Individual Module e-Portfolio including 1,000-word reflective piece

Research Methods and Professional Practice (January 2025)

Word count: 1095

GitHub repository:

https://github.com/busilas/RMPP_UoE

e-Portfolio:

https://busilas.github.io/eportfolio/module7.html

Individual Reflective Piece

What?

The Research Methods and Professional Practice module returned me to the research basics I had learned previously from my academic and professional experiences. During the module, I had the opportunity to review fundamental methodological beliefs that seemed obvious before, alongside receiving reassessment motivation. With eight years of experience in User Experience (UX) design, along with substantial practice in user research and data analysis, I also retain knowledge from my graduate-level research methodology lessons through my MSc in Economics and my MA in Design. The studies in the module revealed fine complexities that tested my assumptions without compromising the foundational understanding of key ideas.

The module covered research methodology frameworks, ethical standards, and academic writing rules combined with distinctions between quantitative, qualitative, and mixed methods research approaches (Saunders et al., 2019). Units on epistemological paradigms and research ethics at the beginning of the program proved beneficial because I had already encountered these topics before. I have made distinctive contributions to peer dialogues in Discussions 1 and 2 through my application of Bryman's (2016) research question and design choice relationship paradigm. Exchanges with my peers improved my basic research methods while enhancing my interest in applying advanced research techniques. According to Field (2018), using statistical worksheets proved to be an essential practical method for utilising theoretical principles to analyse genuine data. Module educational objectives focus on analytical skill development through worksheets that contain structured tasks, such as creating charts, running hypothesis examinations, and result interpretations (Abbott 2014). My experience in completing these tasks has led to improved abilities in outcome evaluation and the connection between theoretical principles and actual practice methods (LaMorte, 2021).

Nevertheless, the summative assignments revealed limitations in the methodological understanding of my research. The literature review about ML for diabetes diagnosis in the first assignment and the research proposal for non-invasive glucose monitoring needed experimental approaches typical of Computer Science (CS) field. Experimental and computational research methods appeared in 79% of papers within my literature review, thus creating the necessity for technical interdisciplinary research adaptation (Creswell & Creswell, 2021). This shift away from my traditional research approaches prompted me to critically evaluate my capacity to adopt different methods.

So what?

The discoveries changed my perspective on research methodology within CS. I previously undervalued the essentiality of experimental designs, algorithmic validation, simulation-based approaches, and data-driven benchmarking, which are vital for computing-related fields. Qualitative and quantitative methods remain essential in UX research and the social sciences. These methods are vital tools due to contemporary CS research makes empirical contributions by following them. Research employs experimental and computational methods to validate hypotheses in machine learning models, according to Kitchenham et al. (2017). Furthermore, contemporary science focuses on testing algorithms, achieving computational reproducibility (Menzies & Shepperd, 2022), and implementing performance benchmarks in software engineering publications (Nagappan et al., 2021).

Established research practices in CS led me to unexpected methods during my early research period. The development of Assignment 2 provided clear evidence of a non-invasive predictive machine learning model designed for glucose monitoring. The implementation of user research, together with the sensor integration principles in my workflow, did not incorporate an essential experimental validation stage, which constitutes a critical component of influential computing research. I faced identical issues regarding blood glucose measurement reliability that I had previously experienced when designing Assignment 2.

My research findings are consistent with recent meta-reviews in the discipline. For example, Wohlin et al. indicated that more than 75% of software engineering studies utilise experimental or quasi-experimental methods, a pattern that my own literature review also reflects. Although the course thoroughly covered both qualitative and quantitative approaches, it paid less attention to computational simulations, model calibration, and algorithm testing, which are crucial in CS research. This insight leads to a sense of both professional and academic humility. Revisiting foundational yet methodologically robust works, such as those by Basili et al. (2018) and Zelkowitz and Wallace (2017), helped me appreciate how structured empirical validation is essential for high-quality computing research. Additionally, recent research by Tariq et al. (2023) and Chen et al. (2022) underscores the importance of reproducible computational experiments, especially when generalising AI and ML models for healthcare and predictive analytics.

Now what?

Recognising this has bolstered my determination to improve my skills in experimental and computational research design, especially as I gear up for my master's thesis. I plan to gain expertise in statistical programming languages like Python and R to support reproducible experiments and simulations. At the same time, I aim to delve into commonly used experimental methods in applied computing research, such as A/B/n testing for comparing algorithms, and cross-validation in predictive modelling (Shahin et al., 2021; Varma & Simon, 2020).

A significant takeaway from this reflection is the value of methodological pluralism. User narrative research linked with behavioural data analysis exists within UX research, yet CS requires additional technical precision. Digital health fields particularly benefit from the synergy formed by merging experimental methods with UX approaches when looking for accuracy and reliability.

This module also contributed to my growth in academic writing and collaborative engagement. The discussion forums offered validation and constructive peer feedback, helping me refine my viewpoints. In my summary posts, I synthesised insights from ethical debates and research paradigms, gaining a deeper appreciation for the variety of methodological approaches represented in the class. Furthermore, my literature review and proposal were praised for their clarity, structure, and critical argumentation. Moving forward, I will apply more intentionality in thematic mind mapping and storyboard drafting to ensure conceptual coherence (Dong et al., 2019; Elsbach & van Knippenberg, 2020).

Unexpectedly, this module turned out to be an intellectually and emotionally transformative experience. At first, I approached it with confidence, assuming it would provide little new information. However, as I engaged with the empirical demands of CS research, I encountered the limitations of my methodological toolkit. This realisation sparked a renewed motivation to develop technical skills and bridge the gap between design-based and code-based inquiry.

Conclusion

This module acted as an excellent learning opportunity for me to unite information from my existing knowledge with new insights. The core principles of qualitative, quantitative methods, alongside mixed methods, came across again in this experience after what I had learned previously. Extensive analysis of the scientific literature in CS and working on assignments has revealed a gap between my methodological training and the contents of this module. The majority of the analysed literature helped to discover new experimental and computational methodologies, applied in the modern CS research. It revealed their significance for contemporary CS, and their usefulness for my forthcoming master's dissertation and project.

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