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Early Assessment in First-Year Transition: Predictor of Success or Catalyst for Intervention?

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Abstract

Early assessment (EA) is a key component of learning, providing students with opportunities to receive feedback, clarify expectations, and build confidence. This is particularly important for first-year students transitioning to university. This study considers whether EA performance is a reliable predictor of future performance, and whether this depends on student group or EA format. Results indicate that for high-performing students, EA is a reliable predictor of future success; however, other groups have mixed results. The ability of EA to predict future performance also depends on EA format, particularly for lower-performing groups. Where EA is not a reliable predictor of future performance, we suggest that it instead, in some cases, serves as a useful catalyst, leading to improved performance. These findings highlight the importance of EA, and the careful consideration required when determining EA format and associated support strategies, to effectively scaffold student success, particularly for lower-performing and at-risk students.

Keywords: First-year transition, early assessment, student success, statistics education.

Introduction and Literature Review

The purpose, value, and nature of formative assessment within higher education (HE) have long been studied. For example, Sadler (1999) argues that feedback on formative assessment is essential for students to objectively monitor the quality of their work and hence proactively self-regulate their learning (Boud & Molloy, 2013; Nicol & Macfarlane-Dick, 2007). Alternatively, a more socio-constructivist perspective posits that formative assessment promotes interaction and dialogue with instructors and peers through which learning occurs (Parmigiani et al., 2025). In terms of promoting student learning, a systematic review by Morris et al. (2021) showed low-stakes quizzing and student-initiated formative feedback are more effective, while Karaman (2021) found technology-based feedback is less effective. While the role of formative assessment in HE is established, its definition can vary in terms of whether or not marks are attached to the tasks it involves. This paper specifically considers early assessment (EA), which we define as low-stakes, and sometimes diagnostic, tasks completed within the first several weeks of a university semester, prior to higher-stakes or summative assessments. Depending on how one defines it, EA could be considered formative, but typically carries a small mark allocation. EA is an important component in the secondary–tertiary transition for undergraduate students and has the potential to help students adjust to university, clarify expectations, and build confidence in preparation for more challenging later assessments (Thomas et al., 2019). Indeed, in the Australian context in which this study is situated, it is mandatory for HE providers to conduct EA for the purposes of providing formative feedback and identifying additional support needs (Australian Government, 2021). Furthermore, poor performance

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in EA is a recognised indicator of low student engagement, which, in turn, can lead to low chances of retention or academic success (van der Meer et al., 2018). However, there is a wide variety of assessment and feedback practices across different institutions and subject disciplines. As a result, establishing which forms of EA provide robust indicators of later performance, and/or which signal the need for intervention, in different contexts is not fully understood.

For example, in a large psychology subject (or course/unit/module) at a Canadian university, performance on early in-class quizzes was predictive of performance in the final summative exam (Kim & Shakory, 2017). Other studies, though, point to EA needing to be combined with other learning analytics measures (e.g., attendance) to predict subject performance (Tempelaar et al., 2024). However, in an online statistics subject — the discipline considered in this study — it was only completion of early quizzes rather than participation in online discussions and forums that predicted attrition (Figueroa-Cañas & Sancho-Vinusa, 2020). It should be recognised that the link between early and final assessments can be moderated by a range of factors. These may include student-specific life events such as unexpected health issues (Hlosta et al., 2022), students unsuccessfully engaging with formative feedback (Robinson et al., 2013), and a university's strategy for targeting interventions towards 'at-risk' students (Linden, 2022).

One interesting case study is Stellenbosch University in South Africa, which implemented a university-wide initiative to embed early, formative assessments for all first-year students, to support the development of effective study habits. Although a coordinated focus on early student success brought some institutional benefits (van Schalkwyk, 2010), the unclear impact on student performance led to some faculties discontinuing the practice (Bruwer & Ontong, 2020). Bruwer and Ontong (2020) analysed the relationship between EA marks and academic outcomes for students registered in two accountancy subjects. Their study design and analysis, which is similar to that employed in this paper, showed that EA format had little impact on the low predictive ability of EA marks on academic performance. They also found that, particularly for at-risk students (based on EA results), the EA could successfully be used to highlight a need for intervention, with many at-risk students subsequently going on to pass the subject.

Academic drop-out in science, technology, engineering, and mathematics (STEM) disciplines is a particular concern, with poor mathematical and numerical proficiency being a factor leading to reduced confidence and failure (Sithole et al., 2017). This study considers a first-year statistics subject taught to students, the majority of whom are enrolled in STEM discipline degrees at an Australian university. Statistics subjects are often regarded as 'harder' subjects amongst non-specialists (Murtonen & Lehiten, 2003) and this has contributed to the rise of the term 'statistics anxiety' to describe the psychological and physiological effects, and consequential poor performance, experienced by many students (Zeidner, 1991). Students with statistics anxiety have been shown to use less self-regulatory and deep processing strategies, resulting in less persistence and achievement in assessment tasks, as their cognitive and attentional resources are distracted by intrusive thoughts and worries (González et al., 2016). As such, statistics anxiety is known to be associated with lower performance and avoidance of study (Macher et al., 2012). Because of this, regular, low-stakes assessments are recommended in order to discourage procrastination where statistics anxiety is prevalent (Chew & Dillon, 2014).

Encouragingly, increasing the amount of low-stakes EA has been shown to both decrease statistics anxiety and build student confidence, and is associated with an increase in student performance (Shaker et al., 2026). Jones et al. (2026) showed that automated feedback to online multiple choice questions, for example, alleviated statistics anxiety by reducing test and class anxiety and help-seeking anxiety, while Hadfield (2023) noted automated feedback improved self-efficacy and achievement in students with statistics anxiety. Students from across the science, engineering, health, and social science disciplines typically encounter statistics as part of their undergraduate studies. Thus, establishing whether EA performance is a predictor of future performance, and whether this depends on student group and/or assessment format, is an open but important question. This question is explored within the context of a large first-year statistics subject; however, the results are relevant to a wide range of disciplines, particularly at the first-year level. The following research questions are explored:

1. What is the correlation between early assessment and future assessment marks, and does this differ by student group and/or early assessment format? [Here, student groups are determined based on students' performances in the EAs, with further details provided in the Methods and Results sections.]
2. Is there a difference between mean early assessment marks and future mean assessment marks, and does this differ by student group and/or early assessment format?

3. Can early assessment be used to predict future academic success in the subject and/or be used for intervention purposes, and does this differ by student group and/or early assessment format?

Methods

Participants

The participants of this study were undergraduate students enrolled in STM1001 *Making Sense of Data*, a large first-year introductory statistics subject (or course/module/unit) at an Australian university, during Semesters 1 or 2 of 2023 and 2024. The majority of students were enrolled in degrees related to either life, applied, or general sciences (48.3%); health sciences (41.7%); or information technology (6.8%). The total numbers of students who received a final result for the subject were 508, 647, 634, and 858 in Semesters 1 and 2, 2023 and Semesters 1 and 2, 2024, respectively. Of these, 22, 22, 18, and 37 students (99 in total across the four semesters in 2023–2024) received a final mark of 0 in their relevant semester of enrolment, respectively. While 19 of these students did not complete the subject and subsequently withdrew late with academic penalty, receiving a fail grade and a mark of 0, most of these 99 students were considered 'ghost students'. 'Ghost student' is a term introduced by Stephenson et al. (2021) and refers to students who, despite remaining enrolled in their subject(s), do not engage with subject learning activities or assessments in any way. These students differed qualitatively from students who engaged with the learning activities and/or attempted the assessments because, regardless of their academic ability or the teaching and assessment conditions in a given semester, there was no evidence of student engagement with the subject, and they subsequently received a mark of 0. As such, including data from these students would distort the analysis and the comparisons being made in this study. Therefore, to allow for meaningful comparisons, data from the 99 students who received a final mark of 0 were removed prior to analysis. The total sample size of this study was therefore 2,548, comprised of 486, 625, 616, and 821 students from each semester, respectively.

Data Collection

Student performance data from the 2023 and 2024 Semester 1 and 2 assessments were analysed in this study. Ethical approval was provided by the university's human research ethics committee with approval number HEC23332.

Course Background

STM1001 was first offered in 2022 as a university-wide first-year introductory statistics subject following a comprehensive design and development phase which included consultation with various stakeholders. The subject has been specifically designed with a flexible modularised format in order to cater to students with diverse educational backgrounds and chosen qualifications (Kuveke et al., 2024). More information on the creation, design, and implementation of STM1001 can be found in Kuveke et al. (2024; 2026).

In order to support student learning, the assessment structure of STM1001 was adjusted between 2023 and 2024. In particular, the overall number of assessments was reduced, the remaining assessments were restructured, and the weighting of remaining assessments was adjusted so that students now completed a larger proportion of the subject marks earlier in the teaching instance (Shaker et al., 2026). The rationale for the restructure and higher weighting for low-stakes EAs was threefold. Firstly, at-risk students could be identified and supported more swiftly (see, e.g., Nicol & Macfarlane-Dick, 2006). Secondly, students would now be assessed on statistical software skills much earlier in the teaching period, helping to promote confidence and build technical skills for subsequent assessments (see, e.g., McArthur, 2023). Thirdly, students' feelings of statistics anxiety could be better mitigated through earlier opportunities for progress, engagement, skill development, and support (see, e.g., Bandura, 1997; Folwell & Brennan, 2025; Wu & Yu, 2025). The assessment changes between 2023 and 2024 are summarised in Table 1.

Table 1

Overview of STM1001 Assessment Structure in 2023 Versus 2024

Year/Assessment Type and Weighting	Quizzes	Assignments	Final Exam
2023	8 quizzes worth 10% (2% each, best 5 kept). Up to 3 attempts per quiz permitted. Timed: maximum of 2 hours per attempt permitted. Due weekly, Weeks 1–8.	4 assignments worth 60% (15% each). Due Weeks 6, 8, 10, 12.	30%
2024	6 quizzes worth 30% (6% each, best 5 kept). Up to 2 attempts per quiz permitted. Untimed. Due weekly, Weeks 1–6.	3 assignments worth 45% (15% each). Due Weeks 7, 10, 12.	25%

Note that while the number of assignments reduced in 2024 and the weighting of the final exam decreased slightly, the main change was the reweighting of the quizzes assessment component from 10% to 30%, with a concurrent reduction in the number of these quizzes from eight to six. In combination, this effectively meant that by the end of Week 5, students now had the opportunity to attain 30% of the total subject marks compared to just 10% in 2023. By just over halfway through the teaching period in 2024, students were now completing assessments worth 45% of the subject total, compared to 25% in 2023. The other notable change was that the EAs (quizzes) included assessment of software skills in 2024, whereas in 2023 they did not. Given the importance of software skills in later assessments, this change allowed for much earlier intervention by staff and/or students where gaps were identified in software skills in the EAs. As discussed in Shaker et al. (2026), a significant issue for students in 2023 was a lack of assignment engagement, which was strongly associated with failing the subject. Successful engagement with the assignments was required for students to demonstrate attainment of the relevant software skills. We speculate that where students had not engaged with the weekly (non-assessed) computer lab material in 2023 and therefore had not cultivated these software skills, this became a significant barrier to assignment engagement later in the semester. Therefore, the inclusion of software skills in the EAs in 2024 was designed to assist students to develop these skills earlier in the semester, thus fostering confidence to engage with the assignments later in the semester and ultimately leading to higher pass rates. While students were permitted up to three attempts per quiz in 2023, with only the mark from the highest attempt retained, this was reduced to a maximum of two attempts in 2024. However, while the 2023 quiz attempts were timed, with a maximum of two hours permitted per attempt, in 2024, the quizzes were untimed. The reason for this was two-fold. Firstly, given the quizzes now incorporated assessment of software skills, the time required to complete them would increase. Moreover, students were encouraged to seek assistance with their quiz work throughout the week if required, including during their allocated computer lab class. Secondly, untimed assessments are known to benefit student performance, particularly where statistics anxiety is prevalent (Onwuegbuzie & Seaman, 1995).

The quizzes are open-book assessments administered via the ‘Quiz’ activity in the university’s Learning Management System (LMS), and so are referred to by staff and students as “quizzes”. However, they do not consist of simple multiple choice questions. Rather, these ‘quizzes’ contain a variety of fully randomised, single choice, multiple choice, and short numeric response type questions created using the R/Exams package (Zeileis et al., 2014). Many of these questions require the analysis of individualised data sets using statistical software and assess higher-order critical thinking skills rather than simple memory recall (Shaker, 2026).

Throughout the semester, students are also provided with targeted support which is influenced by their EA results. Directly following the release of the EA results, tools such as Microsoft Mail Merge and the Student Relationship Engagement System (SRES; Liu et al., 2017) are used to email each student with a personalised message. These emails comment on the student’s EA result, contextualise what this result means for their overall progress in the subject, offer words of encouragement, and provide reminders on upcoming assessments and available subject resources to help keep the student on track with their studies.

For students who perform moderately to poorly on the EA, and thus are considered to be potentially at-risk, further information is included in these personalised emails to proactively guide these students towards available support. There are two main categories of support resources and services available. Firstly, university-wide support services include the Maths Hub (see, e.g., Jackson, 2021), a free mathematics and statistics support initiative available to all students; academic skills and study support skills services; and student health and wellbeing services. Secondly, STM1001-specific support services include subject support tutors who liaise with potentially at-risk students and provide limited in-person and online one-on-one and group support sessions, online resources on addressing and normalising statistics anxiety, and a bespoke artificial intelligence (AI) agent which can answer administrative questions.

For students who do not submit any work for the EA, and who therefore are also deemed at-risk, as a form of staff intervention (Linden, 2022), a more detailed personalised email is sent. This includes an offer to meet with them one-to-one in person or online to discuss their progress and any issues they may be experiencing. Where students respond and meetings are arranged, following these meetings, a tailored plan for each student can be provided for succeeding with their STM1001 studies. The content of these plans is specific to each student but can include, for example, advice on courseload, study techniques, which STM1001 content to prioritise, and how to prepare for upcoming assessments. Note that while many of the students in this category are considered 'ghost students', as discussed in the Participants section, a small percentage do go on to complete the subject following outreach.

From Semester 1, 2024, questions were also embedded within the EAs themselves which assist students in identifying and accessing the support they need. For example, as part of the Week 3 EA quiz, students must complete a short two-minute reflection within the LMS, upon completion of which they are provided with personalised recommendations for support, if relevant. This promotes personal accountability and responsibility, acting as a form of student intervention.

Data Analysis

As per Shaker et al. (2025), clustering analysis was used to identify groups of students with common characteristics based on their EA performance. Also as per Shaker et al. (2025), linear mixed effects models were used to compare student performance over time within each semester. For each semester, an overall model was estimated, as well as separate models for each cluster. Although assessment marks are bounded between 0 and 100, due to the large sample sizes, there were no concerns regarding the normality assumption nor consequently the validity of the linear mixed effects models. A two-sample test of proportions was used to compare pass rates between Semester 1 and Semester 2. Spearman correlations were used to estimate the associations between assessments. Logistic regression models were used to estimate changes in the odds of passing in future semesters compared with Semester 1, 2023 within each cluster. The adequacy of the logistic regression models was assessed using deviance goodness-of-fit tests. Statistical analyses were carried out using R (R Core Team, 2023).

Results

Characteristics of the Student Cohort

Prior to carrying out the main analyses in the following sections, each student was allocated to one of three groups, or 'clusters', based on their performance in the EAs, to allow for comparisons between groups to be made in the analyses. In order to objectively determine the cut-off point for each group, a *k*-means clustering algorithm was utilised. This algorithm allocated students to one of the three clusters based on their EA marks. The *k*-means clustering algorithm works by finding a central point for each group (called a 'centroid', which in this instance represents the average [mean] EA mark within each group) and grouping students with similar marks together. The algorithm aims to form the groups such that students within each group have marks that are as similar as possible. The resulting EA cut-off points distinguishing the three groups, namely 51.4% and 80.2%, are therefore mathematically derived based on the observed EA data, rather than being thresholds chosen in advance. Importantly, however, these cut-offs also align closely with pedagogical expectations and our expert judgement. For example, 51.4% is close to the 50% pass/fail threshold and 80.2% is very close to the 80% threshold for high-performing 'A' students.

To further validate this result, we also considered alternate cut-off percentages of 60% and 80%, since it could be reasonably argued that students scoring above 51.4% but under 60% are barely passing and would also benefit from intervention. However, these adjustments did not lead to any meaningful differences in outcomes or conclusions drawn from our main

analyses compared to the original cut-off percentages of 51.4% and 80.2%, so the original objective cut-off percentages based on the *k*-means clustering algorithm were retained. As a result, we defined the three clusters as follows:

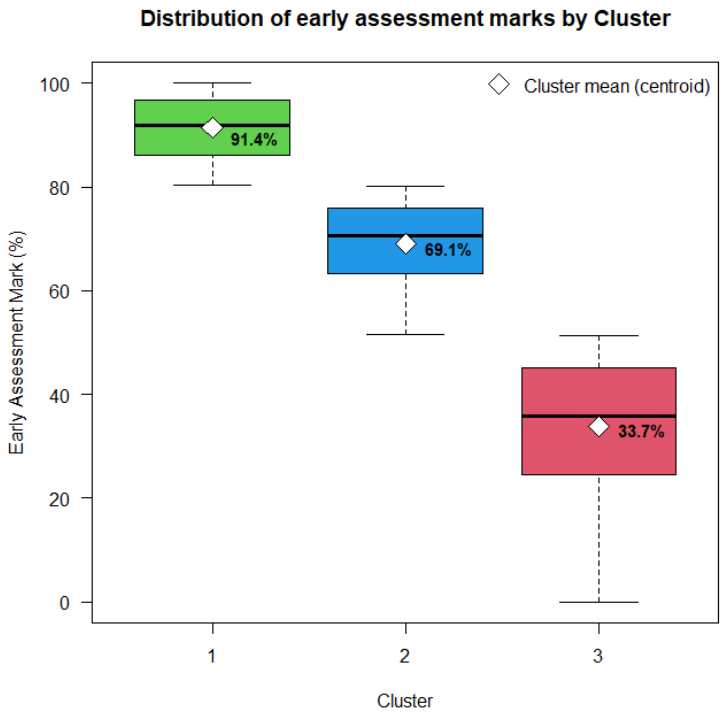
- Cluster 1: Students with an EA mark of above 80.2%
- Cluster 2: Students with an EA mark above 51.4% and less than or equal to 80.2%
- Cluster 3: Students with an EA mark of 51.4% or less.

Given that most students in Cluster 3 obtained a mark of 50% or less for the EA, we considered Cluster 3 to be the at risk group.

To assist with visualising the resulting clusters, Figure 1 displays the distribution of EA marks for each cluster. Also shown is the mean EA mark, or centroid, for each cluster. These cluster means are 91.4%, 69.1%, and 33.7% for Clusters 1, 2, and 3, respectively.

Figure 1

Boxplots Displaying the Distribution and Mean of Early Assessment Marks for Each Cluster



The number of students in each cluster within each semester is provided in Table 2. Of note is that in both 2023 and 2024, there is a higher percentage of at risk students in Semester 1 (16.5% and 18.5%, respectively) compared with Semester 2 (11% and 12.8%, respectively). Across both years, 17.6% of Semester 1 students are considered at risk compared with 12% of Semester 2 students. This is a difference of 5.6 percentage points (95% CI [2.7, 8.5])with a two-sample test of proportions indicating that this difference is statistically significant ($\chi_1^2 = 15.3, p < 0.001$). We speculate that this observed difference may be because in Semester 1, students are also adjusting to the many challenges involved in transitioning to university, such as the shift towards independence in learning and new teaching styles compared to what they may have been used to at school (Mulaudzi, 2023; Worsley et al., 2021).

Table 2

Number and Percentage of Students in Each Cluster Across Semester 1 (S1) and Semester 2 (S2) of 2023 and 2024

Cluster	S1 2023		S2 2023		S1 2024		S2 2024		Total	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
1	273	56.2	391	62.6	265	43.0	442	53.8	1371	53.8
2	133	27.4	165	26.4	237	38.5	274	33.4	809	31.8
3	80	16.5	69	11.0	114	18.5	105	12.8	368	14.4
Total	486	100	625	100	616	100	821	100	2548	100

What Is the Correlation Between Early Assessment and Future Assessments Marks, and Does This Differ by Student Group and/or Early Assessment Format?

Table 3 provides the correlations between the EA and future assessments for each cluster for each semester. We note here that since the EA format changed from 2023 to 2024, observed changes in results between 2023 and 2024 may be at least partially due to differences in EA format. Considering Cluster 1 first, the relationship between EA and the assignments remains significant and moderately strong (0.51–0.62) across both years. For EA and the exam, while the relationship is significant across both years, the association is weaker (0.35–0.39) in 2024. The associations between the EA and future assessments are weaker for Cluster 2. For the assignments, the association is significant but weak (0.4) in Semester 1, 2023. In Semester 2, 2023, there is no evidence of any association between EA and the assignments. During 2024, the association is again significant but weak (0.21–0.3). The pattern is similar regarding the relationship of EA to the exam, but the associations are weaker. For Cluster 3, the highest association between EA and the assignments is in Semester 2, 2024, which is significant but weak (0.36). The associations in the other three semesters are less distinguishable (0.16–0.27) and either significant or close to significant. There is no evidence of an association between the EA and the exam in Semester 2, 2023 or Semester 1, 2024. In Semester 1, 2023 and Semester 2, 2024, there are significant but weak associations (0.24–0.31).

The following sections will provide further insight into these results as we examine the mean marks and pass rates for each cluster. Although high correlations indicate that EA can be a useful predictor of success (or otherwise) in future assessments, low correlations may indicate that, particularly where EA results are low, the EA can serve as a useful catalyst for intervention on the part of the student, the teaching staff, or both.

Table 3

Spearman Correlations Between the Early Assessment (EA) and the Two Future Assessments (Assignments and Exam)

Semester	Cluster 1		Cluster 2		Cluster 3	
	EA and Assignments	EA and Exam	EA and Assignments	EA and Exam	EA and Assignments	EA and Exam
S1 2023	0.62***	0.5***	0.40***	0.28**	0.20`	0.24*
S2 2023	0.59***	0.58***	0.1	0.11	0.27*	0.11
S1 2024	0.51***	0.35***	0.30***	0.14*	0.16`	0.09
S2 2024	0.51***	0.39***	0.21***	0.17**	0.36***	0.31**

Note. Significance is indicated as follows: `significance at the 0.10 level; *significance at the 0.05 level; **significance at the 0.01 level; ***significance at the 0.001 level. S1 and S2 denote Semester 1 and Semester 2, respectively.

Is There a Difference Between Mean Early Assessment Marks and Future Mean Assessment Marks, and Does This Differ by Student Group and/or Early Assessment Format?

To compare average EA marks with those of future assessments, Figure 2 displays the student marks for each semester for each cluster. As Figure 2 shows, for Cluster 1, student marks tend to decrease from the EA to the future assessments, although less so in 2024 than 2023. For both Clusters 2 and 3, marks tend to decrease from the EA to the future assessments in 2023. However, in 2024, marks tend to either stay the same as the EA or increase in future assessments.

Table 4 shows the mean marks for each assessment type, cluster, and semester, as well as the results of linear mixed effects models. This enables us to determine, for a given cluster in a given semester, whether the mean marks in future assessments are significantly different from the EA. Beginning with the Overall models (i.e., including all three clusters together), there is a significant decrease from the EA to both future assessments in all semesters. The same occurs for Cluster 1 across all semesters. It is worth noting, however, that for both the Overall and Cluster 1 models, the decreases from the EA to future semesters are not as large in 2024 as in 2023. Considering Cluster 2, there are large and significant decreases from the average EA mark to future assessments in both 2023 semesters. However, this changes in 2024. There are significant but small decreases in Semester 1, 2024. In Semester 2, 2024, there is a significant decrease from the mean EA to the assignment mark but no significant difference between the EA and exam mark. Finally, within Cluster 3, we again see significant decreases from the EA to future assessment marks in 2023. However, in Semester 1, 2024, there are no significant changes from EA to future assessment marks. In Semester 2, 2024, there is no significant change from the mean EA to the assignment mark, and there is a significant increase between the EA and exam mark for Cluster 3.

Table 4

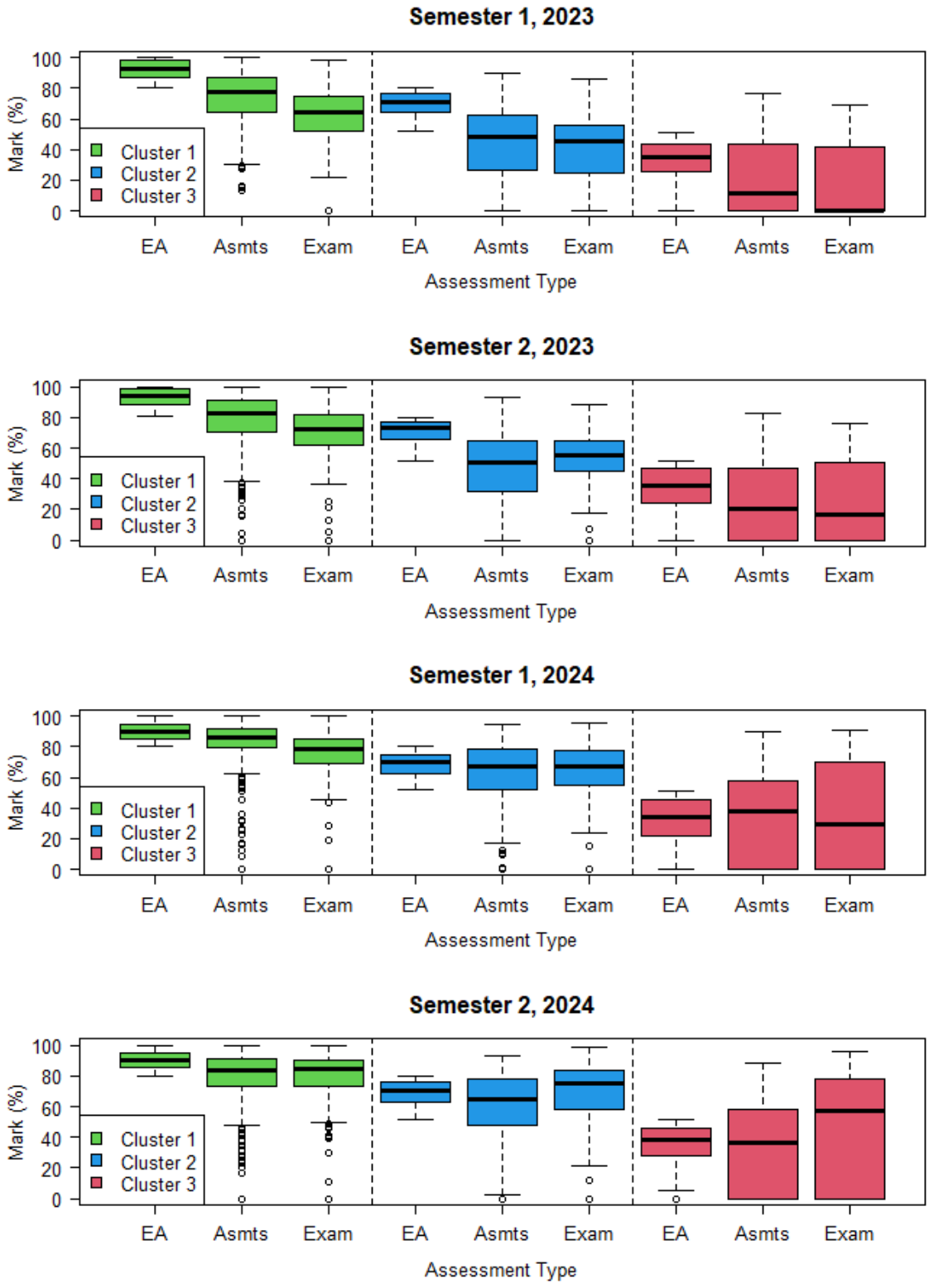
Linear Mixed-Effects Models to Estimate Average Student Marks Across Each Semester

Measure	S1 2023		S2 2023		S1 2024		S2 2024	
	Estimate	***p*-value**	**Estimate**	***p*-value**	**Estimate**	***p*-value**	**Estimate**	***p*-value**
	Overall							
Mean EA	76.2		80.5		71.0		76.1	
Mean Asmt	57.2	< 0.001	63.4	< 0.001	65.3	< 0.001	66.9	< 0.001
Mean Exam	47.6	< 0.001	59.8	< 0.001	62.8	< 0.001	70.3	< 0.001
	Cluster 1							
Mean EA	92.3		93.1		89.8		90.3	
Mean Asmt	74.0	< 0.001	77.0	< 0.001	81.6	< 0.001	79.0	< 0.001
Mean Exam	60.8	< 0.001	70.1	< 0.001	75.6	< 0.001	79.0	< 0.001
	Cluster 2							
Mean EA	69.1		70.2		68.4		69.0	
Mean Asmt	44.7	< 0.001	46.5	< 0.001	62.3	< 0.001	59.8	< 0.001
Mean Exam	37.5	< 0.001	49.9	< 0.001	62.4	< 0.001	**66.8**	**0.149**
	Cluster 3							
Mean EA	33.1		33.7		32.7		35.3	
Mean Asmt	20.4	< 0.001	26.2	0.015	**33.9**	**0.687**	**34.4**	**0.763**
Mean Exam	19.5	< 0.001	25.1	0.006	**33.7**	**0.737**	**42.5**	**0.018**

Note. The estimates are the mean marks for a given assessment, cluster, and semester. The *p*-values indicate whether either the mean assignment (Asmt) or exam mark changed significantly compared to the mean EA mark for a given cluster and semester. Assessments that either did not change significantly, or increased, compared to the EA, are highlighted in bold. S1 and S2 denote Semester 1 and Semester 2, respectively.

Figure 2

Boxplots Displaying the Early Assessment (EA), Assignment (Asmts), and Exam Marks for Each Cluster for Each Semester



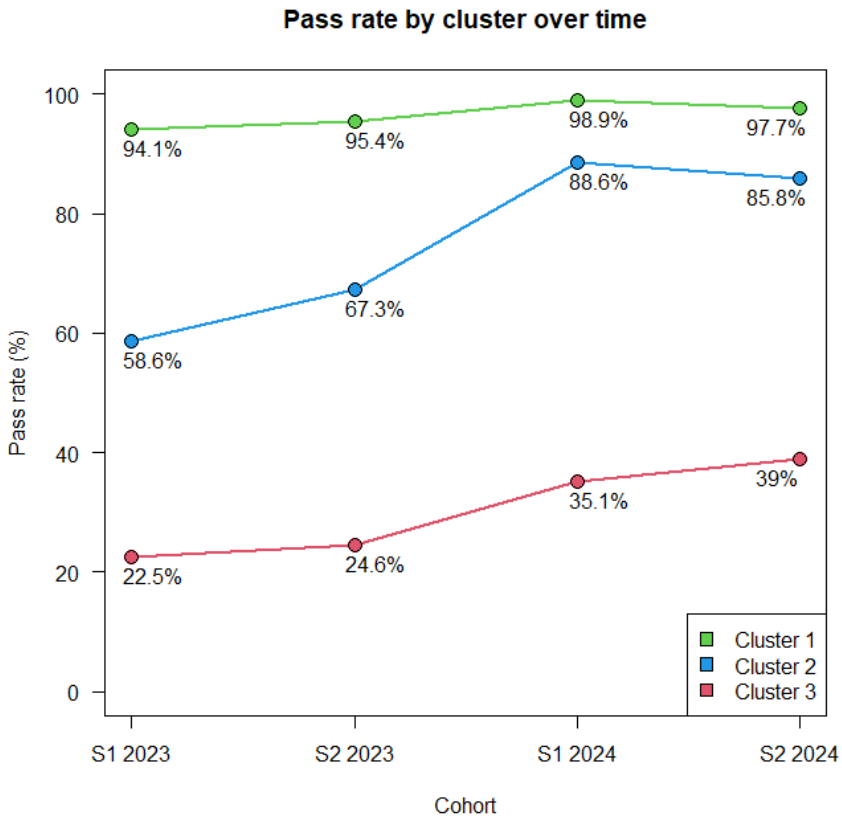
Can Early Assessment Be Used to Predict Future Success in the Subject and/or Be Used for Intervention Purposes, and Does This Differ by Early Assessment Format?

We now consider whether EA can be used to predict future success in the subject or be used for intervention purposes, or both. In considering this, we recall the correlation results from Table 3 but also consider pass rates within each cluster, noting that an overall mark of 50% or higher is required to pass the subject.

Considering Cluster 1 first, although the correlations decrease in 2024, they remain moderately high and, as shown in Figure 3, the pass rate for Cluster 1 is very high in all four semesters. This indicates that most students who achieved high marks in the EA (as indicated by their allocation to Cluster 1), not unexpectedly, passed the subject. As such, for students in Cluster 1, success in EA is a relatively good indicator of future success in the subject. For Cluster 2, Figure 3 shows an obvious increase in the pass rate from Semester 1 to Semester 2, 2023 and then another marked increase in the pass rate from 2023 to both 2024 semesters. This goes some way to explaining the decrease in correlation between EA and future assessments from Semester 1, 2023 to future semesters. That is, in Cluster 2, although the mean EA marks stay relatively the same across all four semesters (68%–70%), student performance in future assessments improves in Semester 2, 2023, and again in both 2024 semesters, such that the overall pass rates also improve. Similar increases in pass rates for Cluster 3 are also evident in Figure 3, although the increases are not as large as for Cluster 2.

Figure 3

Pass Rates for Each Cluster for Each Semester
Note. S1 and S2 denote Semester 1 and Semester 2, respectively.



Given that Figure 3 clearly shows an increase in pass rates from Semester 1, 2023 to future semesters, Table 5 displays the results of logistic regression models used to quantify the increased odds of passing in future semesters as compared with Semester 1, 2023. Considering Cluster 1 first, students are not significantly more likely to pass in Semester 2, 2023 compared with Semester 1, 2023. However, compared with Semester 1, 2023, the odds of students in Cluster 1 passing in Semester 1,

2024 and Semester 2, 2024 increase by 5% (95% CI [2, 8]) and 4% (95% CI [1, 7]), respectively. These small but significant increases may be due to a 'ceiling effect', noting that the pass rate for Cluster 1 is already high in Semester 1, 2023 (94.1%). Considering Cluster 2, the odds of passing increase in Semester 2, 2023, but this is not quite significant ($p = 0.062$). The odds are significantly higher in 2024, however: 35% higher in Semester 1, 2024 (95% CI: 24%–47%) and 31% higher in Semester 2, 2024 (95% CI [21, 42]). Again, for Cluster 3, the increased odds of passing in Semester 2, 2023 are not significant. Semester 1, 2024 saw a close to significant increase in odds of passing (13%, $p = 0.063$), and the increased odds of passing in Semester 2, 2024 are significant (18%, 95% CI [3, 35]).

Table 5

Logistic Regression Models to Estimate the Increased Odds of Passing in Future Semesters Compared With Semester 1, 2023 Within Each Cluster

Term	Odds ratio (95% CI)	*t*-value	*p*-value
	Cluster 1		
Intercept (S1 2023)	2.56 (2.51, 2.62)	85.76	< 0.001
S2 2023	1.01 (0.98, 1.04)	0.88	0.380
S1 2024	1.05 (1.02, 1.08)	3.02	0.003
S2 2024	1.04 (1.01, 1.07)	2.58	0.010
	Cluster 2		
Intercept (S1 2023)	1.80 (1.68, 1.92)	17.10	< 0.001
S2 2023	1.09 (1.00, 1.19)	1.87	0.062
S1 2024	1.35 (1.24, 1.47)	6.99	< 0.001
S2 2024	1.31 (1.21, 1.42)	6.49	< 0.001
	Cluster 3		
Intercept (S1 2023)	1.25 (1.13, 1.39)	4.36	< 0.001
S2 2023	1.02 (0.88, 1.19)	0.28	0.778
S1 2024	1.13 (0.99, 1.29)	1.87	0.063
S2 2024	1.18 (1.03, 1.35)	2.41	0.016

Note. S1 and S2 denote Semester 1 and Semester 2, respectively.

Discussion

Given the above analysis, we may conclude that for students in Cluster 1, EA performance is generally a good predictor of future success in the subject, and that EA format (i.e., comparing between 2023 and 2024) does not have a large impact. For Clusters 2 and 3, EA performance is a less reliable indicator of future success in the subject. For both of these clusters, the increase in pass rates in 2024 indicates that the updated format of the EA may have resulted in it being used for intervention purposes more successfully as compared with 2023. In both years, a significant proportion (22.5%–39%) of at-risk students (Cluster 3) successfully passed the subject, despite achieving marks of 51.4% or less in the EA. In these cases, the EA was a poor predictor of success but served as a useful tool for intervention, resulting in overall success in passing the subject for these students. Moreover, we speculate that the early identification of Cluster 3 (at-risk) students allowed for earlier intervention, which, for many students, was pivotal to their overall success.

These results indicate that EA can be a predictor of future success within a subject but that the reliability of this prediction depends on both student group and the format of the EA. The EA was a very reliable predictor of future success in the subject for students who performed well (i.e., students in Cluster 1, achieving above 80.2% on the EA), with between 94%–99% of these students going on to successfully pass the subject.

EA performance was a less reliable predictor of future success for students in Cluster 2 (EA mark between 51.4% and 80.2%). Correlations between EA and future assessments ranged from no correlation at all to moderately positively correlated. Despite all achieving at least a 'pass' mark on the EA (i.e., above 50%), only 58.6% and 67.3% of students in Cluster 2 went on to pass the subject in Semesters 1 and 2 of 2023, respectively. However, these pass rates increased to 88.6% and 85.8% in Semesters 1 and 2 of 2024, respectively. This increase is associated with a change in the EA format in 2024, whereby the weighting of the EA was increased and essential computer software skills were included in the EA. Additional targeted support was also introduced in 2024 based on EA performance and students' personal reflections on their learning, as discussed previously in the Methods section.

A similar pattern emerged for students in Cluster 3 as compared with Cluster 2. That is, EA performance was a less reliable predictor of future success (correlations ranging from no correlation to weak correlation). Despite most students not achieving a 'pass' mark on the EA (i.e., all EA marks in Cluster 3 were 51.4% or less), 22.5% and 24.6% of students in Cluster 3 went on to pass the subject in Semesters 1 and 2 of 2023, respectively. This pass rate increased to 35.1% and 39% in Semesters 1 and 2 of 2024, respectively. This result indicates that the EA can serve as a useful tool for intervention purposes for both students and staff, and that these interventions became more successful in 2024 and were associated with the change in the EA format. This observation is further supported by the mean marks observed for Cluster 3 in 2024. Whereas, generally speaking, the mean marks of subsequent assessments decreased compared with the EA across clusters and in both years, a noticeable exception was Cluster 3 in 2024, where the mean marks either stayed the same, or significantly increased, as compared with EA marks.

Limitations

A limitation of this study is that, along with the change in EA format between 2023 and 2024, other changes also occurred, including the emergence of readily available generative AI large language model tools (see, e.g., Dunn, 2026; Shaker, 2026). Therefore, although the change in EA format is associated with the observed changes in student performance from 2023–2024 reported in this study, these differences cannot be attributed to the change in EA format alone. Another limitation is that the scope of this study was limited to one subject at one Australian university. While we believe the results are relevant to other contexts and disciplines, further research is also warranted so that results can be further generalised.

Implications for Future Research

Given the low-stakes nature of the quizzes, an interesting question arising from this analysis centres around what impact the provision of multiple quiz attempts has on student performance. In particular, what proportion of students utilise the additional quiz attempt(s), and of those who do, how do their marks on subsequent attempts compare with their first attempt? Since feedback is provided following students' first attempts, regarding correct or incorrect responses and relevant section(s) of the notes to refer back to, analysis of these questions would help us to understand how students benefit from this feedback, if at all. Although these questions are tangential to the focus of the present paper, they represent a potentially fruitful direction for future research and warrant investigation in their own right.

Conclusion

This study has shown that increasing the weight of EA, as well as including the assessment of key software skills in EA, was associated with a significant increase in student success in a large first-year subject, both in terms of overall average marks and pass rates. This supports the theoretical views presented in the introduction of this paper regarding formative and early assessment, for example, that it can assist students in their transition to university and build confidence in preparation for summative assessments later in the semester (Thomas et al., 2019). This study also supports that, similar to formative assessment, EA can assist students to self-regulate their learning (Boud & Molloy, 2013; Nicol & Macfarlane-Dick, 2007), particularly where EA marks are low (Cluster 3) to medium (Cluster 2). We posit that there are three main reasons for the association observed between improved student performance and the changes made to EA in terms of increased weighting and inclusion of software skills. Firstly, as explored and shown in detail in Shaker et al. (2026), students reported an increase in confidence as a result of completing the EAs. While the weighting of the EA was low enough such that each assessment was 'low stakes', it was also high enough such that by the end of Week 5 of the semester, students had already achieved up to 30% of the marks for the subject, thus boosting student confidence. Secondly, including the essential software skills in the EA would have discouraged procrastination in learning this essential skill, a common phenomenon in statistics subjects where statistics anxiety is prevalent, and a reason that regular, low-stakes assessments are recommended (Chew & Dillon, 2014).

Also, as found in Shaker et al. (2026), we observed a significant decrease in student anxiety related to software use, as well as increased engagement with the assignments in 2024, which we believe to have contributed significantly to the increased success rates that year. Finally, the EA provided a clearer mechanism through which to identify at-risk students earlier in the semester, facilitating outreach and intervention, to ultimately improve success rates, for these students.

In conclusion, for high-performing students, EA can be a very reliable predictor of future success. For students who perform moderately or poorly in EA, future success is more difficult to predict. However, our results indicate that EA can successfully be used as a catalyst for intervention by staff, students, or both. Our results also indicate that, particularly for moderately or poorly performing groups, the format of the EA, and targeted outreach based on EA performance, can further support student success amongst these groups. Consequently, we recommend that attention be given to EA format, along with associated tailored outreach strategies. In particular, we recommend increasing the amount and/or weighting of EA where appropriate, along with including the assessment of key skills in EA. We advise the implementation of these strategies, in conjunction with targeted outreach and support based on student performance in early and/or formative assessment, in order to enhance and promote student academic success.

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