User Competence Metrics for Science Gateways: The Case of the KnowCOVID-19 Gateway

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Abstract—This study provides statistical validation of three composite scales designed to calculate metrics for gateway user competence in terms of domain knowledge, technical skills, and problem-solving orientation. Based on an online survey *(N = 365)* fielded by an online panel company (Centiment.co) with US based participants, analyses using SPSS software demonstrated that technical competence varied between age groups (lower scores for participants aged 60 and higher) and educational levels (lower scores for participants without a bachelor's degree) at a statistically significant level (at 95% confidence interval). These findings suggest that gateway developers may need to provide more technical support to users who are senior researchers and when gateways are being introduced into high school classrooms. Conversely, ethnicity and gender were found to be non-predictors of technical competence. These findings suggest the stereotype of white males being more tech-savvy than other ethnic and gender groups may not hold true anymore.

Index Terms—KnowCOVID-19, User Competence, Competence Metrics, Usability, Science Gateway

I. Introduction

The COVID-19 disease created both an alarming patient death rate and a data deluge problem for medical professionals during the pandemic. When medical professionals search online about the disease, they drown in a sea of information available on the Internet. However, science gateways can be a solution to this problem. More specifically, our research team developed a (prototype) science gateway augmented by an AI powered chatbot designed to assist medical professionals to search and filter the results based on different levels of evidence [1], so they can focus on a narrower set of literature to identify the information they need to treat their patients. The gateway is called "KnowCOVID-19" and the chatbot is called "Vidura," named after a wise advisor in Indian mythology.

The use of the evidence pyramid [2] is a common approach in the medical profession to filter research papers. For example, a doctor may specifically want to rely on findings from randomized controlled trials (RCTs) and not observational studies. Methodologically, RCTs and observations are different levels of evidence. A doctor can specify which level of evidence to filter their search results on KnowCOVID-19. This approach helps users to more effectively and efficiently find the information they need, and the Vidura chatbot can assist the users on the gateway platform.

However, two issues remain. First, many gateways face limited funding for usability and technical support; funding is mainly for developing open-source prototypes. Many gateways suffer from usability issues, leading to challenges in user adoption and implementation. Second, different users come to the gateway with different levels of competence. Different users may need different answers even if they ask the same question to the AI chatbot. For example, a medical student in training may need more medical explanation about symptoms associated with COVID-19, but a senior medical doctor who is not familiar with online platforms may need more help with technical navigation on the gateway.

Given these two challenges, the present paper seeks to statistically validate our recently developed approach to measure user competence [3]. Measuring user competence can first help gateway developers to identify the users who need more support. Second, two users with different levels of competence (high vs. low in technical competence; high vs. low in COVID19 knowledge) can be given customized responses based on their competence levels, even if they ask the Vidura chatbot the same question. Having valid user competence metrics is helpful for our gateway and other science gateways across domains. Therefore, we aim to answer the research question, *"How can the user competence metrics (domain,*

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technical, and problem-solving scales) be statistically validated and then be used to generate insights about gateway users?"

In order to report on the work we set out to accomplish, this paper is outlined as follows. First, we provide a brief review of the literature on medical information-seeking and user competence. Second, we describe the methods we employed for data collection and statistical validation of our three composite scales for measuring user competence. Third, we present our statistical validations of the scales and how one example of technical competence varied across demographic groups. The findings show how user competence metrics can be used in practical ways to generate user insights. Fourth, we wrap up the paper with a conclusion.

II. Literature Review

A. Medical Information Seeking

Seeking health information about diseases to provide the best treatments to their patients is of great importance to medical professionals [4]. However, how to source health information in a timely fashion and make the best decisions to help their patients was a daunting task for many during the pandemic [5]. When searching for health information, medical professionals often use strategies such as keywords, Boolean Operators, advanced search, and medical synonyms [5]. However, barriers to seeking health information include insufficient time, lack of information search skills, unawareness of accessible sources, high search costs, organizational challenges, location constraints, inadequate information technology infrastructure, and a shortage of medical librarians [4]– [6]. In a systematic review [5] it was reported that medical professionals spend approximately 2 to 32 minutes to finding answers to health questions. In this paper, we believe that what differentiates those who can find the needed information faster than others may be their user competence, especially when it involves a science gateway.

B. User Competence

The notion of competence, originally proposed by White in 1959 [7], [8] as a motivational concept in psychology, has now become a subject of growing research interest across many disciplines. White defined competence as "an organism's capacity to interact effectively with its environment" [8]. In the case of gateways, this can involve an individual's capacity to interact effectively with the technical environment. Similarly, Rychen and Salganik [9] described competence as the individual capacity or capability to effectively fulfill personal or societal requirements, or to perform a specific action or duty. In the case of COVID-19, it can be a medical professional's capacity/capability to effectively find the most rigorous medical information to treat patients. Conversely, many scholars described competence as the observable and measurable attributes of a person, including a mix of their knowledge, skills, abilities, motivations, and self-perception, that lead to outstanding performance [10]. Computer competence encompasses a wide-ranging concept and overlaps with associated terms such as computer experience, expertise, accomplishments, abilities, and literacy. Related to computer competence, Internet competence is conceptualized as a collection of mindsets related to an individual's self-assessed proficiency and comfort with utilizing internet-based tools and platforms [11].

Prior to the present paper, our research team conducted a usability study with 20 participants with KnowCOVID-19 and Vidura chatbot [3]. Participants were assigned various tasks to complete, and their actions were recorded through screen capture videos while they interacted with the gateway. Based on this prior work, we found three types of user competence: medical domain, technical, and problem-solving competence, and we developed three composite scales to measure them in a questionnaire as presented below. Gateway developers can customize the composite scales to fit their own domains.

Medical Domain Competence (User's expertise or specialized knowledge in COVID-19.)

1) When searching for information about COVID-19, I understand the search task at hand.
2) When searching for information about COVID-19, I know the right search terms, keywords, etc., to specify the search.
3) When searching for information about COVID-19, I am able to assess the relevance of search results vs. secondguessing if I have found the answers.
4) When searching for information about COVID-19, I am able to explain the relevance of search results.
5) When searching for information about COVID-19, I am able to tell when the relevant information is found, and the task is done.
6) When searching for information about COVID-19, I can effectively evaluate the credibility of information during my searches.

Technical competence (User's ability to effectively and efficiently use the search engine gateway's features and tools to locate the information they are seeking.)

1) I have experience with basic browser functions (e.g., opening a new tab, sorting, filtering). 2) I have experience with basic keyboard shortcuts (e.g., Ctrl-F, Ctrl-Alt-Delete).
3) I have experience with basic mouse clicks (e.g., rightclick for features).
4) I have experience with basic Internet terminologies (e.g., URL, hyperlinks).
5) I can move through the necessary steps for a search task (including browser, keyboard, mouse) logically in sequence vs. missing steps and having to backtrack.

6) I can effectively make use of visual content on web pages and confidently navigate different interfaces on new web pages.

Problem-solving competence (Motivation to adapt themselves to any new innovative technologies to complete the assigned task.)

1) I show some level of calmness and/or enthusiasm when using technology rather than being nervous and/or confused.
2) I show confidence with quick actions when using technology, rather than hesitating or pausing frequently.
3) I am willing to act and try something on a technology even when I am unsure about it.
4) I try another approach immediately when my first attempt does not work while using technology.
5) I am willing to work around usability issues when using a technology.
6) I know when to ask for help and guidance when using technology.

III. Methods and Analysis

For data collection, we contracted with an online survey panel company (Centiment.co) to field the survey with paid participants based in the US between 4/26/2024 and 4/29/2024. Data collection yielded a total of 396 responses. However, upon a close examination, we eliminated 31 responses because these participants failed the attention check embedded in the questionnaire, giving us a final sample of 365 responses for analysis. An attention check (e.g., Please select "All of the above" as the answer for this question) is a fake question in a survey designed to test if a participant picked answers without reading carefully. We assessed participants' level of agreement with the 18 items across three composite scales using a 7-point Likert scale. Prior to collecting survey responses, we obtained IRB approval for the study. Table 1 summarizes the descriptive statistics of key demographic variables of the final sample.

TABLE I
DESCRIPTIVE STATISTICS OF THE DEMOGRAPHIC VARIABLES OF THE FINAL SAMPLE

Demographic Variables	Categories	Number of Participants (Percentage of Sample)
	-African Americans -Asians/Pacific Islanders	68 (18.6%) 10 (2.7%)
	Females 181 (49.6%) Males 183 (50.1%) Other 1 (0.3%)	9 (2.5%)
	Whites 254 (69.6%) People of Color 111 (30.4%)	
	Non-Bachelor's Degrees 270 (74%) Bachelor's Degrees	
	Young Adults (18-29) 64 (17.5%) Adults (30-59) 197 (55.0%)	
	-Hispanics	7 (1.9%)
	-Mix	14 (3.8%)
	-Other	3 (0.8%)
	≥	153 (26%)
	Older adults (≥ 60)	97 (26.6%)

Based on the final sample *(N = 365)*, we performed a reliability analysis using the SPSS (Statistical Package of Social Sciences) Software. Specifically, a reliability analysis refers to the process of measuring the consistency of the items in a composite scale based on inter-item correlations. In other words, let's take the medical domain competence scale with six items discussed earlier as an example: if the six items in the composite scale share a high level of inter-item correlations above 0.70, then the composite scale is deemed consistent enough to converge as a coherent measure of the concept of medical domain competence. Similarly for the composite scales of technical and problem-solving competence.

This inter-item correlation score is called Cronbach's alpha, where the value of 1 means a perfect 100% correlation among all 6 items, and a value of 0 means no correlation at all. With a satisfactory alpha score, a composite score for each type of competence can be calculated by averaging the six individual item scores within the three respective composite scales. Then the three composite scores will serve as the domain, technical, and problem-solving competence metrics.

IV. Findings

Based on our analysis, the medical domain competence scale achieved a satisfactory alpha score (α = .93), similarly for the technical competence scale (α = .93) and the problemsolving competence scale (α = .89). While 0.70 is commonly considered the minimum score for a reliability analysis, some sources suggest that a 0.60 score may be acceptable, especially for a scale in progress. However, statistically, our three scales achieved a high degree of reliability.

Recall that we discussed averaging the individual item scores to obtain three composite scores (metrics). These metrics can be used to assess and evaluate the three types of competence in the case of using the KnowCOVID-19 gateway. However, social scientists can use the metrics to explore their relationships with other variables in the same questionnaire. We explored how the three scores varied across different groups based on gender, ethnicity, age, and education at the 95% confidence level ($p < 0.05$). Due to space limitations, we only report findings of technical competence as a case in point.

1) Ethnicity: An independent sample *t*-test assessed whether technical scores differed between Whites and people of color. White participants ($M = 5.72$, $SD = 1.18$) did not differ significantly from people of color ($M = 5.98$, $SD = 1.23$), $t(363) = -1.89$, $p = .059$. Because the difference is not statistically significant, this finding suggests that ethnicity is not a generalizable predictor of technical competence, although people of color scored higher than Whites in the sample.

2) Gender: An independent sample *t*-test was conducted to compare the technical competence between males and females. There was no significant difference between males ($M = 5.82$, $SD = 1.23$) and females ($M = 5.77$, $SD = 1.17$; $t(362) = 0.35$, $p = .730$). This result suggests that gender is not a statistically significant predictor of technical competence.

3) Age Groups: A one-way between-groups *ANOVA* was conducted to assess the differences in technical competence across different age groups: young adults (18-29), adults (30-59), and older adults (≥ 60). The test results showed significant differences in technical competence ($F(2, 355) = 15.63$, $p < .001$, $\eta^2 = .081$) across age groups. Post hoc comparisons using Tukey's HSD test further showed that adults ($M = 6.05$, $SD = 1.06$) had significantly higher technical competence compared to older adults ($M = 5.26$, $SD = 1.22$, $p < .001$). Additionally, young adults ($M = 5.91$, $SD = 1.28$) also had significantly higher technical competence compared to older adults ($p < .001$). However, adults did not differ significantly from young adults in terms of technical scores ($p = .694$). Therefore, the significant differences lie primarily between older adults and the other two groups. The partial eta squared value of .081 indicates a moderate effect size.

4) Education: An independent sample *t*-test was conducted to compare technical competence scores for participants based on education attainment at two levels (bachelor's degree or higher vs. non-bachelor's degree holders). There was a significant difference in scores between participants with at least a bachelor's degree ($M = 6.05$, $SD = 1.05$) and nonbachelor's degree holders ($M = 5.71$, $SD = 1.23$). The *t*-test results indicated a statistically significant difference, $t(363) = -2.39$, $p = .018$. The result suggests having a bachelor's degree or higher is a predictor of technical competence.

V. Conclusion and Future Research

In conclusion, with a sample of 365 participants, we statistically validated three previously developed composite scales to measure user competence in terms of medical domain knowledge, technical ability, and problem-solving orientation. The data collection involved an online survey fielded by Centiment.co, and the reliability analysis was performed using SPSS software to ensure the internal consistency of these scales. The three composite scales achieved satisfactory Cronbach's alpha scores, confirming their reliability for future use as user competence metrics. These validated metrics were then employed to assess competence levels across demographic groups, providing valuable insights into variations in user competence.

Furthermore, we demonstrated how technical competence scores (as an example for demonstration in this paper) varied across age groups and educational levels. Specifically, adults (ages 30-59) and young adults (ages 18-29) both scored higher than older adults (aged 60 and above) at a statistically significant level. This finding suggests that age 60 is the demarcation point, where users aged 59 or younger are technically more competent. Gateway developers may need to provide more onboarding and technical support for users aged 60 or older.

Additionally, participants with at least a bachelor's degree also scored higher than participants without a bachelor's degree in terms of technical competence. Because the majority of gateways are being used by graduate students and faculty who hold a bachelor's degree or higher, gateway developers could expect a certain level of technical competence. Gateway developers may need to provide more technical support to users when a gateway is being introduced into a high school classroom. Future research should investigate the technical competence of undergraduate students who are working towards their bachelor's degrees.

Conversely, ethnicity and gender were not found to be predictors of technical competence at a statistically significant level. Gateway developers may be able to take comfort in our results, which suggest that the digital divides between ethnic and gender groups may have been successfully bridged, at least in our study sample. In other words, the stereotype of white males being more tech-savvy than other ethnic and/or gender groups may not be true anymore today, at least in the case of using online technologies to search for COVID-19 information.

How else can the user competence metrics be used to support the adoption of science gateways? We measured participants' degree of agreement with the 18 items across three composite scales using a 7-point Likert scale. Given this, the value of 4-point represents the midpoint of the Likert scale. Generally, one can consider an individual composite score of 3.9 or below to be "low" and a score of 4.0 or higher to be "high". Other demarcation variations (e.g., using the mean or median instead of the midpoint) can be the judgments of the gateway developers within their particular contexts. Let's say we use 4 as the midpoint of the scale and divide all the users of a gateway into two groups of high vs. low domain knowledge (specific gateway domain), technical, and problemsolving competence, then we can create a 2x2x2 matrix of eight different quadrants. This means each gateway user can be placed in one of these quadrants (e.g., high in domain, low in technical, and high in problem-solving), thus allowing the AI chatbot to customize the responses as discussed in the introduction. However, users are likely to improve on the three competence metrics over time, thus being able to transition from one quadrant to another. This approach can allow our AI chatbot to further customize its responses to the users based on their latest position in the matrix.

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