Capturing Professional Skill Development: A Curriculum Analytics Approach

Vimukthini Jayalath[*]
vimukthini.jayalath@adelaide.edu.au
Adelaide University
South Australia, Australia

Abhinava Barthakur
abhinava.barthakur@adelaide.edu.au
Adelaide University
South Australia, Australia

Ryan S. Baker
ryan.baker@adelaide.edu.au
Adelaide University
South Australia, Australia

Shane Dawson
shane.dawson@adelaide.edu.au
Adelaide University
South Australia, Australia

Vitomir Kovanović
vitomir.kovanovic@adelaide.edu.au
Adelaide University
South Australia, Australia

Abstract

Higher education faces increasing pressure from governments and employers to ensure graduates are equipped with the knowledge and capabilities required for the future workplace. While technical knowledge is assessed through grades, professional skills are complex and remain difficult to evaluate systematically. While curriculum mapping offers a potential solution, it is often applied in a simplistic, accreditation-driven manner that merely records the presence or absence of skills embedded in assessments. Such an approach overlooks the relative contribution of each skill to the assessments and, hence, cannot be used to estimate skill development. Other noted approaches have relied on the use of self-assessment reports or surveys, and as such are subjective and cannot provide longitudinal evidence of skill development. This study addresses these limitations by proposing a novel curriculum analytics method, weighted Performance Factor Analysis, to model skill scores using assessment grades and granular weighted skill-assessment mapping. Students' development of seven professional skills were examined along with how they transition across an accounting degree program. The findings show distinct patterns and trajectories of skill development. Overall, the study makes a significant methodological contribution to measuring skills and offers insights into how graduates develop their professional skills across the curriculum.

CCS Concepts

• **Applied computing → Learning management systems**.

Keywords

Professional Skills, Curriculum Analytics, Performance factors analysis, Skill-assessment mapping, skill transitions

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[*]Corresponding author.

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1 Introduction

Higher education faces growing pressure from governments, industry partners, and employers to demonstrate that graduates are equipped with the skills, knowledge and capabilities necessary for the future workplace [41]. In particular, employers consistently highlight the value of graduates who can demonstrate both technical knowledge and transferable skills that enable them to adapt and thrive in professional environments [6]. In response, universities have emphasised the need for embedding employability skills within the educational experience and outcomes. University courses and programs are the building blocks for integrating professional capabilities aligned to graduate employability, economic development, and an evolving labour market [41]. Despite the importance of cultivating professional capabilities, questions remain about how such skills are integrated within program curricula, how they develop over time, and how they can be accurately measured at scale.

While there is a clear mandate for mapping and integrating professional skills into university programs, progress has been relatively limited. This is in part, due to how the practice of curriculum mapping is undertaken. Curriculum mapping is labour-intensive, prone to human error [4], and relies on simplistic, binary approaches that focus only on the presence or absence of skills linked to a particular assessment [16]. This approach is commonly used for compliance purposes, rather than documenting more meaningful insights into how students develop and demonstrate achievement of these skills over time [10]. The degree to which each skill actually contributes to the overall assessment remains ambiguous and often ignored [16]. To address these limitations, researchers have experimented with alternate measurement approaches, such as student self-assessments [20] or skill tests [5]. While these approaches have expanded our understanding of how students develop skills, several inherent challenges still remain. For instance, the self-report nature of the methods offers limited reliability and lacks a robust evidence base for understanding or enhancing skill growth. Collectively, these current approaches for curriculum mapping are poorly suited for tracking skill development and progression over time [4].

Recent research in the field of Learning Analytics (LA) [40] and more specifically, Curriculum Analytics (CA) [40], have demonstrated potential for monitoring professional skills objectively and longitudinally [38] using log stream [28, 45] and student assessment data [2]. Barthakur et al. [2] employed an LA approach to track students' skill development across an entire higher education program. Their work demonstrated that scalable methods can be deployed to measure the progression and development of professional skills within university programs. However, their methodology relied on binary curriculum mapping to infer skill progression from assessment grades. As a result, the approach does not effectively capture the more nuanced relationships between the individual skills and specific assessments that were shown to be important for student employability [14]. Moreover, other LA studies have tended to focus on individual skills [44] and do not cover a broad suite of skills that could provide a holistic representation of the student over the duration of their program of study. The establishment of a scalable methodology would provide novel insights into how skill development evolves, bringing a deeper understanding of student employability progress [38].

In this study, we present a CA approach to analyse the development of professional skills across a financial accounting degree program. Building on prior work [2], a novel method is presented, combining curriculum and assessment data to comprehensively monitor skill acquisition through the use of learner profiles [2]. Specifically, we extracted weighted mappings between skills and assessments [16] and fit an extension of the traditional Performance Factor Analysis (PFA) to model students' development of seven professional skills across the entire program. Monitoring the skill progression patterns provides valuable insights into how students develop professional skills throughout the degree program, highlighting the skills that students bring into the workforce. Therefore, the study makes a methodological contribution by introducing a novel CA (weighted PFA) approach to obtain skills scores for professional skills, and a theoretical contribution by revealing how graduates develop specific professional skills within a degree, an area that has remained largely unexplored within LA.

2 BACKGROUND

2.1 Professional skills and Graduate Employability

Professional skills commonly refer to the competencies that individuals acquire through education, training, and experience, to enable them to perform effectively in their future employment [42]. Similar terms have been used in the literature, such as 21st century skills, graduate attributes, competencies, qualities, transferable skills, and soft skills [41]. These skills also encompass a broad range of attributes, including technical expertise, analytical thinking, communication proficiency, teamwork, and leadership capabilities. For this study, "professional skills" is used to encompass a range of non-technical skills, including self-management, problem-solving, teamwork, oral/written communication, ethical awareness, and international perspective [16].

Graduate employability has become a major key performance metric for contemporary higher education. In part, this has driven a shift in attention from supporting and evaluating content knowledge towards capturing the professional skills students develop over the duration of their study [17]. Unlike course grades that provide a direct and accepted representation of students' academic achievement on disciplinary content, there is no standardised method or process for measuring and representing the professional skills students acquire [14]. The measurement of professional skills has tended to rely on approaches, such as skill tests [5] and surveys including self-assessments [20, 25] and assessments by peers [26]. However, these methods are subjective, susceptible to self-referential and response biases [16], lacks scalability [36] and may be intrusive, potentially disrupting the learning process [3]. As a result, the measurement of skill development critical for employability has had limited uptake.

In the domain of financial accounting, where the present study is situated, the need to realign education with professional practice has been widely supported [22]. This realignment focuses on integrating core disciplinary knowledge with non-technical skills such as communication, teamwork, and problem-solving into curricula. These professional skills are seen as foundational for future accountants [29]. While research in accounting education has explored the skills required for employability, they have been restricted to a focus on the first year of study [32] or only on individual courses [23] rather than considering the curriculum of the program as a whole. Furthermore, this research has relied on the use of student and staff surveys and interviews [1, 12]. While this brings solid understanding into student development of professional skills, the studies lack generalizability and scalability. Alternatively, scalable approaches exist using LA, such as Cognitive Diagnostic Models (CDMs). However, these studies have concentrated on domain-specific competencies such as interpreting financial statements and analysing performance indicators in accounting, rather than more cross-cutting professional skills such as communication and teamwork [11]. These professional skills are needed as graduates pursue varied roles in accounting, ranging from leadership and client-facing positions [13, 24] to consultancy, and collaborative team-based contexts [21, 31]. To overcome these limitations, this study analyses the full program to assess skill development.

2.2 Curriculum Mapping of Professional Skills

Curriculum mapping is a systematic approach to address the challenges linked to measuring professional skills. It seeks to make explicit where and how specific skills are taught and assessed across a program, thereby providing a structured overview of how professional skills are embedded within the curriculum [15]. Most universities rely on academic staff to evaluate graduates' acquisition of these skills by manually mapping the assessment items to specific skills [10]. While these mappings are predominantly undertaken to meet accreditation and compliance requirements, it can be a time-consuming and labour-intensive process, prone to human error and bias [16]. However, there are gains to be made. For instance, by mapping assessments to the skills they evaluate does provide an opportunity to analyse students' development of professional skills using curriculum and assessment data [16]. In so doing, educators can gain an understanding of how skill development progresses across a wide range of learners and where further support interventions are needed [45]. Unfortunately, most mappings establish only a primary association (a binary mapping) between course assessments and skills, lacking granularity in representing the strength or degree of this relationship. For example, an assessment requiring students to produce an analytical report may necessitate them to exhibit critical thinking and communication skills. While these skills often contribute unevenly to the assessment's objectives, they are treated as equally represented within a binary mapping framework. Such an approach fails to capture the contributions of various skills to student development and eventual graduation, thus limiting the comprehensiveness of skill measurement within the curriculum.

2.3 Learning Analytics approaches for skill modelling

Within higher education, the shift toward skill-based profiling represents a critical step in aligning academic programs with the complex demands of the modern workforce. Several studies have examined the development of professional skills [8, 43], but have mostly focused on a single skill or a single course within a program of study. This clearly limits the generalisability of these findings to bring insights into student skill progression and acquisition. However, recent advancements in CA have introduced novel methods to evaluate latent attributes, incorporating student and curriculum attributes as parameters, which can be more rapidly applied at greater scale. These methods can be used to measure and evaluate skill development, where the skills can be considered latent constructs in the models [7]. For example, Barthakur et al. [4] used Cognitive Diagnostic Models (CDMs) [7] to assess and track the development of graduate attributes and examine different stages in the skill progression through learner profiles. While their study demonstrated the progression of skills, the CDM approach relied on a binary skill-assessment mapping and did not account for the varying degrees to which each assessment contributes to different skills. Similarly, Learning Factors Analysis (LFA), previously used to discover skills within finer-grained learning activity data [19], estimates how student performance improves with practice but ignores differences between correct and incorrect responses and assumes homogeneous learning across students. While these models provide valuable foundations for understanding student learning and diagnostic profiling, their constraints hinder the capacity to model the full complexity of professional skill acquisition.

One particular approach that tries to provide more nuanced modelling than CDMs is Performance Factors Analysis (PFA) [34]. It is a knowledge-tracing model derived from LFA that accounts for the effects of prior successes and failures on subsequent performance and has shown promise for understanding skill acquisition from assessments. Prior work has shown that PFA often outperforms other Knowledge Tracing models, even complex and sophisticated models based on neural networks [9]. PFA is effective in contexts with limited amounts of data [9], where students' progress on skills needs to be monitored continuously, and where evidence of learning is inconsistent over time, such as repeated errors followed by improvement. By explicitly considering both correct and incorrect prior practice, PFA has the potential to produce a multi-item model that retains LFA's strengths for data mining. More recent work has extended PFA in a variety of ways, including incorporating attention mechanisms and additional item-level data [27], and explicitly modelling memory decay [33]. However, these approaches have not considered the case where an assessment is more informative about some skills over others.

The present study introduces a novel weighted PFA approach that maps between skills and assessments in a more complex way, weighing the involvement of each skill within each assessment. This adds flexibility in how information is used, moving away from an "all or nothing" use of a skill within an assessment. We then use this more flexible version of PFA, weighted PFA, to identify distinct learner profiles and study students' skill development over time. While PFA is established in learning analytics, its application to curriculum-level professional-skills assessment is novel.

3 RESEARCH QUESTIONS

While existing studies have explored skill profiling in higher education [2, 45], there has been limited attention given to systematically examining how professional skills are developed in a program [2]. It is important to examine the extent to which each assessment contributes to the development of specific skills, rather than merely assuming their presence or absence. In this regard, the weighted curriculum mapping of assessments to skills provides a valuable approach for highlighting the relative emphasis placed on various skills and understanding how this shapes professional skill development. This preliminary study explores this gap by answering the following research questions.

RQ1: How can the weighted Performance Factors Analysis (wPFA) model, combined with skill–assessment mappings, be used to measure students' development of professional skills within a degree program?

The first research question aims to examine how professional skill development can be measured using CA models. Specifically, how an extension of the traditional Performance Factors Analysis [34] can be adapted to estimate skill scores for professional skills from assessment grades and weighted skill–assessment mapping? Through this question, we aim to build on prior research that has shown the viability of LA methods to measure professional skills [2], and expand the methodology to include granular weighted skill–assessment mapping to better understand the unique characteristics of skill acquisition in a higher education program.

RQ2: What distinct learner knowledge profiles can be identified based on skill development in a degree program?

The second research question focuses on identifying distinct learner profiles among undergraduates in an accounting degree program for each year of their study. By clustering skill scores derived from the weighted PFA model, RQ2 aims to explore patterns in how professional skills are distributed across the cohort, highlighting the opportunities to personalize instruction and student support. Understanding these profiles can help to inform about their possible real-life accounting roles and also inform curriculum/assessment design to support balanced skill growth.

RQ3: How do learners transition between different profiles as they progress in their degree program?

Table 1: Number of assessments related to each skill across three years.

Skill	Year 1	Year 2	Year 3	Total
Problem-Solving	18	14	9	41
Teamwork	3	1	1	5
Written Communication	15	7	8	30
Self-Management	2	0	5	7
Ethical Awareness	5	6	3	14
International Perspective	4	3	2	9
Oral Communication	2	3	3	8

Through RQ3, we hope to investigate how learners transition between different profiles as they progress across their degree program. While RQ2 identified distinct profiles of the learners each year, RQ3 shifts the focus to examining these transition patterns to provide insights into the longitudinal developmental trajectories of professional skills, helping to understand the pathways of skill development.

4 METHODOLOGY

4.1 Study context

The study was conducted at a large public Australian university, focusing on the Bachelor of Commerce (Accounting) program and its associated courses. Ethical approval for this study was obtained from the university from which the data were collected and analysed. The analysis focused on developing the skill scores for Enterprise Skills in the Business School. The seven Enterprise skills defined by the university are as follows: 1) Self-management, 2) Problem-solving, 3) Teamwork, 4) Ethical awareness, 5) Written Communication, 6) Oral Communication, and 7) International perspective. The anonymised assessment grades for all learners who started the three-year accounting program in 2018 and 2019 were collected. The assessment grades from 50 assessments of 20 compulsory courses (a minimum of two per course) associated with this degree were considered for the analysis. Additionally, repeated assessments were included in the analysis as they did not involve identical items. Also, only five of 219 students repeated equivalent tasks, limiting any potential bias. The summary of the number of assessments linked to the seven skills [16] across the three years of the program is provided in Table 1.

The weighted skill-assessment mapping (Table 2) was obtained by analysing curriculum data, including course outline, assessment description (see online supplementary materials) and initial mapping provided by the department, for all the courses in the program [16]. Two human coders independently annotated the curriculum data, achieving a Krippendorff's α of 0.70, and finalised the weighted mapping through consensus discussion. Each assessment was mapped to one or more skills, with weights adding up to 100 per assessment. Table 2 includes an example of such weighted skill-assessment mapping. This distribution of weights provides a more nuanced understanding of how each skill contributes to an assessment compared to binary mapping (indicating merely the presence or absence of skills), allowing for more accurate and fine-grained modelling of students' skill development over study programs.

Table 2: Example of weighted skill–assessment mapping.

Course ID	Assessment	PS	TW	WC	SM	EA	IP	OC
10704	Continuous Assessment	30	20	20	0	0	0	30
10704	Examination	60	0	40	0	0	0	0
105460	Assignment	10	0	80	10	0	0	0
101178	Case Study Reports	80	0	20	0	0	0	0

4.2 Data analysis

For this study, the inputs for the analysis were the mappings between assessments and skills (Table 2), along with learners' assessment grades. Using the weighted PFA model, the outputs were skill-level mastery probabilities and overall mastery estimates per assessment. The skill level mastery probabilities were then used for the second phase of the analysis (clustering analysis) to obtain learner profiles. The analysis was implemented in Python for multi-skill weighted PFA for skill score estimation and clustering.

4.2.1 Weighted PFA Model Formulation. Prior to the analysis, the student grades were mapped to a 0–1 scale. An ordinal time variable was created by using the term data (year-term) to track learners' progress longitudinally. Skill–assessment mappings were preprocessed to a format where each row corresponds to a student skill–assessment instance, with an associated skill weighting. For each assessment (i), Successes (S_i) were computed as the scaled grade, while failures(F_i) were computed as $1 - \text{grade}$. Cumulative successes (CS_i) and failures (CF_i) were calculated by summing all prior observations for the same student–skill pair, excluding the current assessment.

In both PFA's standard form and our extension, m is a value representing the accumulated learning for student i for one or more skills j [34]. A skill's difficulty is captured by the β parameter, and the improvement associated with prior practice for each item (assessment) is a function of the n prior observations for student i with skill j. s tracks the prior successes for the skill for the student,f tracks the prior failures for the skill for the student,and γ and ρ scale the effect of these observation counts(the grades in the context of this study).Then the logistic function is used to convert m values to predictions of the probability of correctness. The PFA model can be used for observations requiring multiple skills by summing the βs and γ and ρ frequency components for all j skills needed.

A weighted extension of the PFA model was introduced in this study to obtain skill estimates when the assessment to skill mapping is non-binary (e.g. in the instance when some skills are more important within an assessment than others). For each skill k, three parameters were estimated:

- β: baseline difficulty/ease
- γ_k: learning rate related to prior successes
- ρ_k: learning rate related to prior failures
- $w_{i,k}$: weight for each skill k in assessment i (given by the assessment–skill mapping)
- CS_i, CF_i: cumulative successes and failures

To predict the performance of a student on a given assessment, the student's degree of mastery is first estimated for each of the relevant skills individually (inside the parentheses). Then the formula sums across each of the skills. Different than classic PFA, each skill is weighed separately for each item. This weighted extension of PFA allows more granularity than binary correctness and captures the differential contribution of each assessment to skills.

$$\text{MasteryScore}_{i,k} = \beta_k + \sum_{i=0}^{n} \left(\gamma_k \cdot w_{i,k} \cdot CS_i + \rho_k \cdot w_{i,k} \cdot CF_i \right) \tag{1}$$

The estimated student grade on the assessment (which would be a probability of correctness if the grades were binary) is then obtained via a sigmoid transformation for Performance Prediction.

$$M_{i,k} = \frac{1}{1 + e^{-\text{MasteryScore}_{i,k}}} \tag{2}$$

Model parameters (β_k, γ_k, ρ_k) were estimated using L-BFGS-B optimisation, which minimises the mean squared error (MSE) between predicted probabilities and observed student grades. Bounds (-5 to $+5$) were set for each parameter to ensure numerical stability. After optimisation, the estimated parameters were used to compute both mastery scores and the probability of success for a student on an assessment, based on their learning history of skills. In the next section, we use the final Performance Prediction ($M_{i,k}$) scores obtained during the last assessment of each of the three years to develop learner profiles, as these final measures contain the information of skill progression.

4.2.2 Learner Profile Clustering. To address RQ2, we conducted a clustering analysis for each year based on the skill scores derived from the PFA analysis. The analysis was restricted to learners who completed the degree within the standard three-year timeframe, comprising 219 students overall. As a result, each student was assigned a cluster for each year to identify the skill profile. To ensure comparability, the mastery scores were scaled within each skill to avoid over-weighting based on different variable scales. These scaled values were then used for clustering. Skill mastery scores were selected as features (EA, IP, OC, PS, SM, TW, WC), and K-Means clustering was conducted using sklearn.cluster. KMeans (from scikit-learn) in Python. Two methods were used to determine the optimal number of clusters: the Elbow method (which focuses on the within-cluster sum of squares) and Average silhouette width; the final selection of the number of clusters was made based on qualitative interpretation of the clusters. Based on this analysis, four clusters were chosen. Cluster membership was linked with average skill scores at both the skill and cluster levels to visualise how mastery in specific skills within each cluster is distributed, to identify characteristics of student learning, and to understand how skills develop during the program.

4.2.3 Transition Analysis. Finally, to address RQ3, we adopted a similar approach to that of Barthakur et al. [2] to explore how learners progressed through the degree program by tracing their trajectories of learner profiles across the three years of study. We aimed to capture whether students remained in the same profile or shifted between different profiles as they advanced, and whether there were some characteristic pathways. To visualise these transitions, we used a Sankey diagram implemented in Python, which allowed us to clearly represent the flow of learners between profiles across successive years. Additionally, we applied Chi-square tests to statistically assess whether the observed changes from one year to the next provided evidence of meaningful developmental patterns.

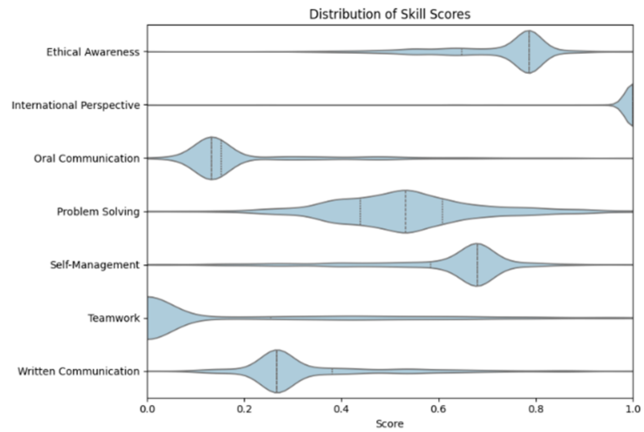

Figure 1: Overall distribution of scores

5 RESULTS

5.1 RQ1: Using weighted mapping to measure skill mastery scores

To address RQ1, we examined the results of the weighted PFA model, introduced in section 4.2.1, that provided the probability for each skill associated with each assessment as the learners go through the three years of the accounting program. When the Performance Prediction output was compared with learners' grades, the model achieved an RMSE of 0.21 and a Pearson correlation of 0.43, indicating that the aggregated scores alone do not provide sufficient information to accurately predict student grades.

The distribution of scores across the cohort for seven professional skills (Figure 1) indicates consistently high scores for International Perspective and Self-Management, suggesting that learners generally developed these skills. In contrast, teamwork and oral communication showed variability, with many learners demonstrating very low mastery, indicating uneven development in collaborative and communication skills. Ethical awareness, written communication, and problem-solving have moderate distributions, with most learners achieving mid-range scores. However, this may also reflect the limited number of assessments mapped to skills such as international perspective, ethical awareness and teamwork, which can inflate/deflate overall scores.

5.2 RQ2: Skill profile development

In this section, we present the findings of the clustering analysis. To determine the optimal number of clusters, we did a clustering analysis with clusters from 3 to 6, as done in a previous study [4]. We used the elbow method and the average silhouette width to determine the optimal clustering solution. Using these metrics, we concluded that the four-clustering solution best represents the data.

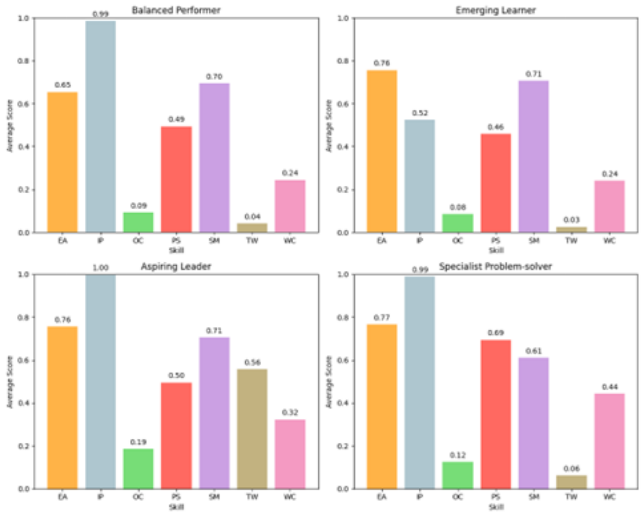

Figure 2: Average skill scores for the learner profiles

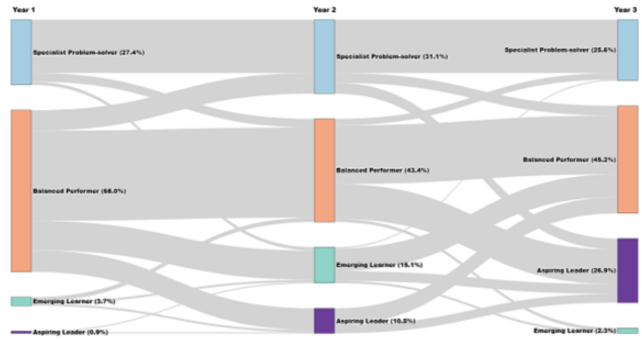

Figure 3: Profile Transitions

Figure 2 shows the variations in skill development among learners across the seven enterprise skills. The clustering quality statistics (Interia: 40.14 and Silhouette width: 0.32) suggested a four-cluster solution as optimal for capturing distinct learner profiles within the cohort. In the cluster analysis, the clusters were labelled to aid the interpretation as follows:

- `Balanced Performer`: This cluster has average scores similar to other clusters in WC, SM, PS, and OC, with a better understanding of IP compared to Emerging Learners.
- `Emerging Learner`: This cluster shows no dominant skill when compared to other clusters; learners in this group can be considered emerging within the cohort.
- `Aspiring Leader`: Learners in this cluster demonstrated exceptional TW skills along with strong OC and WC, representing more advanced skill development across the cohort.
- `Specialist Problem-solver`: Learners in this cluster exhibited strong development in PS and very low levels of TW, suggesting a profile that prioritises independent problem-solving skills, while other skills are comparable to the remaining clusters.

These clusters highlight the different ways in which learners acquire the seven enterprise skills, providing insights into anticipated accounting roles that align with their profiles.

5.3 RQ3: Transitions of profiles across the entire program

Figure 3 presents the progression of students' developmental profiles across three years of study. In Year 1, most students were classified as Balanced Performers (68.0%) or Specialist Problem-solvers (27.4%), with only small proportions identified as Emerging Learners (3.7%) and Aspiring Leaders (0.9%). By Year 2, the share of Balanced Performers declined to 43.4%, accompanied by notable growth in both the Emerging Learner (15.1%) and Aspiring Leader (10.5%) categories, while Specialist Problem-solvers increased slightly (31.1%). In the final year, the distribution shifted again: Balanced Performers (45.2%) and Specialist Problem-solvers (25.6%) remained substantial, but the Aspiring Leader profile expanded to 26.9%, emerging as a key outcome by graduation. Meanwhile, Emerging Learners reduced to 2.3%, indicating that most students advanced into more developed profiles over time.

Table 3 presents the yearly cluster transitions for the same students based on their learner profiles. Student #1020217365 began as a Balanced Performer in the first year but experienced a decline in performance, being classified as an Emerging Learner in both the second and third years. Student #1510217343 similarly demonstrated fluctuation in skill development, transitioning from Balanced Performer in the first year to Emerging Learner in the second year, before returning to Balanced Performer in the third year. This high-level cluster view provides instructors with an accessible overview of individual learners' trajectories, highlighting periods of strength and challenge. At the cohort level, these cluster transitions also reveal broader patterns of change across the program.

To determine whether the shifts in students' learner profiles across consecutive years were significant, a Chi-square test was conducted. There were statistically significant changes between the students in student cluster assignments between years 1 and 2, as well as between years 2 and 3 (Table 4). These findings align with the transition plot in Figure 5, which illustrates that many students moved into a relatively better profile from what they started before graduation. Overall, Practical achiever and Specialist problem solver initial profiles largely retained the profile they had established from the start, whereas the Emerging Learner and Leader profiles had the most substantial changes.

Table 3: Transition of profiles for two students

Student ID	Year 1	Year 2	Year 3
1020217365	Balanced Performer	Emerging Learner	Emerging Learner
1510217343	Balanced Performer	Emerging Learner	Balanced Performer

Table 4: Chi-square comparison of skill clusters

Comparison	Chi-sq	df	p-value
Course year 1 – Course year 2	45.33	3	0.000
Course year 2 – Course year 3	37.68	3	0.000

6 DISCUSSION

This study aimed to address persistent challenges in evaluating professional skill development within higher education programs. Traditional methods involving curriculum mapping and self-assessment surveys are limited by their subjectivity, lack of granularity, and inability to track skill progression over time. To address these limitations, we introduced a novel CA approach that integrates a weighted extension of PFA with detailed skill-assessment mappings. This approach allowed us to estimate skill mastery across multiple competencies and trace students' development over the course of an academic program. Through this method, we explored how students in an undergraduate accounting program acquired seven professional skills, identified distinct learner profiles based on their skill development, and analysed how these profiles evolved. The study makes a methodological contribution by advancing a scalable and fine-grained model for measuring complex skills as well as raising more actionable and timely insights into curriculum design and employability-focused education.

6.1 RQ1: Weighted PFA for measuring professional skills

This study introduces a weighted PFA, which allows for non-binary, proportional mappings between assessments and skills. While the weighted PFA model provided new insights into learners' skill development, the performance metrics suggest that its predictive accuracy is moderate. The RMSE of 0.21 and the Pearson correlation of 0.43 indicate that the aggregated mastery scores do not fully align with student grades. It is not yet clear what level of success might be expected in a case like this, where any assessment represents a complex collection of tasks that cut across multiple skills – considerable information is collapsed into a single grade, much more than in the finer-grained tasks where knowledge tracing is more often applied. The differences in measurement scope and granularity highlight why direct alignment between mastery scores and grades can be challenging. For skill measurement in practice, this suggests that mastery scores' primary value may not be as predictors of grades but instead as complementary indicators that capture dimensions of learning not visible in final marks [30]. It is worth noting that this has been the historical use of another knowledge tracing approach, Bayesian Knowledge Tracing, which has had relatively poor performance compared to more recent algorithms [9], but has been highly useful for reporting to teachers and for driving mastery learning [35]. While grades provide a snapshot of performance at a single point in time, mastery models reflect ongoing development, including partial learning and the role of encountering the same skill in different courses. Predictive performance may also have been reduced by factors such as uneven skill–assessment mappings, the varying emphasis placed on different skills across courses, and the relatively small number of assessments linked to certain professional skills. Addressing these issues through more regular coverage of skills across the curriculum would improve assessment reliability and also support students' steady development of professional skills.

6.2 RQ2: Evaluating learner profiles of skill development

Addressing RQ2, our findings align with an existing LA research that reported variability in students' development of skills [2]. Examining the skill scores, we identified four distinct profiles in the accounting program. The first profile we refer to as "the learners" is associated with the Aspiring Leader cluster, which is very similar to the Well-rounded profile identified in the study by Barthakur et al. [3]. The characteristics of this grouping showed high mastery in both technical expertise and interpersonal skills, which are commonly linked to leadership positions or client-facing accounting roles [14, 25]. The second profile is the Specialist Problem-Solver and is similar to the diligent learner group reported in a similar study [41]. This group included learners who are generally systematic and demonstrate strong technical capabilities [41]. They thrive in solving problems but have lower capabilities in teamwork, indicating their suitability for roles such as auditors, analysts, or consultants, where independent analytical capabilities and deep dive work are needed [32]. The third profile, referred to as the Emerging Learner, encompasses learners who are somewhat value-driven and resemble the Moral Advocates group [41]. This cluster of students presented lower overall skill mastery compared to other profiles and may be better suited for supportive roles where tasks are more routine and supervision is available, as this presents the general idea of variability in skill mastery among graduates [21]. Finally, the fourth profile is the Balanced Performer. This profile represented learners with higher-than-Emerging Learner skills, positioning them well for operational roles in accounting, such as accounting teams or consultancy work [31]. The findings highlight the variation in how the development of professional skills manifests across a diverse cohort of learners. The resulting profiles were discussed with program directors for quality-assurance purposes, confirming their interpretive value. This raises the need for more personalised interventions that serve to strengthen skills such as teamwork and communication, preparing graduates for advanced careers in accounting. The analyses from this study show that while the present accounting program successfully develops the core professional skills for the majority of learners, there remains some variability. These results can better inform future curriculum changes and support practices to ensure that all students are well-equipped with the professional skills required for their chosen professional career.

6.3 RQ3: Longitudinal analysis of profile transitions

This study highlights how the identified learner profiles can be applied to track students' progression to explore the diverse trajectories they followed in developing professional skills (RQ3). The visualisations in Figure 3 and Table 3 reinforce that skill development does not follow a steady path but fluctuates over time [37]. These insights are especially valuable for course instructors and program coordinators, who can access progress information at varying levels of detail, whether at the cohort level (Figure 3) or through individual learner profiles (Table 3). These findings align with prior work on learner profiling [2], which has shown promise for capturing the distinct pathways learners adopt in their learning journey. For instance, the number of learners within the Aspiring Leader profile exhibited a progressive increase throughout the duration of the program. This trend suggests a developmental trajectory, indicating that learners were progressively acquiring both technical competencies and interpersonal skills crucial for effective workforce integration. Conversely, the Specialist Performers profile remained relatively stable and exhibited fewer transitions, implying they may have distinct career aspirations. These findings underscore the importance of tailoring support strategies to meet the specific needs of different learner groups, contingent upon their individual progression and goals [3]. Additionally, integrating a granular mastery-based profile of skill development could help inform curriculum design, ensuring that opportunities for skill development are systematically embedded across programs [17]. Taken together, these findings emphasise that skill development is a dynamic process that requires guidance to ensure students are fully prepared with the skills and competencies needed for their professional careers [2, 37].

6.4 Limitations

While these findings offer valuable insights into learner profiles, the study focused only on one accounting program at a single institution, limiting the generalizability of the results. It could be extended by analysing multiple programs and disciplines, which would allow comparison of learner profiles across different educational contexts. Also, due to imbalances in the number of assessments linked to each skill, some skill scores (such as teamwork or international perspective) can be under-/over-represented in profiling compared to more frequently assessed skills (problem-solving or written communication). These constraints highlight the need for more systematic, scalable, and automated approaches to skill–assessment mapping in future research.

7 CONCLUSION

There is growing interest in using curriculum analytics (CA) to measure professional skills. Recent initiatives have explored the use of data-driven solutions to improve the measurement and evaluation of professional skills in complex and multidisciplinary contexts [18, 39]. This study presents a method to capture how professional skills are embedded across an accounting degree program using assessment-skill mapping and the weighted extension of the Performance Factors Analysis model. The findings provide insights into how uneven opportunities for skill development led to highly variable outcomes. Four distinct skill-based learner profiles were identified, highlighting different pathways of skill development and their alignment with potential professional roles. The study presents several implications for curriculum improvement and skill development. First, curriculum designers and educators can use these insights to strengthen underrepresented skills by embedding them more systematically across assessments, to ensure balanced exposure to skill development. By embedding these skills more systematically across assessments, programs can ensure that students receive balanced opportunities to develop the full range of professional competencies. This addresses a common issue in accounting curricula, where certain skills (e.g., teamwork) may be underemphasised compared to other skills. Second, the learner profiles offer a foundation for aligning professional skill sets with industry expectations [29]. Different profiles highlight diverse trajectories that students follow in skill development. This opens opportunities for targeted interventions, such as supplemental workshops for students with weaker communication or enhanced teamwork experiences for those lacking collaborative competencies [31]. Additionally, students with distinct career aspirations can be provided with more targeted interventions that help them become professional experts in the domain of their liking. Finally, the comprehensive representation of students' academic success within the LA literature is at best limited to a single course and at worst, completely missing [3]. This study provides a novel CA approach to measuring and representing learners' skill development across an entire higher education program.

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