This e-Portfolio presents the evidence of my learning throughout the *Research Methods and Professional Practice* module. It brings together the statistical exercises from Units 6 to 9, my literature review *The Future of Farming – A Machine Learning Approach*, and my *Climate-Adaptive Agriculture* research-proposal presentation. Collectively, these activities strengthened my understanding of research design, quantitative analysis, and academic writing while helping me link theoretical statistics to real-world data-science applications.

Working through Units 6 to 8 helped me progress from calculating simple descriptive statistics to interpreting inferential tests.  
In Unit 6 I calculated summary measures such as mean, median, quartiles, and inter-quartile range using Excel functions like AVERAGE, STDEV, and QUARTILE

Unit 6 - Summary Measures Works…

This exercise taught me not only how to compute them but how to interpret dispersion and central tendency. Comparing Diet A and Diet B in the worksheet showed that numerical summaries can immediately communicate real-world outcomes—in this case, the relative effectiveness of two diets.

By Unit 7, I had advanced to hypothesis testing. Performing paired-sample and independent-sample t-tests gave me my first real sense of what it means to *accept or reject a null hypothesis*. I learned that we never “prove” anything statistically; we only assess whether data make a null hypothesis unlikely (p < 0.05). The worksheet on diet data reinforced this when the *t*-statistic indicated that Diet A produced a significantly greater mean weight loss than Diet B (p = 0.0028)

Unit 7 - Hypothesis Testing

Understanding p-values clarified for me why most empirical research in behavioral and social sciences adopts a 5 % significance level (Fisher, 1925).

Unit 8 then consolidated these ideas by introducing inference and sampling distributions. I came to appreciate the logical foundation of all statistical testing—the idea that we draw samples from populations and use probabilities to decide whether observed effects are likely due to chance

Unit 8 - Inference Notes

Concepts such as Type I (α) and Type II (β) errors were particularly revealing: setting α too high risks false positives, whereas setting it too low increases false negatives. I realized this trade-off mirrors the challenges of machine-learning model tuning, where precision and recall often move in opposite directions.

Collectively, these units taught me to approach data critically. I now understand that the rigor of research depends as much on the assumptions behind a test (normality, independence, homogeneity of variance) as on the calculations themselves (Field, 2013). This awareness prepared me to design my own quantitative research confidently.

Unit 9 focused on transforming numeric results into meaningful visuals. Using Excel to create bar charts, clustered columns, and histograms improved my ability to present data in ways that reveal trends and outliers

Unit 9 - Charts Worksheet

I learned that an effective chart is not decoration but interpretation—each axis label, color, and scale decision subtly frames the story the data tell.

When plotting frequency distributions, I noticed how visualizing variability made it easier to communicate statistical results to non-technical audiences. This experience later informed the design choices for my research proposal prototype, where accessibility for farmers was crucial. Unit 9 therefore bridged the gap between computation and communication: understanding the mathematics is essential, but clarity of presentation ensures impact.

My literature review, *The Future of Farming – A Machine Learning Approach*, investigated how artificial intelligence and predictive analytics can support sustainable agriculture. Synthesizing sources such as Liakos et al. (2018) and Van Klompenburg et al. (2020) gave me a clearer understanding of existing models for crop-yield prediction and irrigation control. The review’s major strength was its breadth—I explored agronomic, environmental, and data-science perspectives, which reflected the interdisciplinary nature of modern research. However, I later realized that I could have strengthened it by discussing limitations in data accessibility and algorithmic bias in developing regions.

Building on that review, my research proposal—*Climate-Adaptive Agriculture: A Global Predictive Platform for Sustainable Farming*—translated theoretical knowledge into an actionable research design

Transcript Research Proposal

It proposed a machine-learning system integrating global climate, soil, and satellite data to predict optimal planting times. Developing the methodology section forced me to apply statistical reasoning practically: defining variables, identifying potential confounders, and planning cross-validation. Concepts from Units 6–8 directly informed this design. For example, understanding normal distribution and p-values helped me justify using quantitative metrics such as Root Mean Square Error (RMSE) for model validation.

Ethics and data integrity formed another crucial part of my proposal. Reviewing GDPR compliance, bias testing, and explainable AI (SHAP, LIME) reminded me that technical accuracy alone does not guarantee responsible research (IPCC, 2022; FAO, 2023). Reflecting on this helped me recognize how ethical transparency underpins professional credibility in data-driven fields.

Finally, presenting the proposal as a recorded talk strengthened my communication skills. Translating complex technical language into accessible terms—explaining why a 1 % p-value matters to farmers—taught me to balance scientific precision with audience understanding. Altogether, the combination of statistical exercises, academic writing, and proposal presentation provided a holistic learning journey from theory to application.

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