of-fit metric, these data suggest that the TAM models users' acceptance of KAT reasonably well.

Discussion

The TAM predicted user acceptance of KAT reasonably well. The survey instrument used

Table 4 Rotated component matrix[a]

	Component			
	1	2	3	4
PEOU1	.105	.673	.442	.400
PEOU2	.322	.823	.319	.090
PEOU3	.200	.919	.137	.087
PU1	.408	.345	.686	.390
PU2	.434	.322	.791	.105
PU3	.539	.413	.619	.283
AU1	.895	.201	.298	.161
AU2	.861	.293	.246	.248
ITU1	.816	.207	.374	.341
ITU2	.486	.179	.235	.795

Extraction method: Principal Component Analysis. Rotation method: Varimax with Kaiser Normalization.
[a]Rotation converged in five iterations.

Table 5 Analysis of model goodness-of-fit using common indices

Model goodness-of-fit index	Recommended value	Observed value
Chi-square/degrees of freedom	≤ 3.0	1.135
Goodness-of-Fit Index (GFI)	≥ 0.90	0.841
Adjusted Goodness-of-Fit Index (AGFI)	≥ 0.80	0.791
Normalized Fit Index (NFI)	≥ 0.90	0.926
Comparative Fix Index (CFI)	≥ 0.90	0.990
Tucker-Lewis Index (TLI)	≥ 0.90	0.986
Root mean square error of approximation (RMSEA)	≤ 0.08	0.061

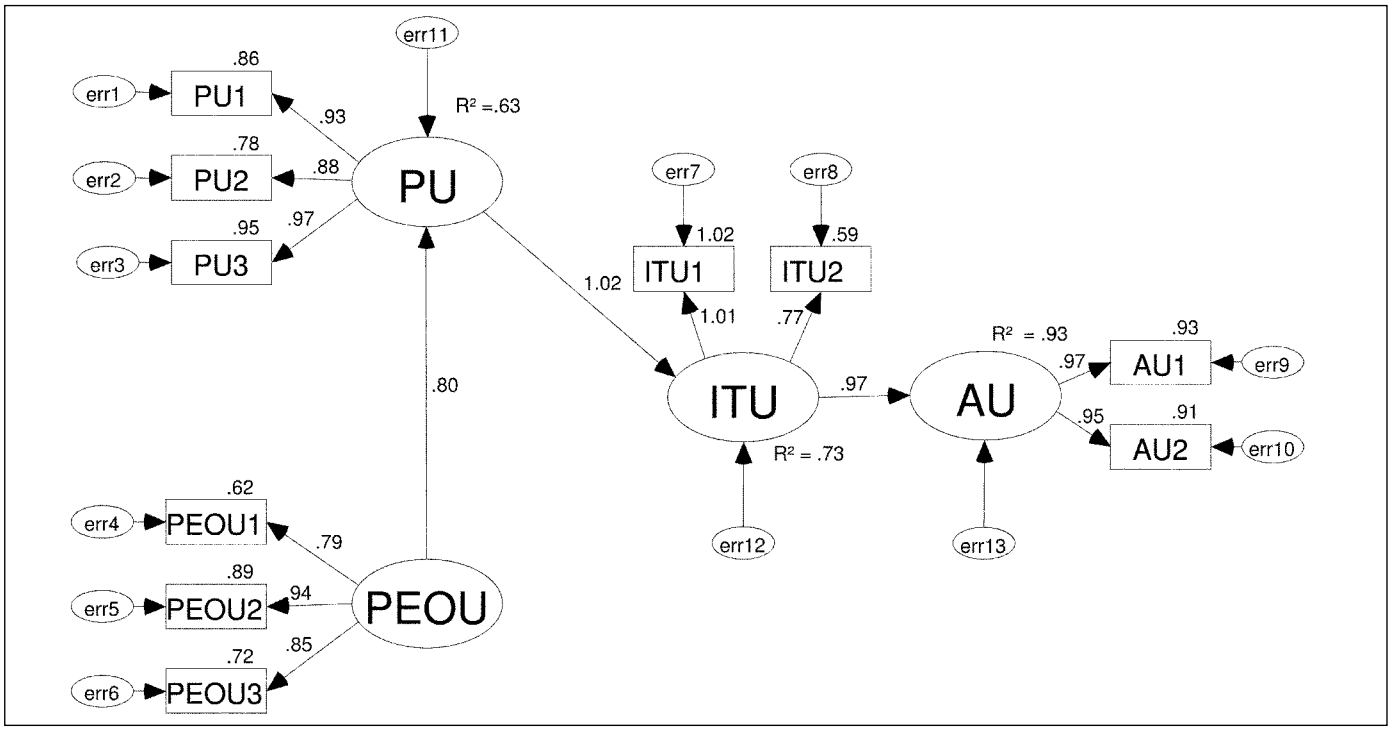

Fig. 2 Significant TAM relationships as applied to KAT. The TAM showing standardized estimates. Measured items (survey questions) are illustrated in rectangles (e.g. PU1). Latent variables (constructs for which the questions were designed to measure) are represented by ovals; smaller ovals indicate error of measurement terms. The significant associations (at the 0.05 level) are portrayed by arrows; the direction of the arrows implies prediction. Factor loadings are noted at the top right of rectangle items. Coefficients are noted for each association. Variance (R^2) is noted near each latent dependent variable.

exhibited very good reliability as shown by the Cronbach's alpha scores for each of the constructs. The questions in the survey instrument also demonstrated relatively good discriminant and convergent validity, further validating their use as an instrument for conducting this experiment.

The data collected from our survey fit within significant ranges for five of seven goodness-of-fit metrics. It is also interesting to note that the AGFI score was nearly within acceptable ranges, since Bollen et al. noted that AGFI may underestimate fit for small sample sizes [47]. There is undoubtedly room for improvement in modeling the acceptance of KAT amongst knowledge base authors, but the TAM provides a solid initial model from which to explore new underlying variables.

All but one of the relationships predicted by TAM were upheld by the data obtained from our study. The lone departure from this set was the non-significant relationship observed between PEOU and ITU. This is not an entirely new finding, as both Hu and Chismar found that PEOU did not significantly affect ITU [37, 38]. Unlike their studies, however, our findings do confirm a significant relationship between PEOU and PU as hypothesized by TAM. We can infer that PEOU affects a user's intention to use KAT only indirectly, in that it affects his or her perceptions regarding the usefulness of the software, which in turn affects their intentions toward the software. It is possible that this is a statistical aberration due to a relatively small sample size used in the study. It is also possible that this is a reflection of limitations to TAM's applicability to knowledge base development, or the clinicians who use KAT to author clinical knowledge content.

It is also possible that software acceptance amongst clinicians does not follow the same patterns as the users previously studied by TAM. Hu postulated that the non-significant relationship between PEOU and ITU as postulated by TAM amongst clinicians may be due to the high proficiency required by their profession [37]. It is possible that physicians and nurses assimilate new technologies more quickly and easily than typical software end-users. As a result, ease of use may be largely de-emphasized amongst them, in favor of increased functionality or effectiveness. Further studies would be particularly enlightening to determine if the importance of PEOU decreases as users' computer competency levels increase.

The findings of this study have implications for local software development at IHC as well. Although it is unfair to proceed with development assuming that only perceived usefulness is important in determining user acceptance, it is important to focus first on functionality, and aspects of the software that contribute directly to its usefulness. As represented by the findings of this study, PEOU is important, but only indirectly as it relates to contributing to PU. Furthermore, it underscores the need to better understand what specific factors or aspects of KAT contribute to PU amongst local knowledge base authors.

Limitations

Several key limitations do apply to the findings of our study. Our study does include a

relatively small sample size. Some researchers submit that SEM analyses require a minimum of 100 subjects for definitive results. We could have increased the number of potential respondents to our survey, but would have done so at great risk. Inclusion of other users would have potentially incorporated a large number of individuals with virtually no experience with the software. Rather than risk skewing the results by including these individuals, we opted to pursue the study with fewer respondents. It is notable however, that Hoelter's critical N statistic for our study is greater than our sample size for both the 0.05 and 0.01 levels. The Hoelter's critical N statistic is the largest sample size for which the results of the SEM analysis should be accepted [48]. A follow-up survey should be conducted as a larger group of clinical authors are now actively using KAT to develop and maintain our enterprise knowledge base. Systematic non-response bias may also be contributing to our results. We were encouraged by the high response rate to our survey, yet it is possible that higher proportions of the more motivated end-users took the time to complete the survey. Finally, it is important to highlight that the findings of our study are also specific to our knowledge authoring software and our group of authors.

Future Research

It would be particularly informative to conduct a similar study amongst authors using different authoring tools for similar purposes (i.e. QMR-KAT, GEM cutter, Protégé etc) to confirm if the same findings hold true. Future studies could also explore extensions to TAM that have been derived since its inception. Venkatesh et al. developed the Extended Technology Acceptance Model (TAM2) in 1990 [49]. It includes a series of other latent factors that help explain what factors predict PU, namely output quality, job relevance, experience, image, subjective norm, voluntariness, and result demonstrability. Future studies involving questions related to these factors would help explain specific factors that influence PU amongst knowledge base authors.

Conclusions

The findings obtained in this study provide a key first step in understanding the motivations behind user acceptance (or rejection) of authoring tools for knowledge base development. The survey data obtained suggests that TAM is a good, though not entirely perfect, predictor of user acceptance of knowledge authoring tools. Perceived usefulness directly influences users' intentions to use the software, whereas perceived ease of use does so only indirectly. Further studies will be necessary to confirm whether such findings are applicable to clinical knowledge authoring software and audiences in a general sense. They will also be key in determining what factors contribute to perceived usefulness amongst authors.

Competing Interests
None listed.

Authors' Contributions
NCH and RAR planned the investigation jointly. NCH drafted the questions to be used in the survey, and GDF coordinated the creation of the survey in electronic format. NCH collected and analyzed the data. NCH wrote the manuscript with extensive review from RAR and GDF.

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Appendix

Survey Questions

Each question was rated on a scale ranging from 1 to 5, where 1 = strongly disagree and 5 = strongly agree (unless otherwise indicated). Reliability scores for each construct are shown in parentheses.

PEOU: Perceived Ease of Use ($\alpha = 0.907$)

PEOU-1 I find KAT to be flexible to interact with
PEOU-2 My interaction with KAT is clear and understandable
PEOU-3 I find it easy to get KAT to do what I want it to do

PU: Perceived Usefulness ($\alpha = 0.953$)

PU-1 Using KAT allows me to increase my productivity in authoring clinical knowledge content (order sets, guidelines, protocols, procedures, etc.)
PU-2 Using KAT in my job allows me to accomplish authoring tasks more quickly.
PU-3 I find KAT to be a useful tool in doing my work

ITU: Intention To Use ($\alpha = 0.841$)

ITU-1 I intend to use KAT on a regular basis
ITU-2 How frequently will you use KAT?(seldom, infrequently, occasionally, often, routinely, daily)

AU: Actual Use ($\alpha = 0.956$)

AU-1 How many times do you use KAT during a week?(not at all, less than once a week, one or two times a week, several times a week, about once a day, several times each day)

AU-2 How long do you believe that you use KAT every week?(less than 30 minutes, 30 minutes to an hour, Between one and two hours, two to five hours, five to ten hours, more than ten hours)

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