# ASSESSING A STATISTICS CAPSTONE COURSE AGAINST A UNIVERSITY'S GRADUATE PROFILE ATTRIBUTES FRAMEWORK

Rachel Passmore and Maxine Pfannkuch
Waipapa Taumata Rau | University of Auckland, New Zealand
r.passmore@auckland.ac.nz

*Compulsory capstone courses were introduced in 2019 for all undergraduates in the Faculty of Science in recognition that students required support to transition from being a student of a discipline to a practitioner. These capstone courses required the University of Auckland graduate profile attributes to be assessed. This research aimed to discover how a generic institutional framework could be used and if it provided insights into the statistics discipline. Coursework submitted by two cohorts of students enrolled in the statistics capstone course were examined. This paper demonstrates that the use of a generic framework provided a new lens on statistics capstone course assessment and prompted an awareness of the skills and knowledge needed to improve the transition from university.*

## INTRODUCTION

The compulsory capstone courses introduced for all Faculty of Science undergraduates at the University of Auckland (UoA) had few guidelines but were intended to support the transition of graduates to future employment or further study. Most Universities now agree that simply equipping graduates with disciplinary knowledge is not sufficient for future workforce requirements (Barnett, 2004; Robley et al., 2005). Several researchers have stated that graduate profile attributes (GPAs) are now recognised as of equal importance to academic results when considering a student's employment prospects (Gilbert et al., 2018, Lamb et al., 2017). For the first time the UoA capstone courses, rather than treating GPAs as simply aspirational, included a requirement for them to be assessed. As part of a larger research project, which ascertained whether the UoA GPAs could be assessed and demonstrated in a statistics capstone course, the purpose of this paper is to show how the UoA's graduate profile framework can provide useful insights and possibly alternative perspectives on what attributes should be developed during an undergraduate statistics course, if future professional statisticians and data scientists are to be adequately equipped for success.

## BACKGROUND TO RESEARCH

A review of the literature revealed little research on how to assess science-based capstone courses against institutional GPAs. Bilgin et al. (2019) and Beckman (2019) have both written about assessment in statistics capstone courses but not in relation to an institutional graduate profile.

### *UoA graduate profile attributes framework*

A UoA graduate profile has been in existence since 2003 but has been updated and amended several times. The profile describes six attributes representing the capabilities that the University aims to foster and develop during a student's undergraduate journey. These six attributes are further broken down into generic descriptions of how they might be demonstrated by students in different Faculties. The six GPAs of the UoA graduate profile are (1) Disciplinary Knowledge and Practice, (2) Critical Thinking, (3) Solution Seeking, (4) Communication and Engagement, (5) Independence and Integrity, and (6) Social and Environmental responsibilities. Generic examples of how each GPA might be demonstrated by Faculty of Science students were provided by UoA. For instance, GPA 1, Disciplinary Knowledge and Practice had the following three examples: (1) Explain, apply or justify concepts, theories, methods and empirical results in the chosen major; (2) Display practical, analytical and/or research skills; (3) Display a level of numeracy, literacy, and computational competency of qualitative and quantitative information as required. Research, however, conducted by Gilbert et al. (2018) suggested that generic frameworks such as the UoA graduate profile benefit from interpretation within disciplines. For example, they found that descriptions of effective communication skills were very different in the six disciplines they examined: English, chemistry, psychology, law, music, and dance.

In this research descriptions were developed to illustrate how each of the six UoA GPAs could be demonstrated in the discipline of statistics. The first author's experience as a statistician and educator

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as well as a literature review of guidelines and frameworks with a statistics or data science focus (listed below), were used in the development of descriptions for the assessment of each GPA.

- Four Dimensions of Statistical Thinking (Wild & Pfannkuch, 1999)
- Statistical Thinking and Practice Themes (Pfannkuch & Wild, 2000)
- American Statistical Association (ASA) Curriculum Guidelines for Undergraduate Programs in Statistical Science (2014)
- ASA Ethical Guidelines (2022)
- Data Investigation Framework (Lee et al., 2020)
- Association for Computing Machinery (ACM) Ethical guidelines (2018)

For example, three assessment criteria were developed for demonstrating GPA 1, Disciplinary Knowledge and Practice in statistics: (1) Analytical Tool Selection and Application, (2) Software and Coding skills, and (3) Data Management skills. The number of criteria for each GPA ranged from two to seven, resulting in the focus of the research being on discovering whether the capstone course developed in the Department of Statistics provided *opportunities* for the six GPAs to be assessed and whether this could be done in a meaningful way for the discipline of statistics. In cognisance of the fact that students would be demonstrating the criteria at different achievement levels, the research needed to be couched within a suitable learning theory for capstone courses.

*Theoretical Framework*

Following Nilsson et al.'s (2018) recommendation that statistics education research include the use of background theories, six learning theories or frameworks were considered for this research. The theoretical lens eventually adopted was cognitive apprenticeship theory (Collins et al., 1989). Other established theories examined were found to contain aspects of importance to capstone courses but cognitive apprenticeship (CA) theory most closely aligned with the goals of capstone courses. CA supports the integration of prior knowledge and promotes processes and strategies that students can employ to solve novel problems about complex situations. The journey a student experiences from apprentice or novice towards expert status, the theory suggests, can be supported by employing a range of pedagogical approaches to guide student learning, such as, modelling, coaching, scaffolding with fading, articulating, reflecting, and exploring. Thus, in a capstone course students could be expected to need some scaffolding for early assessments and to work independently in later assessments. The assessment criteria needed to account for what constituted an acceptable level of attainment for a final year undergraduate to be able to transition to employment or further study.

## METHODOLOGY

The statistics capstone course was developed and taught by two lecturers. Students enrolled in the course were either statistics or data science majors. The course was one semester (14 weeks) in length and required students to engage with 12 tasks, about one per week, with nine completed in a small team. Data in the form of coursework submissions, the 12 tasks, were collected from two cohorts of students ($n$=47) and coded. The tasks were varied such as creating a poster, explaining a statistical concept, and investigating a problem using a given dataset (see Passmore, 2024). Some tasks involved oral presentations. Although access to the oral presentations was not provided, accompanying PowerPoint presentations were made available and were coded. The codebook developed for this research utilised the structure of an existing set of rubrics, Valid Assessment of Learning in Undergraduate Education (VALUE; American Association of Colleges & Universities, 2009). These rubrics appeared to align well with the UoA GPAs; the codebook adopted four development levels (Novice, Developing, Extended Developing and Capstone), and used a similar language style to describe differences between development levels to that used in the VALUE rubrics. Initial attempts at coding a small number of submissions revealed superfluous and repetitive codes and one redundant development level (Novice). Template Analysis (King, 1998) was used to develop the codebook since it permitted use of a priori codes, which in this instance were the six GPAs (Passmore, 2024). Four iterations of coding were conducted, and the final template was uploaded into NVivo software as were student coursework submissions. All submissions were then coded to determine which GPAs had been demonstrated and to what level.

For example, GPA 2, Critical Thinking, contained four subcategories, Justification of Tool Selection, Appreciation of Variance, Solving Problems, and Synthesis of Contextual and Statistical Knowledge, each with three levels of demonstration. Development levels for the subcategory, Justification of Analytical Tool Selection are shown in Table 1.

*Table 1. Criteria for subcategory Justification of Analytical Tool Selection for GPA Critical Thinking*

| **Justification of Analytical Tool Selection (GPA 2), levels of development.** | **Description** |
|---|---|
| *Capstone* | Tool selection completed independently with justification of choice, with few errors |
| *Extended Developing* | Can select appropriate tool from a small list of suggestions and apply correctly |
| *Developing* | Needs support to select and apply appropriate tool |

Each of the six GPAs was similarly divided into multiple sub-categories that provided descriptions of attributes in a meaningful manner for the discipline of statistics. This resulted in a final codebook that included twenty sub-categories each described at three different development levels.

## RESULTS

Firstly, examples of the coding of student coursework submissions for two tasks for two sub-categories of GPA 2, Critical Thinking, Justification of Analytical Tool Selection, and Solving Problems, are presented to illustrate the type of tasks offered and to highlight differences in development levels. Second, an example using data across four tasks from Week 4 to Week 12 illustrates overall student progress in developmental level for GPA 4, Communication and Engagement, sub-category Written Communication. These GPAs were chosen as they are not usually part of traditional assessment in statistics. Finally, an overall picture of results across all GPAs is presented.

### *Example of coding, Tongariro Heather Invasion*

In this task, student teams were asked to decide which of four possible treatments (some chemical and some natural) should be recommended to reduce heather ground cover and increase native monocot and dicot ground cover. Data were available for the years before and after treatment. In this task students were asked explicitly to include reasons for their choice of analytical tool.

Several subcategories of GPAs were demonstrated in this activity including Analytical Tool Selection and Application and Software and Coding (GPA 1); Justification of Analytical Tool Selection and Synthesis of Statistical and Contextual Knowledge (GPA 2); and Analysis and Representation including transnumeration (GPA 4). Examples of how students demonstrated one subcategory of GPA 2 in the Tongariro Heather Invasion task are presented in Figure 1. Justification of Analytical Tool Selection was deemed a critical thinking skill (GPA 2), and distinct from Analytical Tool Selection and Application, which was included as a subcategory of GPA 1.

**Example of GPA 2, Justification of Analytical Tool Selection, Capstone level**
We had a strongly significant result but when testing the assumptions that MANOVA rests upon: multivariate normality and equality of within-group variances, both failed their respective tests. Our nonparametric test (PERMANOVA) was significant however and not subject to violations of core assumptions.
Source: Students B4, B5, B11, B15 (*Tongariro Heather Invasion*)

**Example of GPA 2, Justification of Analytical Tool Selection, Developing level**
We chose to …. build a linear regression model. We use the treatment method as the explanatory variable. This model is appropriate for use here.
Source: Students B6, B35, B39, B40 (*Tongariro Heather Invasion*)

*Figure 1. Student examples of one subcategory of GPA 2 at capstone and developing level.*

### *Example of coding, Crime Busters*

*Crime Busters* was the last team activity of the course. Students were directed to the Police website (www.police.govt.nz), from where they had to select data, an aspect of crime, and an audience for a formal report. Assistance was given in terms of definition of *mesh blocks* and the use of supporting information from Stats NZ, but students essentially had to source and clean their own data.

Again, this task gave students the opportunity to demonstrate multiple graduate profile attributes including Analytical Tool Selection and Application and Software and Coding (GPA 1); Solving Problems, Synthesis of Statistical and Contextual Knowledge, and an Appreciation of Variance (GPA 2); and Analysis, Representation including transnumeration, and Sources and Evidence (GPA 4). Students demonstrated the Solving Problems subcategory (GPA 2) at *Capstone* level by providing a description of their problem-solving approach, how that approach was developed, and a recognition of the consequences of their solution. The example in Figure 2 below, coded at *Capstone* level, provided both an overview of the problem-solving approach adopted and how the approach was developed.

**Examples of GPA 2, Solving Problems, Capstone level**

Due to the strong seasonality present, we decided to deseasonalise the data using seasonally adjusted models, Moving average (MA) and Seasonal trend lowess (STL). Looking at decomposition plots for both models, STL showed a smoother trend so we decided on investigating STL over MA.

The STL model over time showed significant autocorrelations in the ACF plot of the residuals and the residuals vs fitted showed the same non-linear trend as seen with the original data. Due to this, we decided to fit lagged response variables and add Month as a variable and a quadratic term. For the linear vs quadratic models, there was no significant difference in the residuals plot and the R-squared values were very similar. Quadratic also had a larger residual standard error, and overall, it did not improve the fit of our data, so we determined a quadratic wasn't needed. The month variable was also deemed redundant. Hence, we decided the lagged linear STL model was the best fit.

The Holt-Winters forecasting approach was also tried but the fit wasn't ideal and the RMSEP value was high. We also looked into MA forecasting to confirm our STL model and as expected due to visual inspection, its predictions had a higher RMSEP.

Source: Students B1, B12, B13, B32 *(Crime Busters)*

*Figure 2. Student example of one subcategory of GPA 2 at capstone level.*

*Example of student progress in developmental level for GPA 4*

In general students demonstrated improvement in developmental level as the semester progressed, particularly in GPA 4, Communication and Engagement. Figure 3 shows how the percentage of capstone codes in GPA 4, sub-category Written Communication, increased gradually from two earlier tasks in Weeks 4 and 6, 38.5% and 56.8% respectively, to 81.7% in the Week 10 task.

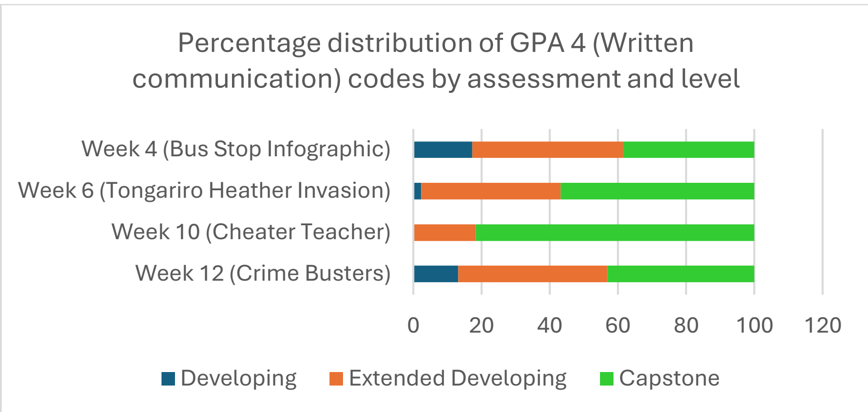


*Figure 3. Percentage distribution of GPA 4 by assessment and level*

The exception to this gradual improvement was the Week 12 task, *Crime Busters*. In this assessment only 43.1% of students demonstrated a capstone level of competence, just a small improvement over the first assessment. The two lecturers on the course, were not surprised; they mentioned that substantial student support had been provided at the beginning of the course but gradually decreased until the final assessment when no support was provided. This pedagogical approach of gradually withdrawing support was consistent with strategies suggested by cognitive apprenticeship theory. This finding revealed that some students had not yet reached a stage where they could successfully negotiate tasks without support.

*Overall Findings*

The main findings from this research showed students had multiple opportunities to demonstrate three of the six GPAs (Disciplinary Knowledge and Practice, Critical Thinking and Communication and Engagement), slightly fewer opportunities existed to demonstrate a fourth GPA (Solution Seeking), but very few examples were found of students demonstrating GPAs Independence and Integrity and Social and Environmental responsibilities (Table 2). Several factors impacted the distribution of codes: some assessments, for example, were very short and some were substantial reports. Many assessments were designed to provide opportunities to demonstrate specific GPAs rather than all of them.

*Table 2. Total number of codes per GPA*

| GPA 1 Disciplinary Knowledge & Practice | GPA 2 Critical Thinking | GPA 3 Solution Seeking | GPA 4 Communication & Engagement | GPA 5 Independence & Integrity | GPA 6 Social & Environmental Responsibilities | Total Codes |
|---|---|---|---|---|---|---|
| 264 | 276 | 126 | 847 | 14 | 10 | 1537 |

The lower number for GPA 3, Solution Seeking codes was viewed positively, since this required students to demonstrate solution of problems similar to those demonstrated in previous courses. In a capstone course, the focus is more on providing opportunities for students to demonstrate GPA 2, Critical Thinking, for which a student will have to examine and solve novel problems in unfamiliar contexts, an aspect that is not traditionally assessed. Noteworthy was that students in the course had multiple opportunities to develop communication skills and work collaboratively (GPA 4), soft skills that are not assessed in UoA undergraduate statistics. The tasks included writing and presenting for a variety of audiences, and data visualisations as well as working as part of a team. Sub-categories of GPAs 5 and 6 that were seldom demonstrated were:

GPA 5
1. An understanding and appreciation of discipline specific ethical standards.
2. Responsibilities to research subjects, employers, and colleagues.
3. Responsibilities regarding misconduct allegations.

GPA 6
1. Recognition of the significance of Te Tiriti o Waitangi.
2. Civic awareness, an appreciation of equity and social justice and a personal and professional sense of responsibility to help create a sustainable future.

The absence of ethics (first subcategory in GPA 5) in the capstone assessments was not surprising given that at UoA explicit instruction about ethics is included in postgraduate but not undergraduate courses. It does, however, raise the question as to whether consideration of ethical perspectives, which in many areas of statistics and data science are of considerable importance, should be included in at least some undergraduate courses. Opportunities to demonstrate the other two GPA 5 subcategories could be incorporated into a Work Integrated Learning-style capstone course as they relate more to an employment setting. The prevalence of teamwork in the UoA statistics capstone course, however, meant that students could develop a sense of responsibilities to their colleagues. One task required teams to devise a formula for the fair allocation of team marks and students regularly provided oral and written peer assessments of each other's work. However, they failed to acknowledge each colleagues' contribution to a task in submissions. Although specific examples of students demonstrating responsibilities to colleagues were seldom found in coursework submissions, end of course reflections did provide some evidence. One student commented on how she had learned to listen to others' ideas constructively and to articulate her own skills for a task proactively, while another reflected that a positive teamwork environment is something that can be cultivated.

The absence of the opportunity to demonstrate the first sub-category of GPA 6 is perhaps more surprising given the institution's strategic vision to enhance and promote recognition of the significance of the Te Tiriti o Waitangi. Recognition of indigenous data sovereignty rights was absent from the documents consulted with a statistics focus, which again was unexpected given the rise in interest during the last five years, particularly on data concerning the different impacts of COVID on indigenous groups (Carroll et al., 2021a). In Australia and New Zealand, demands for recognition of the rights of indigenous people and for more culturally sensitive pedagogical practices has been growing. An emerging body of research is providing support for tertiary institutions keen to improve in this area (Cawthorne, 2023; Coates et al., 2021; Whiteford et al., 2017). Students had opportunities to demonstrate a sense of *civic awareness or appreciation of equity and social justice*, the second subcategory of GPA 6, but did not, again a surprising result in today's climate.

## IMPLICATIONS OF RESEARCH

Suggestions on how the omissions mentioned above might be incorporated in a course are now considered. Tractenberg (2022) made ten recommendations for integrating ethics into statistics and data science instruction. A good place to begin, she suggested, is an examination of the ethical guidelines produced by ASA (2022) and ACM (2018). A separate course focussing on ethical perspectives is not required; instead, ethics should be integrated into existing courses. She urged instructors to encourage students to *apply* ethical practice not simply *recall* ethical standards.

The growth of indigenous data networks under the umbrella of the International Data Sovereignty network provides unique resources for students to develop advocacy arguments for improved outcomes for individual ethnic groups. New Zealand and Australia have indigenous data networks including, Te Mana Rauranga, a Māori Data Sovereignty Network (Te Mana Raraunga, 2023) and the Maiamnayri Wingara Aboriginal and Torres Strait Islander Data Sovereignty Network (Carroll et al., 2021b). Multiple resources to improve students' civic awareness and appreciation of social justice in the discipline of statistics have been created by the ProCivicStat (2018) project. The aim of the three-year project was to promote responsible citizenship and to improve awareness of key social phenomena that affect many aspects of everyday life (Nicholson et al., 2022). Ridgway (2022) suggested "teaching traditional statistics to students is insufficient to prepare them for engagement with Civic Statistics" (p. 62). For students to engage with Civic Statistics, Ridgway (2022) suggested that examples from current national and international issues must be included in teaching and learning activities and assessments. Dispositional skills, such as curiosity, scepticism and perseverance also require development to support critical evaluation of Civic Statistics. Such traits, Lee et al. (2022) suggested, cannot be developed in one data investigative experience; they need to be nurtured and supported over time, an implication of which might be to adopt alternative capstone course models that are longer than one semester.

## CONCLUSION

Overall, it was shown that the statistics capstone course could be assessed against the UoA GPAs, but this process benefitted from an interpretation of the institutional framework of GPAs in the discipline of statistics. The university interdisciplinary graduate profile framework provided a new lens on what to assess in a statistics capstone course. On the one hand, it revealed several omissions that suggest that undergraduate statistics and data science programmes may need to broaden their range of learning experiences offered to students such as dispositional skills, skills to handle ethical issues, skills required to improve civic and environmental awareness as well as social justice and the rights of indigenous people (Passmore, 2024). On the other hand, the UoA graduate profile prompted the necessity to assess communication and novel problem-solving skills, resulting in many opportunities for students to experience and demonstrate these skills.

This research has demonstrated that examining the learning outcomes of a statistics capstone course against an institutional interdisciplinary framework has not only provided evidence of new additions (communication and critical thinking) but also several omissions. The results also raise questions about where and how such omissions might be addressed during a capstone course or embedded in a statistics undergraduate programme. Tasks offered in the UoA capstone course had potential for students to demonstrate some of the omissions, (e.g., ethical considerations of weed eradication in Tongariro National Park), but students did not take the opportunity to demonstrate them in their assessments. In terms of teaching and learning, perhaps there is a need to make factors such as ethics, civic awareness, social justice, rights of indigenous groups and sustainability more explicit so that capstone students realise the importance attached to such factors by professional statisticians and data scientists, as they transition to future employment.

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