End of Module Assignment - Individual e-Portfolio including 1,000 words reflective piece

Module 6: Research Methods and Professional Practice

MSc Artificial Intelligence

University of Essex Online

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ePortfolio link: https://spike2025-art.github.io/eportfolio-uoe/

E-PORTFOLIO DESCRIPTION AND STRUCTURE

Introduction and Purpose

This e-portfolio documents my learning progression through Module 6: Research Methods and Professional Practice. In contrast to the previous technical modules focusing on AI implementations, this module improved my understanding of how research is conducted, how knowledge claims are justified and how ethical considerations permeate every aspect of the research process. The portfolio demonstrates achievement of learning outcomes through reflective activities, statistical exercises, literature synthesis, and research proposal development.

The portfolio encompasses both registered outputs and a reflection on the learning experience.

ePortfolio Structure and Key Activities

The e-portfolio is organized on my GitHub Pages website (https://spike2025-art.github.io/eportfolio-uoe/) under Module 6, presenting work chronologically across ten units. Each unit contains specific deliverables demonstrating progressive skill development.

Unit 1 introduced research fundamentals through a case study examining ethical implications of automated response weaponry. The case highlighted the gap between what can be built and what should be built, a distinction that recurred throughout the module.

Units 2 and 3 covered research questions, literature reviews, and research design types. I learned to distinguish between quantitative, qualitative, and mixed methods approaches, understanding when each is appropriate rather than defaulting to familiar quantitative methods. The work on formulating research questions taught me the importance of specificity (vague questions yield vague research).

Unit 5 presented case studies on survey misuse, including Cambridge Analytica's data practices and CDC's misleading survey on bleach consumption during COVID-19. These cases demonstrated how poor research design or unethical data use can cause real harm. They reinforced that methodology choices aren't merely technical decisions but carry ethical weight.

Units 7-9 constituted the statistical core of the module, where I completed mandatory exercises in inferential statistics, data visualisation, and validity assessment. These exercises moved beyond calculation to interpretation and communication, skills I will detail in Section 2.

The hypothesis testing work in **Unit 7** challenged my understanding of p-values and statistical significance. I could run the tests, but explaining what a p-value of 0.03 actually means—that's harder than it sounds. Does it mean the null hypothesis is probably false? That the result is probably real? That there's a 3% chance of error? None of these interpretations are quite right, yet they're all common misunderstandings.

Working through confidence intervals helped clarify this. A 95% confidence interval doesn't mean there's a 95% probability the true value falls in that range—the true value is fixed, not probabilistic. Rather, it means that if you repeated the study many times, 95% of the intervals you constructed would contain the true value. That's a conceptually different claim, though the practical implications are similar.

In **Unit 8**, Exercise 8.1 involved creating percentage frequency bar charts to compare brand preferences across two demographic areas. Producing the charts was not difficult, but interpreting them properly took more thought. In Area 1, around 60% of responses fell into the “Other” category, which suggests a fragmented market and relatively low loyalty to the main brands. In Area 2, preferences were more concentrated, with Brands A and B together accounting for 54.4% of the total. Across both areas, Brand B performed better than Brand A, indicating a stronger overall preference for Brand B.

Exercise 8.2 focused on heather species prevalence and used clustered column charts to compare two locations. The difference between the sites was clear. Location A showed 46.4% abundant coverage and only 14.3% absence, whereas Location B showed 45.5% absence and only 22.7% abundant coverage. The results suggest that the two locations are affected by different environmental conditions, such as soil quality, climate, or land management. This task showed how quickly visualisation can highlight patterns that are easy to miss in a table, but it also reminded me that interpretation still depends on subject knowledge and context.

Exercise 8.3 used relative frequency histograms to compare diet effectiveness. Diet A produced an average weight loss of 5.3 kg with a standard deviation of 2.5 kg, and the distribution was fairly symmetric. Diet B produced a lower average loss of 3.7 kg with a standard deviation of 2.8 kg, and results were more spread out, including some cases of weight gain. Overall, Diet A appeared to be the better option, both because it led to greater average weight loss and because outcomes were more consistent.

Across these exercises, I found that visualisation is not simply a way of presenting results. It shapes how patterns are noticed and how conclusions are formed. At the same time, it can also lead to misleading impressions if the design choices are poor or if the viewer does not have enough context to interpret what they are seeing.

The Power BI work in **Unit 9** introduced interactive dashboards. These dashboards make it easier to explore results, show interactions and explore the mulitple data dimensions and interactions. The application of such a powerful tool support the in depth analysis and the clearer communication, particularly because users can view the same dataset from different perspectives. The dashboards however, have also highlighted that interactivity is not neutral. Design choices on the available filters to the default view and how the dashboard is laid out can shape what users focus on and, in turn, how they interpret the findings.

In **Unit 10**, the focus moved towards the development of my research proposal on the economic crisis prediction using enhanced visualisation techniques. This required me to refine a clear research question, justify the methodological approach, and position the proposal within the wider literature in a way that was structured and logically consistent.

EVALUATION OF MAJOR SUBMISSIONS

Literature Review Assessment

The literature review on data visualisation for economic crisis prediction involved synthesising over 20 sources across nearly three decades, and it required far more than simply summarising individual papers. Instead, it demanded identifying recurring themes, tracing how different approaches developed over time, recognising points of disagreement, and acknowledging areas where the evidence remains inconclusive.

A clear structure emerged through the progression from early threshold-based warning systems (Kaminsky et al., 1998), to network-based perspectives on systemic risk (Battiston et al., 2012), and more recent work integrating machine learning methods (Beutel et al., 2019). Importantly, the critical evaluation went beyond describing findings: it assessed the strength of the evidence, highlighted methodological weaknesses, and considered how far conclusions could reasonably be generalised. The inclusion of institutional applications from organisations such as the IMF and the ESRB also helped anchor the academic literature in real-world decision-making and policy contexts.

My previous engagement with qualitative studies was rather limited, which likely reflects an underlying quantitative bias in how I approach evidence. In addition, some of the contradictory findings in the literature could have been examined in greater depth and will be in focus in my decertation . More specifically, Frankel and Saravelos (2012) suggest that traditional indicators performed strongly during the 2008 crisis, whereas later machine learning studies often report only modest gains. Exploring why these results diverge—whether due to differences in data, modelling assumptions, or evaluation methods— have strengthened the review. Similarly, the discussion of emerging LLM-based approaches felt more like an add-on than a fully integrated part of the argument.

Overall, the literature review reinforced that synthesis is a research skill in its own right. It involves identifying patterns across studies, recognising how methodological choices shape conclusions, and being transparent about the limits of current knowledge. These are capabilities I expect to draw on directly in my dissertation work.

Research Proposal Evaluation

The research proposal presentation on enhanced visualisation for crisis prediction models brought together aspects from throughout the module. The core research question—how can visualisation improve ML model interpretability without sacrificing accuracy?—emerged directly from contradictions identified in the literature review. The proposed mixed-methods approach combined quantitative performance assessment with qualitative evaluation of stakeholder comprehension.

Strengths of the proposal include a clear articulation of the interpretability-accuracy trade-off, the specific methodological details about which visualisation techniques would be employed (SHAP values, LIME, partial dependence plots) and explicit acknowledgement of limitations. The ethical considerations section demonstrated awareness of responsible AI deployment in financial contexts.

Areas for improvement include the sampling strategy, the timeline (which may be optimistic) and the evaluation criteria for what constitutes "sufficient" interpretability. The proposal also does not fully address how to handle situations where visualisation reveals model behaviour stakeholders find problematic or hard to justify. These gaps don't invalidate the proposal but indicate areas requiring further development.

Reflective Analysis: Module 6 Research Methods and Professional Practice

Description of Experience

The Module 6 was a shift from the technical AI modules previously completed, to the research process itself. This included the way to ask the right questions, to design detailed literature reviews and to communicate findings effectively. The module tried to bridge the fundamental research design and the advanced statistical analysis and reach in developing a comprehensive research proposal on economic crisis prediction using data visualisation techniques.

The module started with foundational concepts around research ethics and methodologies, requiring critical thinking about real-world case studies, including the ethical implications of automated response weaponry and the misuse of survey data by organisations like Cambridge Analytica. These were real life examples of poor research practices or ethical lapses with consequences.

The middle section introduced inferential statistics and hypothesis testing. I worked through exercises analysing brand preferences across demographics, heather species prevalence in different locations, and diet effectiveness comparisons. Each exercise required not just calculating statistics but interpreting what the numbers actually meant for decision-making. The visualisation work in Unit 8 proved particularly valuable, transforming raw data into charts that told coherent stories.

The literature review component required synthesising research spanning nearly three decades, from Kaminsky's 1998 early warning systems through to 2025 machine learning approaches. I examined how visualisation techniques evolved from simple threshold-based systems to complex interactive dashboards used by institutions like the IMF and European Systemic Risk Board. This wasn't just reading papers—it involved critically evaluating methodologies, identifying research gaps, and understanding how different approaches addressed the fundamental challenge of predicting rare events like financial crises.

The research proposal presentation brought everything together. I had to articulate a coherent research question, justify the methodology, and demonstrate how enhanced visualisation could improve the interpretability of machine learning models without sacrificing accuracy. This meant balancing technical depth with accessibility, a tension that ran throughout the module.

Analysis and Interpretation

This module enforced further my relationship with data and research. Having a rather lengthy professional carrier in Financial Risk management I am familiar with data set analysis and results interpretation.

Studying for this module however, have forced me to slow down and think in more details what about I was studying even when I had to analyse the simplest statistical charts. Why this test rather than another? What assumptions am I making? How might the sample or measurement approach introduce bias? What does this result tell me about the real world?

The ethical case studies landed differently than I expected. Reading about Cambridge Analytica's data practices or Uber's "God View" tracking wasn't just academic—these were organisations making conscious choices about how to use data and research methods. The CDC bleach-survey incident showed how even well-intentioned organisations can cause harm through poor survey design. These cases made me realise that research methodology isn't neutral. Every choice about what to measure, how to measure it, and how to present findings carries ethical weight.

The statistics work help me to remind myself on the use of hypothesis testing, decision criteria, how to run t-tests, etc. but more importantly help me to see the way of explaining what these methods and results meant to non-technical audiences. The visualisation exercises helped bridge this gap. Creating those charts for brand preferences or diet effectiveness forced me to think about what story the data was telling and how to make that story accessible. That's a different skill from technical competence—it's about translation and communication.

The literature review proved more challenging than anticipated. I expected to find clear answers about whether complex visualisation techniques improved crisis prediction. Instead, I found nuanced, often contradictory evidence. Some studies showed modest improvements from machine learning approaches; others suggested simple traditional indicators performed just as well. The field hadn't reached consensus and I had to stay with that ambiguity rather than reaching for premature conclusions. That discomfort with uncertainty feels like genuine progress in my thinking.

Working on the research proposal exposed difficulties I can confess that I am still facing with. There is the fundamental trade-off between model accuracy and interpretability. The most accurate models are often the least transparent. But in financial crisis prediction, stakeholders need to understand why the model is flagging a risk. They won't act on black-box predictions, no matter how accurate. My proposal tries to address this through enhanced visualisation techniques, but I'm acutely aware that this is only a partial solution. The interpretability-accuracy trade-off remains a genuine dilemma without easy answers.

The module also highlighted that even with the use of rigorous methods, researchers required to make choices at every stage, e.g. what to study, how to operationalise concepts, which analytical approaches to employ, how to interpret results. This dependency between research and subjective judgement should be acknowledged in a constructive manner on the research findings.

Application and Future Development

Moving forward, several things need to change in how I approach research and data analysis. First, I need to maintain a critical stance towards the output of the statistical models and their output. When I encounter research findings—whether in academic papers, news reports, or business contexts—I should ask about sample characteristics, measurement validity, potential confounds, and alternative explanations. This is not about dismissing research but about evaluating it more carefully.

The Unit 8 and 9 exercises showed me how powerful good visualisation can be for communication, but they also revealed how much additional thinking required in the developing of effective charts. I plan to explore tools like Power BI more systematically, studying both the technical aspects and the design principles that make visualisations work.

In addition the ethical dimensions need to stay front and centre in my practice. I want to develop a regular practice of asking "who might be harmed by this?" and "what am I not seeing?" when working on data projects. Creating an action plan means setting concrete steps rather than vague aspirations about being more ethical.

Another major outcome from studying this module is the need to focus on understanding the quality of evidence/data and use it appropriately in order to apply them appropriately in the selected methodology. This applies directly to my professional work in financial risk management, where decisions must often be made with incomplete information.

Finally, the research proposal revealed certain weaknesses in my writing and presentation skills. I can explain technical concepts to technical audiences reasonably well, but communicating with diverse stakeholders—policymakers, business leaders, general audiences—requires different approaches. I want to practice translating complex research into accessible language without oversimplifying or losing essential nuance.

In summary this module helped me to recognise that research is not only about learning techniques, but also about developing sound judgement. This will influence how I approach my dissertation and more broadly, how I engage with research and data throughout my career.

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