Co-sharing secondary qualitative research data to understand technology adoption in engineering education courses

Dr. Michelle Jarvie-Eggart
Engineering Fundamentals
Michigan Technological University
Houghton, MI, USA
mejarvie@mtu.edu

Dr. Dominik May
School of Mechanical Engineering and Safety Engineering
University of Wuppertal
Wuppertal, Germany
dommay@uni-wuppertal.de

Deborah Mayoki
Engineering Education Transformations Institute
University of Georgia
Athens, GA, USA
deborah.moyaki@uga.edu

Katrina Carlson
Coganitve and Learning Sciences
Michigan Technological University
Houghton, MI, USA
katrina@mtu.edu

Landon Smith
Engineering Education Transformations Institute
University of Georgia
Athens, GA, USA
Landon.Smith1@uga.edu

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***Abstract*— This work in progress paper we explain our process of co-sharing secondary qualitative data from separate projects funded by the National Science Foundation to better understand factors which influence faculty technology adoption in engineering education and provide a high-level presentation of preliminary results. Study A conducted 21 interviews of engineering faculty at a Midwestern US, STEM-centered university. These faculty were interviewed about the factors influencing their adoption and teaching of new engineering technologies, with a focus on programming languages, software, and instrumentation. Technology adoption models were applied as a theoretical lens for results analysis. Study B conducted 9 interviews with faculty in the College of Engineering at a Southern US university on the adoption of online laboratories in their instructional settings. The interviews focused on how faculty make use of online laboratories in electrical engineering as an essential resource. Innovation and propagation theories were applied as a theoretical lens for data analysis. The two data sets were co-shared for secondary analysis by each research group, using their own theoretical approaches. Preliminary findings lead us to believe that co-sharing of secondary data can expand qualitative data sets while providing a means for theoretical triangulation, improving data analysis.**

Keywords*— *secondary data sharing, qualitative research, technology adoption, engineering education

I. Introduction

In the engineering education research space, secondary analysis of data is rare. Over 500 grants have been funded by the Engineering Education Centers (EEC) Division of the National Science foundation, but less than a dozen have involved secondary data analysis [1, 2]. Within qualitative research, data sharing allows the maximal utilization of data from difficult to assess populations and topics sensitive to research subjects [3]. In so doing, researchers are also able to save time and resources, and, in the words of Case, et al., "be better stewards of our data by analyzing it more completely" [1], which honors the time participants offer to our research [2].

The search for ideas different from an original work's research interest or the application of new lenses to offer alternative interpretations to an original work highlights the basic purpose of secondary data analysis irrespective of data type [4]. Jones et al., categorizes the numerous benefits of data sharing into descriptive, scientific, and material [5]. Descriptive benefits include the opportunities to bear witness to prior and existing context in teaching students on research methods; scientific benefits include the support for reliability and transparency of data that increases potential for scaling of findings; and material benefits include the efficient utilization of limited time and funding resources. While the driving forces behind data sharing have been identified by Corti and Thompson as: 1) historical description through primary sources 2) follow-up work for the original study 3) re-analysis for a new purpose 4) research design and methodological advancement, and 5) verification of original results [6]. This secondary data co-sharing project seeks the scientific benefits of verifying each research team's results through analysis by a different research team applying a different theoretical lens to each teams' data; as well as the material benefits of not having to fund or conduct additional studies to expand our available data sets.

Secondary analysis of qualitative data occurs less frequently than for quantitative data. Of the handful of secondary data projects funded by the EEC, the majority utilized quantitative methods [1]. Qualitative data sharing of videos and transcripts is a relatively new research practice because it is fraught with issues of intent and confidentiality. Despite the opportunities qualitative data sharing provides to research, major ethical considerations about secondary data sharing exist surrounding anonymity and confidentiality of subjects, obtaining informed consent of subjects, ensuring copyright, and anonymity of researchers in terms of data archiving [7]. Additionally, Walther et al., caution researchers to consider the communicative validity of their secondary data analysis [8]. However, qualitative data can be shared between researchers to preserve the intent and context in which it was first collected and analyzed [9]. Brakewood & Poldrack encourage researchers to consider the Belmont Principles when considering secondary research, especially when sharing anything biological in nature [10]. It is important to ensure that the rights of participants are respected in addition to considering the benefits versus risks of secondary research. As noted by Hunter & Brown, collaborative research for re-analysis of data for a new purpose that is done with the original context in mind is not only a time saving measure but also a way to build on and advance the original research [9]. They encourage conversation between researchers who were not collecting the original data together to preserve the original context and intent of the research. Our team, including two primary researchers, their respective graduate students, and an undergraduate researcher, met frequently to discuss these issues. This study involves informal secondary data sharing, a major mode of qualitative data sharing as outlined by Heaton [11].

A. Frameworks for Understanding Technology Adoption

As the presented research on data sharing connects two research projects, we use several theoretical models on how technology is adopted or rejected among faculty. In the following, we will briefly discuss each of those models.

The most commonly used models to predict technology adoption were developed to predict IT systems usage. The Technology Adoption Model (TAM), developed by Davis, comprises two main constructs, Perceived Usefulness and Perceived Ease of Use, which contribute towards a user's intention to use a technology [12]. The TAM was later revised to the TAM2, adding additional constructs influencing Perceived Usefulness [13]. However, as the variance of the model was still around 60% [14]. Venkatesh went on to combine the TAM2 with other models, such as the Theory of Reasoned Action [15] and the Theory of Planned Behavior [16], into the Unified Theory of Acceptance and Use of Technology (UTAUT) [17], later revising it to the UTAT2, which included the following constructs that influence the Behavioral Intention to Use a technology: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit [18]. However, the TAM versions remain the most widely used model for the adoption of instructional and communication technologies by faculty [19].

Another theoretical model that can guide the understanding of technology adoption within educational settings is the Framework of Propagation, which Froyd developed to display the connection of fit, efficacy, and adoption of educational innovation [20]. From this theory, it follows that adopted innovations are both highly effective and fit instructional circumstances. Froyd et al.'s work draws on the Diffusion of Innovation framework by Rogers [21], which has been widely adopted in research about how technology diffuses or is adopted into use cases [22-24]. Based on the Diffusion of Innovation framework, the characteristics of an innovation that encourage its adoption include: relative advantage, compatibility, complexity, trialability, and observability [20]. All the above-named factors are at play to different extents whenever someone adopts an innovation (from early adopters to laggards).

B. Research Foci

Study A examined the factors which influence engineering faculty's technology adoption. The central research question of Study A focused on identifying the barriers and supports to faculty adoption of engineering technologies, such as engineering software, computer programming languages, and instrumentation. Instructional and communication technologies (ICTs), such as discussion boards and iClickers, were not a main focus of this research. Study A employed the TAM2 [13] and UTAUT2 [18] as theoretical lenses for interpreting their results. Preliminary results indicated that personal traits not included in the existing models affect technology adoption [25]. The study also provided a breakdown of the facilitating conditions supporting faculty technology adoption, including other people, digital resources, non-digital resources, formal training, and time [26]. To encourage the adoption of industry-relevant engineering technologies into university courses, Study A suggested interventions to promote the adoption of engineering technologies by faculty [27]. This work also argued for the development of a genre of technical writing aimed at educators, and not just learners, of technologies [28].

Study B was directly motivated by the COVID-19 crisis and aimed at investigating how faculty, independently from their prior knowledge or experience about educational technology, adopted online laboratories into their teaching [29, 30]. An online version of a combined lecture/lab 'Fundamentals of Circuit Analysis' course was developed and served as a context for our research activities. The study's central research question focused on examining how faculty members either resist or fully embrace online experimentation technologies. To guide our understanding of technology adoption, we used the Diffusion of Innovation [21] and the Propagation Framework [20], which identifies effectiveness and fit as critical factors in the successful adoption of innovations. This qualitative study identified four major themes regarding technology adoption into online laboratories: Scheduling flexibility and individualized support, learning outcome differences, the connection between lecture and the lab, and student engagement [31].

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II. Methods

Prior to sharing data, it is important to ensure that the secondary analysis does not violate the expectations of the consenting participants. Both Study A and Study B gathered qualitative data sets under informed consent for the purpose of studying the technology adoption of engineering faculty, with expectations of participant anonymity. Walther et al. caution that secondary analysis "maintain a commitment to the values and purposes that informed and motivated the primary study" [8]. Due to the overlapping foci of the research projects, co-sharing secondary data met with the purpose for which intent was given. As in other secondary data sharing projects, we anticipated benefits to the participants aligned with those of the original studies [2]. No additional risks would be posed to the subjects through the co-sharing of data. Both data sets were completely anonymized prior to original analysis. Additionally, the data sets were gathered by comparable methods. Interviews were conducted by faculty researchers in both studies, with student researchers contributing to analysis.

A. Study A Methods

In the 2020/21 academic year, 21 faculty members within the College of Engineering (COE) at a Midwestern US Technologically focused institution, were interviewed to determine factors which influence their adoption of new engineering technologies. Interviews were selected with the intent of providing representation across gender, career stage, time spent within industry, and faculty appointment focus (teaching and tenure track). Among the 21 interviewees were 14 male identified and 7 female identified faculty. Perspectives of COE administrators were also represented among the interviewees. The approximately hour-long interviews were all conducted via the Zoom platform with informed consent obtained. Transcripts autogenerated by Zoom were anonymized and corrected against the original recording by a graduate student researcher.

Analytic induction methods were applied to analyze the data through combined deductive and inductive coding [32, 33]. Constructs from the TAM2 [13] and UTAUT2 [18] provided preliminary deductive codes, as well as codes from previous unpublished focus group results, and additional codes from literature. Two researchers coded each interview separately, and convened to discuss and resolve differences within their coding, updating the code book definitions with each coding cycle until interpretive convergence was met. Concept coding included a code for each idea related to technology adoption applied to text blocks of at least one sentence. Simultaneous coding was employed, in which more than one code could be applied to a block of text, as some excerpts encompassed ideas represented by more than one code [34]. After common themes were identified within the data, results were member checked by one focus group of two administrators within the COE, one focus group of two interviewees considered by the researchers to be high technology adopters, and one focus group of two interviewees self-identifying as low adopters. Results were also peer-checked by the project's Mentor Advisory Board, including expertise in engineering education and human factors research. Proposed interventions were peer-reviewed at an FIE workshop [26].

B. Study B Methods

Study B included two rounds of interviews. The first round included five interviews with electrical and computer engineering faculty at our college (male=4, female=1). During the COVID-19 pandemic, four faculty members used the online laboratories, either during Summer 2020 courses or in Fall semester 2020, to deliver electrical engineering courses on circuits building online. One faculty member decided not to use online labs and developed a workaround for their class. However, the study still included this person in the interviews to also hear from faculty still critical about online experimentation. In terms of seniority, the interviews ranged from young faculty with less than three years of teaching experience to faculty members with teaching experience longer than ten years.

Interviews were performed during Fall 2020 (one) and Spring 2022 (four), and the interview time ranged from about a half to a full hour. In order to analyze the interview data, the interview recordings were transcribed and anonymized. To develop a deep and thorough understanding of the faculty's perspective, the study applied a thematic analysis approach in the form of topic coding [35], in which the research team identified passages across all five interview transcripts that were linked by a common theme or idea allowing them to both highlight the faculty perspective on switching to online lab instruction and answer our research question. A second round of interviews with the same faculty were performed one year later as a follow-up, in Spring 2022. Those interviews allowed the research team to gain insights into the faculty perspectives on online laboratories a year later, at a time when in-person classes were possible again, and whether or how online labs were being integrated with traditional instruction. Contrasting this second set of interviews with the first set of interviews helped the researchers to understand more about what sticks with faculty in terms of online experimentation and, hence, has a chance to prevail in the future.

C. Goals of Co-Sharing Secondary Data

We began our work together by establishing open discussions about the process of data analysis and the publication of shared results to ensure our teams had compatible goals.

Study A was focused on faculty adoption of engineering technologies for their research and teaching, and not the ICTs within the classroom used to deliver content. However, as the interviews were conducted during the pandemic, and faculty were asked about the last technology they learned, many brought up distance teaching technologies. This data was largely unexplored as out of focus of the research questions of Study A, and fit well within the focus of Study B. Study B included both software to remotely use engineering equipment and modeling/simulation software - which are not necessarily ICT technologies - and had a focus on educational laboratory settings, which was absent from Study A. Through co-sharing, each team gained an expanded participant data set aligned with the focus of their research.

Studies A and B held a common aim of understanding the technology adoption of engineering faculty and integration into their teaching, gathering data using comparable methods of researcher-conducted interviews. However, each study used a different theoretical lens for results analysis, with Study A employing the technology adoption models [13, 18] and Study B employing diffusion and propagation models [20, 21]. Sharing secondary data between our research teams provided the opportunity to improve our data stewardship and validity, though the application our respective theoretical lenses to each other's data sets. The primary goals of data sharing were to expand our own data sets, provide a triangulation of each of our results through the application of different frameworks [36, 37], and identify universal themes across the studies.

D. *Methods for Analyzing Shared Data*

Study B data was analyzed by Study A researchers using deductive coding through the application of the final established codes within Study A. Two researchers independently coded all of the Study A interview transcripts with NVivo, applying simultaneous coding techniques and meeting to resolve coding differences. Memoing was utilized to note the where code definitions from Study A were expanded in their application to Study B.

Similarly, the Study B researchers used the data from Study A and analyzed the data through inductive analysis. Using Nvivo, the broader coding approach was used to allow new insights into the large amount of data recorded. After finding specific themes inside the interviews, Study B researchers created a coding tree to continue on with a more deductive process.

During the on-going analysis process, the researcher teams have met multiple times to share and discuss results across studies, identifying and discussing the common themes within their data sets. Analysis memos have been generated independently by each team during analysis. Both teams then met to discuss the themes we saw in each other's data, generating memos during discussion to document our shared results.

E. *Positionality*

The researcher in a qualitative study is the primary instrument of data collection and analysis. Engaging in reflexivity by reflecting on the team members' positionalities and how they shaped the study design helps to enhance the reliability of findings. A positionality/researcher orientation statement describes an individual's worldview in relation to their ontological (assumptions of reality) and epistemological (assumptions of knowledge) beliefs [38]. It plays an integral role in qualitative research as it aids an understanding of how researchers' social identities shaped the study, contextualization of existing literature, the identification of novel perspectives, and contexts for future inquiry [39, 40]. To enhance the transparency, understanding, and quality of our study, positionalities represented within the research team are explained below.

Our team includes both student and faculty perspectives, including an undergraduate researcher, PhD student researchers, and faculty. Our team is composed of ⅗ female-identified researchers, and ⅖ male. We represent a global perspective - with 3 US-born researchers, one German-born researcher and one Nigerian-born researcher. The research team represents two research universities, one in the Midwest and one in the Southeast region of the United States. The diversity of our team helps us to see the distributive justice issues with regards to availability and access to technology. In terms of an academic background, the team connects engineering education research, environmental engineering, electrical engineering, mechanical engineering, applied cognitive science and human factors, and educational technology, resulting in this secondary data co-sharing project.

III. Prelimiary Results

This work-in-progress manuscript only provides a very high-level, preliminary description of the results we gained through the co-sharing process. The analysis of the data sets is still ongoing and will be the foundation for further publication. In the present manuscript, our focus lies on the process and goals of secondary data sharing.

Preliminary results of the analysis of Study B's data using study A's interpretive lens of their existing code structure has revealed the following common themes recognized between the data sets: a) Access to technologies, b) Performance Expectancy (how well the remote labs technologies mimicked real labs), c) Experience (using the technology previously), d) Utility for teaching, e) Facilitating Conditions (available resources to support learning the technology), and f) Perceived Ease of Use. As for Study B's researchers using Study A's data, the following common themes were found using a mixture of inductive and deductive coding: a) Accessibility to Technologies, b) The Relevance of Technologies in Use, c) The Multitude of Help Resources and How That Affects the Learning Process, d) A Faculty Member's Background and its Effects on the Technologies Being Taught, e) A Faculty Member's Time Commitment, as well as f) The Difficulties in Learning New Technologies from Both a Student and a Faculty Perspective. Further examination of these themes will be conducted in subsequent papers.

IV. Conclusion

Secondary data co-sharing allowed both research teams to expand their datasets while preserving conditions of consent. Peer analysis of shared data utilizing alternative frameworks is ongoing, which will culminate in the identification of universal themes across the studies - for faculty technology adoption and teaching in both remote and in-person contexts. In that light, we found several benefits in sharing data with each other for analysis. Apart from the new perspective on existing datasets by a different theoretical lens and also by the diverse background of the other research team, we also found the exchange about methods and practical approaches for the research activities to be beneficial for our respective own research. We experienced many discussions about the data, how our results match with each other and also how they differ from each other. These deliberations lead to informed considerations about the differences in study context, approaches, and also theoretical considerations for further follow-up studies.

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