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Review and Revision of the IPEC Core Competencies for Interprofessional Collaborative Practice

Analysis of the Survey of IPEC Member Groups:

Stakeholder Feedback

October 2021

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Introduction and Background

As a part of the core competency revision directed by the Board of Directors of the Interprofessional Education Collaborative (IPEC), a survey instrument was developed by the members of the IPEC Advisory Group. The survey was validated through review and discussion of each question by the 7 members of the Advisory Group and other IPE experts who are members of the Working Group named by the IPEC Board of Directors to represent their stakeholders in the revision process[1]. The Advisory Group has seven members from health professions education organizations, while the Working Group includes a representative selected by the Health Professions Education Association for each of the 21 professions who are members of the IPEC:

- Accreditation Council for Education in Nutrition and Dietetics (ACEND)
- American Association of Colleges of Nursing (AACN)
- American Association of Colleges of Osteopathic Medicine (AACOM)
- American Association of Colleges of Pharmacy (AACP)
- American Association of Colleges of Podiatric Medicine (AACPM)
- American Association for Respiratory Care (AARC)
- American Council of Academic Physical Therapy (ACAPT)
- American Dental Education Association (ADEA)
- American Occupational Therapy Association (AOTA)
- American Psychological Association (APA)
- American Speech-Language Hearing Association (ASHA)
- Association of Academic Health Sciences Libraries (AAHSL)
- Association of American Medical Colleges (AAMC)
- Association of American Veterinary Medical Colleges (AAVMC)
- Association of Chiropractic Colleges (ACC)
- Association of Schools and Colleges of Optometry (ASCO)
- Association of Schools and Programs of Public Health (ASPPH)
- Association of Schools of Advancing Health Professions (ASAHP)
- Council on Social Work Education (CSWE)
- National League for Nursing (NLN)
- Physician Assistant Education Association (PAEA)

This report, prepared by IPEC Advisory Group member Mark Speicher, PhD[2] acknowledges the work of Christine Chai, PhD in developing the methods for this analysis and assistance[3]. While most surveys contain both text and numerical data, most people follow survey analysis guidelines (e.g. SurveyMonkey, n.d.; Statistical

[1] The Leadership Group, Advisory Group, and Working Group members are here: 2021-2023 Core Competencies Revision (ipecollaborative.org) (Accessed 10/12/2021.)
[2] American Association of Colleges of Osteopathic Medicine, Bethesda, MD
[3] Text Mining in Survey Data | Published in Survey Practice

Services Centre 2001) and focus exclusively on the numbers. This is understandable because text data are unstructured, and text is generally more difficult to analyze than numerical answers (Schuman and Presser 1996), and generally involves an iterative coding process among several researchers. This survey, however, involved only two questions whose responses could be quantified. The remaining four questions were long text responses. There were also two questions aimed at the respondents' profession and institution. A copy of the survey is attached to this White Paper. Responses were received from at least one representative from each of the 21 sponsoring associations. At least one association, ASAHP, reached out during the survey to hold focus groups or otherwise support the survey. ASAHP submitted responses from all five respondents in a single summary document; otherwise, all responses were from individuals at single institutions.

Survey Summary

The responses to the first question revealed that 42% of the respondents to the survey were very familiar with the IPEC Core Competencies, 52% were somewhat familiar with the competencies, and 6% were unfamiliar with the competencies.

These free text responses provided more diverse explanations of respondents' experiences, which was the goal of the survey, than quantitative responses. However, survey text analysis is still relatively rare, and when conducted, it is often done manually (Roberts et al. 2014), which tends to be expensive (Grimmer and Stewart 2013). Moreover, human coding in surveys is subjective and prone to intra-coder variability, even in trained, experienced professionals (Patel et al. 2012; Yamanishi and Li 2002). For these reasons, the IPEC working group decided to test an automated text coding system using natural language processing ('text mining") statistical techniques. This method does not suffer from the inconsistencies that human coders do, so incorporating text mining in survey analysis would be useful for extracting information from the free text responses. Given these benefits, text mining has been applied successfully in many settings. Many text mining algorithms are unsupervised, including latent Dirichlet allocation (Blei, Ng, and Jordan 2003) and pattern clustering (Quan, Wang, and Ren 2014). Unsupervised text mining algorithms use text as the sole input and identify topics from the corpus.

However, the IPEC survey uses both categorical ratings (a type of quantitative data) and text responses. The sLDA (supervised latent Dirichlet allocation) is a solution to combined analysis of text and numerical data; this algorithm uncovers latent topics from a corpus with "labeled" text documents, i.e. each document in the corpus is associated with a rating or a category (Blei and McAuliffe 2007). The sLDA has many existing applications, but most are in the computer science field, such as video activity recognition (Hughes 2010) and credit attribution of bookmarking websites (Ramage et al. 2009). This White paper applies sLDA on the IPEC survey to jointly analyze text and numerical ratings.

Dataset Description and Preparation

The survey response file contains individual responses from 82 respondents, and one large text response that comprises five respondents' information. The text was all combined into a single corpus for each of the four text responses. The paired categorical-text question was as follows:

Please indicate the extent of the IPEC Core Competencies have been integrated into your local educational program? (Possible responses: To a great extent, Somewhat, Not at all); combined with How are the IPEC Core Competencies used at your institution? (Text response)

The other text response only questions were:

Are the interprofessional competencies you use connected to assessment of learning or program outcomes? Please explain.

What gaps exist in the 2016 IPEC Core Competencies?

If you make changes for the next version, what would they be?

For the categorical question, It is implicitly assumed that everyone rated on the same scale. In reality, the same assessment of a situation (such as the use of an educational competency) can result in different ratings in different people. For example, one may rate a program that uses a single competency as "somewhat" while another person might think the use so low as to rate it "not at all."

Data Cleaning

To prepare the dataset for analysis, we first needed to reduce the vocabulary size. We achieved this by stemming and tokenizing the words (word or token are used interchangeably here) using the wordStem function in the R package SnowballC. This function uses the Porter algorithm (Porter 2001) to assign words of the same stem to the same token. For example, "carry" and its past tense "carried" are assigned to the same token "carr-." (Where – is a wildcard character indicator.) The Porter algorithm addresses details of English grammar – "fitted" becomes "fit," where the double "t" is removed. It also includes a dictionary to avoid over-stemming – "reply" becomes "repl-," not "rep" (which is also an abbreviation for "representative").

The next step was to remove stop words (words with little semantic meaning like "a" or "and"). To simplify the analysis, we also removed punctuation (Francis and Flynn 2010). While certain punctuation, such as repeated exclamation marks, !!!, can be used as an intensifier (Liu 2015), we did not need to address this issue because the data contained only two single exclamation points, one in a statement that the respondent would have more to share in the future and the second in a comment expressing gratitude.

Antonym Replacement

In this survey, no examples were found where a respondent used an antonym, such as "not good" for "bad". Rather, negative words were used to answer questions like "What changes would you make?" "None." In these cases, the negative word did not change the meaning of the answer.

Topic Model: Supervised Latent Dirichlet Allocation (sLDA)

To jointly analyze the text and ratings, we implemented the sLDA, a Bayesian data generative process which assigns a topic assignment vector to each word (Blei and McAuliffe 2007). For instance, given three topics, a word's topic assignment vector can be (0.2, 0.5, 0.3). This means the word has proportions 20% in Topic 1, 50% in Topic 2, and 30% in Topic 3. Proportions in topics are defined using word counts.

Implementing sLDA allows us to utilize the Bayesian framework. First, the Bayesian topic model produces credible intervals for each topic, so researchers can directly say "this topic has 68% posterior probability to be in this range of scores." Moreover, in sLDA, each topic is a probabilistic distribution over the words. It is possible to allow certain words (e.g. "supportive") a higher probability in ratings 6-10, so the topic model can "grow" in a particular direction.

Algorithm Description

The sLDA algorithm requires a preset number of topics, and it first draws topics from a Dirichlet distribution as the prior, then updates the probabilities using the words in the documents as the likelihood. Finally, sLDA draws the numerical response variable for each document from a normal distribution using the posterior topic assignments.

Dr. Speicher applied the sLDA methodology using the R package lda, with sample code available in demo(slda). First, demo(slda) uses the main iterative function slda.em to produce the topic model and the topic assignment results, where "em" means variational expectation-maximization – an approximation to the maximum likelihood estimation (Blei and McAuliffe 2007). Next, demo(slda) generates the plot of credible intervals for each topic. Finally, demo(slda) uses slda.predict to predict the response variable (category) using the sLDA model and plots the output probability distribution.

In the survey dataset, each "document" is an individual's survey response, so the number of documents is 82, and the K = 3 topics refer to the three categories of responses to the first question. The parameters are set to the default values . We set 10 iterations for the expectation step and 5 iterations for the maximization step.

Using the results from sLDA, we generate the top.topic.words for each score, as in Table 1. The R function top.topic.words selects up to five words with the highest posterior probability to appear within each topic. In mathematical terms, the posterior probability is ; i.e. the probability of getting word given topic and the data. Higher ratings are associated with negative words, e.g. "challenge" and "lack," while lower ratings are associated with positive topics, e.g. "opportunity."

Table 1: Selected words (tokens) for each topic and rating.

Rating	How are the IPEC Core Competencies used at your institution?	Are the interprofessional competencies you use connected to assessment?	What gaps exist in the 2016 IPEC Core Competencies?	If you were to make changes for the next version, what would they be?
7	Don't use/don't know			
6	Foundational			
5	Varies profession	No/not assessed		
4	Guides curriculum	No individual assessments	Public health and social determinants	
3	Guides teaching	Event day assessments	Justice and bias	Cases and tools
2	Course objectives	Accreditation	Need more tools/cases	Expand health professions
1	Not longitudinal	Program assessment	Not longitudinal	Include different settings

Text Mining Results

The “top” topic words in Table 1 are descriptive, though not 100% accurate. Additionally, Dr. Speicher understood the context of the survey and the interprofessional competencies, so interpretation augmented the findings. For example, the most common negative responses to the question, “How are the IPEC Core Competencies used at your institution” included the words “don’t,” “use,” and “know.” A review of the results indicated to Dr. Speicher that the meaning was that the respondent didn’t know or didn’t use the competencies at the institution. The table represents the most common combination of words by topic, ranging from negative topics (higher rank) to more positive topics (lower rank).

Discussion

Text mining scales well to big data (Martin and Hersh 2014), so automated text mining in surveys is helpful in analyzing large amounts of free text responses. Our survey contains only 82 responses, but the responses were relatively long, comprising more than 8000 words. It would have required several researchers many hours to manually read through all the text answers and code them, and more hours to develop meaningful categories from the codes.

While asking open-ended questions in a survey can potentially increase response rates (O’Cathain and Thomas 2004), researchers should be prepared to analyze the free text responses before collecting the data (Boynton and Greenhalgh 2004). Our straightforward method of survey text-rating analysis allows researchers to be more confident in collecting and analyzing survey text responses, which may lead to publishing better insights from surveys.

While Dr. Speicher is confident in these results, the IPEC Core Competency Revision has many more sources of data to triangulate with our analysis, and we encourage this. In this way, the IPEC Core Competency Revision can be based on the best possible summary of stakeholder feedback.

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IPEC Stakeholder Survey

IPEC Core Competencies Feedback

With the revision of IPEC's Core Competencies for Interprofessional Collaborative Practice underway (details here), and the updated set expected by early 2023, IPEC is researching if and how members are using the competencies.

IPEC is interested in hearing about your experience with and use of the competencies. Your feedback will help us with the revision process.

All responses to this survey will be kept strictly confidential. The survey data are reported only in aggregate form or in a manner that does not allow individual responses to be identified.

Thank you for participating in this survey. If you have any questions, please call Shelley McKearney at 202-463-6930 ext. 260 or email smckearney@ipecollaborative.org.

The full survey contains 7 questions and should take no longer than 5-7 minutes to complete. Again, your feedback is valuable and appreciated.

* 1. Which IPEC Member Association are you affiliated with?

* 2. What is your institution and school/department? For example - University of DC School of Dentistry or DC University Department of Rehabilitation Sciences.

* 3. Please indicate the extent of the IPEC Core Competencies have been integrated into your local educational program?

- ◯ Not at all
- ◯ Somewhat
- ◯ To a great extent

* 4. How are the IPEC Core Competencies used at your institution?

* 5. Are the interprofessional competencies you use connected to assessment of learning or program outcomes? Please explain.

* 6. What gaps exist in the 2016 IPEC Core Competencies?

* 7. If you make changes for the next version, what would they be?