Evolutionary Clustering of Apprentices' Behavior in Online Learning Journals for Vocational Education

Paola Mejia, Mirko Marras, Christian Giang, Alberto Cattaneo and Tanja Käser

***Abstract*—Learning journals are increasingly used in vocational education to foster self-regulated learning and reflective learning practices. However, for many apprentices, documenting their working experiences is a difficult task. Thus, providing personalized guidance could improve their learning experience. In this paper, we profile apprentices' evolving learning behavior in an online learning journal throughout their apprenticeship. We propose a novel multi-step clustering pipeline based on a pedagogical framework. The goal is to integrate different learning dimensions into a combined profile that captures changes in learning patterns over time. Specifically, the profiles are described in terms of help-seeking, consistency, regularity, effort, and quality of the activities performed in the learning journal. Our results on two populations of chef apprentices interacting with an online learning journal demonstrate that the proposed pipeline yields interpretable profiles that can be related to academic performance. The obtained profiles can be used as a basis for personalized interventions, with the ultimate goal of improving the apprentices' learning experience.**

***Index Terms*—Vocational education, workplace learning technologies, learner profiles, time series analysis, evolutionary clustering, longitudinal study**

I. Introduction

THE increasing digitization has been drastically changing the way we live and work. The workforce is being challenged to continuously adapt to the evolving working environments, roles, and tasks. Consequently, Vocational Education and Training (VET) systems must prepare the future workforce to become lifelong learners who can adapt their competencies to the changing demands. Lifelong learners must have the ability to self-regulate their learning process and to reflect on their learning experiences and activities [1].

Learning journals have the potential to foster self-regulated learning (SRL) and reflective learning practices [2], [3] and are consequently increasingly adopted in VET [1]. Typically, apprentices use the learning journals to take notes on the tasks and the skills acquired during their workplace experiences [4]. In addition, the journals can also help apprentices connect the theoretical knowledge learned in the vocational schools to the practical situations experienced in the workplace [5], [6].

The use of learning journals is, however, not effective *per se* [7], [1]. Independently documenting learning experiences is a challenging task for many learners [8], [9], [10]. Thus, providing *personalized* guidance has the potential to improve the learning processes. Profiling learners allows us to identify groups with similar patterns of SRL behaviors, building a basis for targeted interventions. Unfortunately, previous work on learning journals has mainly focused on their effectiveness rather than analyzing and identifying profiles (e.g., [11], [12])).

In contrast, there exists an extensive body of work on profiling learners through clustering in a range of digital learning environments and settings (e.g., massive open online courses (MOOCs) [13], intelligent tutoring systems [14], and flipped classroom courses [15]). Nevertheless, there are some limitations regarding the potential use of the suggested techniques for learner profiling in online learning journals in the context of VET. Firstly, most of the prior research on profile identification focuses on clustering learning behavior for only one period (e.g., the duration of a MOOC [16], one semester of a course [17]), and only a few works consider the evolution of clusters over time (e.g., learner sessions with an intelligent tutoring system [14]). Secondly, within a period, the use of aggregated features [18] is more common than treating interactions (e.g., within a session) as time series [19], [20]. Lastly, in the context of SRL, prior work has primarily focused on only one dimension of self-regulation (e.g., consistency [19], regularity [13]). This practice does not consider possible inter-dependencies across learning dimensions [21].

In this paper, we profile apprentices' SRL behavior in an online learning journal throughout their apprenticeship. We propose a novel multi-step clustering pipeline that is based on a pedagogical framework of SRL in formal education and workplace contexts. The pipeline consists of two clustering steps. In the first step, we cluster the apprentices separately for important dimensions of SRL. We transform apprentices' log data into time series, enabling us to retrieve the shape of behavioral patterns over time (e.g., increasing engagement towards the end of a semester). In the second step, we perform another level of clustering based on the cluster labels of the individual dimensions to obtain multi-dimensional learner profiles. The proposed pipeline features several important advantages: 1) in contrast to prior work, we combine time series modeling (e.g., [15], [20], [22], [23]) and evolutionary clustering (e.g., [24], [14]), enabling us to capture complex temporal patterns over a semester and analyze profile evolution throughout the apprenticeship; 2) by integrating single dimensions of SRL into multi-dimensional profiles, we can represent dependencies across dimensions, leading to a more realistic learning model; 3) the proposed pipeline is *transferable*, i.e. it can be applied to other learning environments by adapting

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the features describing the different learning dimensions.

We apply our pipeline to data from two independent populations of chef apprentices from different vocational schools. Both populations interacted with an online learning journal over their three-year apprenticeship. With our analyses, we address four research questions: Can we identify interpretable profiles of apprentices integrating different behaviors, and are these profiles related to academic performance (**RQ1**)? How do these profiles evolve throughout the apprenticeship (**RQ2**)? What type of behavioral patterns (in terms of effort, quality, consistency, help-seeking behavior, and regularity) can we observe during a semester (**RQ3**)? How do the emerging learner profiles compare across vocational schools (**RQ4**)?

Our results show that we can identify both interpretable apprentice profiles and interpretable patterns for specific aspects of SRL. We further observe some significant differences in academic performance between the profiles. While apprentices move between profiles throughout their apprenticeship, they tend to move to similar profiles between two consecutive semesters. Finally, only a subset of the obtained profiles is shared between the two populations. The profiles identified through our pipeline, therefore, contribute to the teachers' and in-company trainers' understanding of the different apprentices' SRL behaviors and build the basis for targeted interventions. Furthermore, our findings confirm the diversity of learning patterns across apprentices and the importance of the context (i.e., the community of practice of the apprentice).

II. Related Work

A. Learning Journals in VET

Learning journals (also called learning diaries or portfolios) collect learners' work or evidence of work accompanied by reflective comments. These journals have the potential to foster SRL and reflective learning practices [2]. Consequently, learning journals are increasingly used in VET. They may support apprentices in connecting theoretical and practical knowledge [5], [6], acting as boundary-crossing objects [4], [25], or in providing a shared space that allows apprentices to collect and reflect on experiences from different VET contexts (i.e., vocational school, company, and inter-company courses). However, according to the 'Erfahrraum' model [6], reflection is not spontaneous but can profit from reflective prompts and concrete traces of experiences. For example, in craftsmanship professions, apprentices can use pictures as evidence of their experience to enhance reflection. A considerable amount of research has examined the effects of learning journals in professional education (e.g., nursing [11], physiotherapy [12]).

Online learning journals have brought additional advantages compared to their paper-based counterpart. Not only online learning journals are ubiquitously accessible, but they also facilitate the integration of visual artifacts (e.g., photos or videos), which can be particularly beneficial in the context of VET [26]. Moreover, they can facilitate the creation, editing, and storing of text and media entries [27]. From a pedagogical perspective, having visual traces of the to-be-commented experience immediately available serves as a trigger to access concrete memory [6]. [28] found that learners engaged more in reflection and generated more entries with online learning journals as compared to the paper-based ones.

However, the use of learning journals is not effective *per se*. Their appropriate usage by both apprentices and supervisors is needed to effectively support the learning process [1]. Research in the Swiss VET system has shown that stakeholders often do not share the same conception of the aims and functions of learning journals [7]. Moreover, documenting learning experiences is a hard task for many apprentices [8], [10]. Providing scaffolds, therefore, has the potential to improve the learning process. [29] showed that apprentices' SRL strategies can be improved by scheduling regular meetings with supervisors, where they receive advice on the development of their learning portfolio. [30] found that scaffolding peer-feedback improved the quality of the learning documentation.

The digital format of learning journals allows to record apprentices' interactions with journals, derive detailed insights into learning strategies, and facilitate automatic interventions. For example, [1] manually tagged apprentices' reflections and found a positive correlation between several cognitive and meta-cognitive learning strategies and academic performance. Unfortunately, the potential of learning analytics still appears to be unexploited in VET learning journals.

B. Learner Profiling

Extensive research has been done to identify learner profiles in learning environments using clustering. We focus below on prior work based on the three key aspects in our paper: SRL strategies, time series clustering, and cluster evolution.

A vast part of the prior work has focused on clustering students based on SRL strategies. For example, [17] explored effort regulation patterns in university students and found a significant correlation with academic performance. [31] studied student's commitment and consistency in MOOCs. In a blended course, [19] observed that students have different consistency patterns over time. [20] studied the change of learning strategies and found that students working consistently had a higher academic performance. [23] studied patterns of macro-level processes of planning, engagement, evaluation, and reflection in log data. [13] quantified regularity levels in online education and found that regular students outperformed their peers. Finally, in [16], student groups were detected based on their help-seeking behavior in MOOCs.

Apart from using log data, SRL strategies have been explored via other data sources (e.g., surveys). For instance, [32] conducted a latent profile analysis with online and blended students to identify SRL profiles from survey answers. Likewise, [33] ran a latent class analysis on the answers to the PISA learning strategy survey, to investigate learners' strategies. [20] did a latent class analysis to study behavioral engagement in the context of MOOCs. Finally, [15] studied the relationship between detected and self-reported strategies.

Prior work on learner profiles has mostly used aggregated features (e.g., the total number of watched videos in a MOOC [31]). Yet, log data usually represents a time series of events. Hence, recent work on SRL profiling focused on time series. For instance, [15] encoded trace data as action sequences and computed the sequences distance using an optimal matching method. Likewise, [23] used Markov models to represent time series. [22] showed that Dynamic Time Warping (DTW) is more effective than Euclidean distance to compare time series.

Finally, there is limited literature on cluster evolution and how profiles change over time. For example, [20] studied the transition of learning strategies across course weeks. However, transitions were aggregated over the whole course, and it was not possible to see whether some strategies (dis)appeared or were more (less) frequent across weeks. [24] clustered student interactions in a digital learning environment separately at different points in time. [14] proposed an evolutionary clustering approach to obtain temporally consistent clusters.

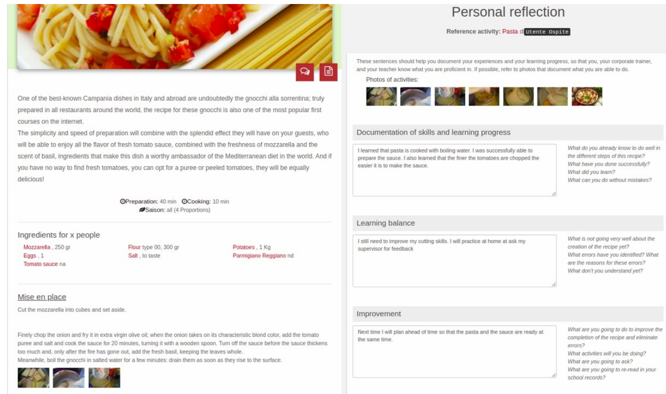


Fig. 1: An example of a recipe (left) and a journal entry (right).

III. Context

Our work studies data from chef apprentices using an online learning journal designed under the Swiss Dual-T project (2015 - 2020) [6]. The Swiss vocational education is organized as a dual system, with apprentices alternating between lessons in vocational schools and their workplaces in companies.

A. Apprenticeship Learning

Apprenticeship learning represents an interactive participation in cultural practices and shared learning activities rather than a process in individuals' minds [34]. Thus, the apprentices' learning process is affected by the learning environment and explained as a legitimate peripheral participation in communities of practice (CoP) [35], [36]. The latter are the social contexts apprentices participate in. For chef apprentices, in-company trainers, chefs, and waiters working at a restaurant are part of their CoP. The participation must be legitimate (i.e., apprentices should have access to the practices and the community), and it is at first peripheral (e.g., chef apprentices may chop vegetables before designing restaurant menus).

In a dual-track VET system (like the Swiss one), vocational apprentices alternate between the vocational school (learning- and technical-oriented) and the workplace (production- and practice-oriented) [37]. A challenge arising from this system is integrating theory and practice [5]. Articulation and reflection are two methods that foster generalization across contexts [34]. The first one involves externalizing thoughts or cognitive processes, while the second one allows us to examine past professional practices. The 'Erfahrraum' model is a pedagogical model that aims to connect theory and practice [6]. It assumes that experiences alone do not lead to knowledge but rather knowledge is constructed through reflection processes. The online learning journal in our study implements this model.

B. Online Learning Journal for Chef Apprentices

The learning environment in our study is an online learning journal platform for chef apprentices (Fig. 1). The goal of the platform is to support apprentices in linking the theory learned at school with their hands-on workplace experiences. [38] showed that the platform is effective in improving apprentices' learning outcomes (e.g., their declarative knowledge acquisition, meta-cognitive skills development, and mastery in practice). The platform supports two main types of entries: *recipes* and *experiences*. Recipes cover all aspects related to food, while experiences are associated with topics (e.g., hygiene, work safety). For both types of entries, apprentices can enter a title and a description, upload images, add appropriate tags (about learning topics related to the entry), and, for recipes, specify the ingredients. Each entry is linked to a learning journal that prompts apprentices to reflect on what went well and identify areas for improvement. Finally, the platform allows apprentices to ask for feedback from their in-company trainers.

C. Participants

We study log data belonging to two populations of chef apprentices, coming from two VET centers located in two different language regions of Switzerland, using an online learning journal for their apprenticeship (6 semesters).

The data set of the first vocational school `VS1` was used to answer **RQ1**-**RQ3**. It contains the log data of 139 apprentices (101,579 entries) from a VET center in the Italian-speaking part of Switzerland. The training was organized biweekly: apprentices went to school for two days every other week. The data set of the second vocational school `VS2` served to compare learner profiles across contexts and answer **RQ4**. It contains the log data of 44 apprentices (20,957 entries) from a VET center in the French-speaking part of Switzerland. Their training was organized weekly: apprentices went to school for one day per week. All participants were informed about the research and had the right to withdraw at any point in time. The study was approved by the responsible institutional review board (HREC number: 0050-2020/05.08.2020).

IV. Method

To study apprentices' SRL over their apprenticeship, we propose a multi-step evolutionary clustering pipeline based on a framework of SRL in formal education and the workplace.

A. Pedagogical Framework

The concept of SRL has been studied extensively in education and psychology over the last three decades. There exist several different models/conceptualizations of SRL (see

[39] for an overview), which can be divided into two main categories. Models using a 'process-oriented' perspective see SRL as a proactive process organized as a set of (repeating) learning phases [40], [41]. Models employing an 'aptitude-oriented' perspective characterize SRL by individual differences and identify cognitive, metacognitive, motivational, and emotional aspects of learning [40]. An important assumption of this category of models is that aptitudes are *adjustable*.

A large body of research on SRL targets formal education settings (e.g., [40], [41]). Given that learners may use a variety of SRL strategies as part of their learning, many works (e.g., [17], [19], [20]) examined the relationship between SRL strategies and (academic) performance. In this sense, [42] performed a meta-analysis to investigate the effect of different categories of SRL strategies on academic achievement in an *online education* setting. They used the nine subscales of the Motivated Strategies for Learning Questionnaire (MSQL) [43] as a basis for their meta-analysis and found a significant association to academic achievement for five of these subscales: metacognition (awareness and control of thoughts), time management (ability to plan study time and tasks), effort regulation (persistence in learning), critical thinking (ability to carefully examine learning material), and help-seeking (obtaining assistance from supervisors/instructors).

Much less work focused on studying SRL in the workplace. In contrast to formal education, workplace learning is an interactive participation in cultural practices and shared learning activities (see Section III-A). In workplace settings, SRL is highly social and structured by work tasks [44]. Other research [45], [46] emphasizes the importance of knowledge artifacts created in the workplace for SRL. [47] have found that the workplace learning context is a predictor SRL. Finally, [48] have explored the effects of technological scaffolding of SRL on workers in European organizations.

Our use case (online learning journals of apprentices) spans formal education (vocational school) and workplace learning, although the use of the online learning journal is controlled through the school (i.e. the teachers instruct the apprentices to document their recipes and workplace experiences). Our framework, therefore, combines elements from SRL concepts in formal education and workplace learning. Given our goal of identifying patterns of SRL behavior of individual learners, we assume an 'aptitude-oriented' perspective of SRL. Furthermore, we acknowledge that SRL behavior is influenced by the environment and the context (in particular in the case of workplace learning, see for example [47], [49]). Therefore, we assume that apprentices' SRL behavior evolves over their apprenticeship and varies within a semester (see also [50]). Given that we access log data only, based on the findings of [43], we understand apprentices' learning behaviors in the system as manifestations of SRL processes. Following the findings of [42], we represent apprentices' SRL as a composition of effort regulation (*Effor*t), time management (*Regularity*, *Consistency*), and help-seeking (*Help-Seeking Behavior*). We study time management in short-term [13] (*Regularity*) and long-term [51] patterns (*Consistency*). The nature of our use case and log data does not allow us to measure metacognition or critical thinking. We capture the influence of the specific workplace by incorporating interactions between apprentices and in-company trainers into the help-seeking dimension. Finally, given the importance of knowledge artifacts in workplace learning [45], [46] and journal entries completeness [3], [1], we also integrate an additional *Quality* dimension into our representation of SRL behavior.

B. Multi-Step Evolutionary Clustering Pipeline

Our multi-step evolutionary clustering pipeline (exemplified in Fig. 2) integrates different dimensions of SRL and consists of three main steps that are taken for each semester.

In the first step, we transform the log data into meaningful features (indicators) that can describe important dimensions of SRL. The features are computed as time series (Section IV-B1). Thus, per feature and apprentice, the output from the first step is a time series (vector) of length equal to the number of (bi)weeks in the semester. The goal of the second step is to study and cluster each dimension individually (Section IV-B2). Therefore, we compute the similarity matrix between apprentices separately for each feature ($N \times N$, where N is the number of apprentices). Then, to integrate the features from the same dimension, we add their similarity matrices and obtain the dimension similarity matrix ($N \times N$). Next, per dimension, we account for the apprentices' behavior from previous semesters by smoothing the dimension similarity matrix ($N \times N$). Following, to identify the behavioral patterns, we perform Spectral Clustering. We use as input the smoothed similarity matrix and obtain a vector of labels (indicating the cluster an apprentice belongs to), which we interpret using domain knowledge. In the third step, we integrate the information from the SRL dimensions into a multi-dimensional learner profile (Section IV-B3). We perform a second clustering step via *K*-modes using the five vectors of labels obtained in the second step (one vector for each dimension) as input.

In the following, we describe each step of the pipeline. We provide information on the technical and implementation details as well as the code on our GitHub repository[1].

1) Dimensions of Self-Regulated Learning: As described in Section IV-A, we represent learners' SRL behavior using five dimensions: *Effort*, *Quality*, *Consistency*, *Help-Seeking Behavior*, and *Regularity*. Practically, from the log data, we extracted features serving as indicators for these SRL dimensions.

Table I shows the dimensions and the corresponding features of SRL behavior. The Regularity features are scalars, while the other features are time series. Prior work has showed that SRL profiles are dynamic [50]. Students shift their learning across domains and even within a course in response to contextual factors. Modeling features as time series instead of aggregated values allows to account for this temporal perspective. Hence, we computed the features per (bi)week to build a time series of length equal to the number of (bi)weeks in the semester.

The ***Effort*** dimension monitors the intensity of the apprentices' engagement, which is fundamental for learning success (see e.g., [17], [42]). In line with [17], we characterize

[1] https://github.com/epfl-ml4ed/evolutionary-srl-clustering/

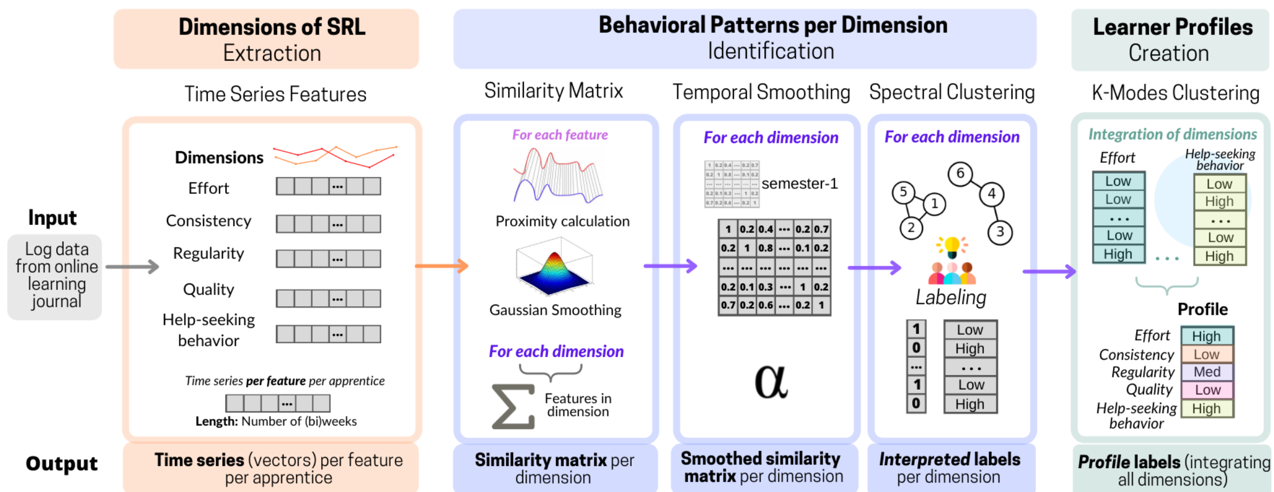


Fig. 2: **Proposed Pipeline**. In the first step, we take as input the log data aiming to extract meaningful indicators of behavior (Dimensions of SRL). In the second step, we study each dimension of behavior individually. We take as input the time series features to cluster apprentices for each dimension (Behavioral Patterns). In the third step, to obtain multi-dimensional profiles, we do another level of clustering using the cluster labels from the second step (Learner Profiles).

Dimension of SRL	Feature Name	Feature Description
Effort	Platform usage Number of writing events	How many minutes did the apprentice spend on the platform? How much did the apprentice use the platform to write/edit content?
Quality	Average reflection length Image ratio Ingredients ratio Tags ratio	On average, how many characters did the apprentice write in their reflections? Out of all recipes and experiences, how many of them have at least one image? Out of all recipes, how many of them have at least one ingredient? Out of all recipes and experiences, how many of them have at least one tag?
Consistency	Average session duration Relative platform usage Relative number of writing events	On average, how many minutes did an apprentice session in the platform last? How many minutes did the apprentice *relatively* spend on the platform? How much did the apprentice *relatively* use the platform to write/edit content?
Help-Seeking Behavior	Feedback request ratio Feedback response ratio	Out of all the recipes and experiences, how many of them had a feedback request? Out of all the feedback requests, how many of them received an answer?
Regularity	Peak of (bi)weekday Periodicity of day hour Periodicity of (bi)week hour	Does the apprentice tend to work more on certain days than others? Does the apprentice tend to work more on certain hours of a day than others? Does the apprentice tend to work more on certain hours and days than others?

TABLE I: Extracted features for each SRL dimension considered in our study.

learners' effort in absolute terms by calculating the total time spent on the platform and the total number of writing events.

The ***Quality*** dimension aims to capture the completeness and richness of the descriptions about recipes and experiences. Prior work has emphasized the importance of the learning documentation completeness [3], [1]. In learning journals for baker apprentices, [1] found a significant positive correlation between the learners' performance and the number of pictures in the recipes., and also highlighted that a relevant characteristic of the reporting quality is the richness of usage rather than the intensity. Hence, we use four features as a proxy of quality: the average reflection length, and the ratio of recipes with at least one ingredient, image, or tag related to the syllabus.

In contrast to Effort, the ***Consistency*** dimension focuses on the relative shape rather than the absolute magnitude of events. It measures how learners' effort varies throughout the semester and so estimates their intra-course time management skills. These skills are important in learning journals, where the accumulation of material should be made over a period of time, not 'in one go' [3]. Regular journal entries can update the cognitive structure and promote the absorption and connection of new knowledge into the updated cognitive structure. We used three features as indicators of this dimension: the average session duration, the relative time of sessions, and the relative number of writing events. The last two are the unit vectors of the features used in the *Effort* dimension; we normalized the time series per learner to have a norm equal to one.

The ***Help-Seeking Behavior*** dimension measures learners' ability to ask for support when needed. Recall that apprentices can request feedback on recipes and experiences from their in-company trainers. We describe help-seeking behavior with the feedback request ratio (the number of entries with a feedback request divided by the total number of entries) and feedback response ratio (the number of feedback requests with a response). These two features can (partially) represent the workplace context [49] and CoP of an apprentice [35], [36].

The ***Regularity*** dimension assesses apprentices' intra-week and intra-day time management patterns (i.e., capturing whether an apprentice is regularly engaged on specific week-days or day times). Prior work has analyzed this dimension in

MOOCs [13] showing its relation with student performance. Building on this study, we included three features of apprentice regularity from [13]: periodicity of day hour (being more active on certain hours of the day), periodicity of weekday (being more active on certain days of the week), and periodicity of week hour (being more active on certain hours **and** weekdays).

2) Behavioral Patterns: The second step of the pipeline aims at identifying distinct SRL behavioral patterns per dimension and semester. We first compute the pairwise similarity matrix per semester and dimension, then smoothen it based on the previous semester, and finally perform a spectral clustering.

Similarity Matrix. For each feature, we compute the pairwise distance between the apprentices to build the distance matrix of size $N \times N$ (where N is the number of apprentices). To calculate such distances, we use the Euclidean distance for the regularity features (real values ≥ 0). For the other features (time series), we use the DTW distance (e.g., [22]). DTW is a distance measure that searches for the optimal alignment between two given time series. Compared to Euclidean distance, DTW is more flexible and tends to correctly identify similar patterns (such as peaks) despite small variations (shifts) in time. Then, we sum the distance matrices of all the features in the same dimension. Following, we compute the similarity matrix S by applying a Gaussian kernel. Thus, the outputs from this step are five similarity matrices (one per dimension) per semester that are used as input for the following step.

Note that, for each feature in the dimension, we obtain the standard deviation (σ) of the Gaussian kernel and the window size w that constrains the DTW degree of flexibility via a grid search in the range $0.5 \leq \sigma \leq 1.5$ with steps of 0.1 for sigma and range $0 \leq w \leq 4$ with increments of 1 for the window size. We choose the optimal values to maximize the *Silhouette* score of the *Spectral Clustering* (see next subsection).

Temporal Smoothing. The apprentices as well as their working contexts and learning (e.g. from peripheral to more complex tasks) will evolve over apprenticeship and, therefore, we can also expect an evolution of their SRL behaviors [47], [49]. One possible approach to represent apprentices evolving SRL behavior is to feed the similarity matrices into a standard clustering method, yielding a separate cluster solution for each dimension per semester. However, this type of approach does not make use of the temporal information available and can be very sensitive to noise, leading to temporally inconsistent clusters. Therefore, we use the evolutionary clustering approach proposed by [14] and smoothen the current similarity matrix using the similarity matrix of the previous time frame. The assumption is that the similarity matrix S is the sum of the unknown true similarity matrix Ψ and random noise N. Instead of performing clustering directly on S, the *true* similarity matrix Ψ is estimated for every semester t. The premise is that Ψ is free from noise and clustering it instead of S will lead to clusters of higher quality. The true similarity matrix is computed as follows:

$$\Psi_t = \alpha_t \, \hat{\Psi}_{t-1} + (1 - \alpha_t) \, S_t, \tag{1}$$

where α_t controls the amount of smoothing applied to Ψ. The optimal smoothing factor α_t depends on the amount of new information S_t contains compared to the similarity matrix of the previous semester and the estimated noise in S_t: if large differences between S_t and S_{t-1} (the similarity matrix of the previous semester) are observed, α_t will be low (to be able to capture novel behaviors). If S_t is very noisy, α_t will be large.

Spectral Clustering. Finally, we apply *Spectral Clustering* [52] to cluster the smoothed similarity matrices Ψ per semester and dimension. In contrast to K-Means, Spectral Clustering is not limited to clusters that form convex sets and is particularly good at identifying outliers [53]. The idea behind spectral clustering is that points in a data set can be represented as nodes of a graph and the (weighted) edges connecting the nodes denote the similarity between the points. The clustering task is therefore turned into a graph partitioning problem where the similarity matrix (Ψ) is the weighted adjacency matrix. Then, k-Means Clustering with $k = K$ is applied to the first K eigenvectors of the Graph Laplacian (see [53] for its definition). As output, we obtain the index (number) of the cluster each apprentice belongs to. Using domain knowledge, we interpret and describe them with meaningful labels. The interpretation describes the dimension in terms of magnitude (*Low*, *Medium*, *High*), shape (*Decreasing*, *Increasing*, *Normal*), and peaks (*Low Peaks*, *High Peaks*, *Alternate Peaks*). The magnitude labels are used when the magnitude of the dimension is more or less consistent over the semester. The shape labels describe how the magnitude changes over the semester: high magnitude at the beginning of the semester (*Decreasing*), high magnitude at the end of the semester (*Increasing*), or magnitude following a normal distribution (*Normal*). Finally, the peak labels are relevant only for the regularity dimension. *High Peaks* denotes clusters with a strong preference for working on specific days of the (bi)week/hour of the day, *Low Peaks* indicates a slight preference, and *Alt. Peaks* (Alternate Peaks) represents apprentices who prefer specific days, but not hours of the day.

Model Selection. To find the optimal number of clusters, we chose the *Silhouette* score [54] over other heuristics because it is easy to interpret. It ranges from $-1, ...1$, with higher values indicating that a cluster member is close to its own cluster and far away from the other clusters (high separability). We compute the optimal number of clusters for each dimension and semester via a grid search for $k = 2, ..., 10$ clusters.

3) Learner Profiles: Learning is a process involving elements that follow different sets of logic and work together in a complex interaction [21]. Thus, in this step, we integrate the different dimensions of SRL. This integrated profiling enables us to obtain a complete picture of apprentice behavior and insights into dependencies between dimensions. To obtain the profiles per semester, we take as input the five annotated cluster labels per dimension and semester. Then, we use K-Modes to cluster the annotated labels (the input) and output the multi-dimensional profile each apprentice belongs to (see [19] as an example). K-Modes extends K-Means to cluster categorical data. Specifically, the former uses the mode (most frequent element) instead of the mean to compute the cluster centroids. We again use the *Silhouette* score to determine the optimal number of clusters, using the same selection strategy adopted for the Spectral Clustering.

V. Experimental Results

To answer research questions **RQ1**-**RQ3**, we applied our pipeline to the data set of the first vocational school (`VS1`). Our results show that we can obtain interpretable apprentice profiles related to academic performance and capture apprentice behavior over time. We then applied our pipeline to profile apprentices from a second vocational school (`VS2`) to answer **RQ4**. While the proposed pipeline yields interpretable profiles also for `VS2`, only a subset of the obtained profiles are shared between the two populations.

A. Profile Exploration

We profiled the apprentices in `VS1` using biweeks as the time unit (features per apprentice per biweek), yielding clusters over the six semesters of apprenticeship. Biweekly time units were chosen to adhere to the apprenticeship format in `VS1`.

Apprentice Profiles. We hypothesized that our pipeline could identify different profiles of apprentices (**H1**). Our hypothesis is based on the assumption of an 'aptitude-oriented' conceptualization of SRL, that describes SRL based on individual differences (see [39]), and on the findings of [49], who showed that the quality and the intensity of participation (learning) under modern apprenticeships varies widely. We further assumed that these individual differences are manifested in apprentices' learning strategies (see [43]). Based on the findings of previous work on the relationship between SRL strategies and academic achievement (e.g., [17], [20], [23], [19]), we also hypothesized that there would be significant differences in academic performance between profiles.

In a first analysis, we therefore examined the resulting apprentices' profiles from the multi-step clustering for the six semesters of the apprenticeship. Table II shows the resulting profiles per semester (rows) and dimension (columns). While the results of all semesters are aggregated for conciseness reasons, we ran the pipeline separately for each semester. The profile descriptions were obtained using the cluster centroids for each profile (see Section IV-B2). Given that we used K-Modes, the centroid is the most frequent label per dimension. For example, 95% of the apprentices in profile *B* in semester 1 had *Low Peak*s in Regularity whereas 5% had *High Peaks*. Thus, the centroid for Regularity is *Low Peaks*. Following the example, the centroids per dimension for profile *B* in semester 1 are *Low* (Effort), *Low* (Quality), *Increasing* (Consistency), *Low* (Help-Seeking Behavior), and *Low Peaks* (Regularity).

At a first glance, using the cluster centroids as cluster representatives to interpret the different behaviors is straightforward [19]. However, while profile *B* exhibits a clear pattern per dimension in semester 1, for some combinations of profile-dimension-and-semester, we do not observe a clear majority. For example, for profile *C* in semester 1, the Help-Seeking Behavior dimension is labeled as *Low*. Nonetheless, for this semester, profile *C* has 57% of the apprentices in cluster *Low* and 43% of the apprentices in cluster *High*; therefore, the provided interpretation is misleading. To address this limitation and to make meaningful interpretations, we provide a confidence estimate for each profile, dimension, and semester combination in Table II. We indicate four different confidence levels depending on the percentage of apprentices in the majority class: *** ($\geq 90\%$), ** ($\geq 80\%$), * ($\geq 75\%$), + ($\geq 65\%$). For example, more than 90% of the apprentices in profile *A* and semester 1 have *High* Effort (in this case, *High* Effort is the majority class), thus, in Table II there are three stars (***) for profile *A*, semester 1 and dimension Effort. We consider an interpretation as valid only if at least $2/3$ of the apprentices belong to the majority class. If, for a certain profile-semester-and-dimension, the majority of the apprentices' labels accounts for more than 65% of the apprentices in that profile, that interpretation is this valid. Otherwise, there is a white space on the table. For instance, for profile *C* and dimension Help-Seeking Behavior, the interpretation for semester 1 is invalid.

Out of the 13 distinct profiles, four are present in more than one semester. Profile *B* has the highest frequency, occurring in four out of six semesters; profiles *A, C* and *F* are found in two semesters; and the rest of the profiles appear only once. It is interesting to note that the first semester has three frequent profiles *A, B*, and *C* and the last semester, in contrast, has three unique profiles *K, L* and *M*. Moreover, there are two to three categories per dimension, yielding 956 possible combinations. In semester 3, 5, and 6, Effort and Quality have three categories, thus the probability of both being *Low*, *High* or *Medium* is one third. It is therefore surprising that the majority of the profiles in these semesters (6 out of 10) have matching Effort and Quality. In addition, some profiles are very similar to each other. For instance, the pair of profiles *A* and *C* and the group of profiles *B, F*, and *H* only differ in Consistency; while profiles *E* and *K* simply varies in their Help-Seeking Behavior.

Academic Performance. We then checked if there were significant differences between the profiles in terms of apprentices' semester grades. Grades range from 1 to 6, with 6 being the best grade and 4 indicating a passing grade. Based on a significant Levene's test ($F(12, 821) = 2.22$ $p = 0.009$) indicating unequal variances, we used the non-parametric Kruskal-Wallis test to assess whether there were significant differences between profiles ($\chi^2(12) = 65.97$, $p = 1.8e\text{-}09$). We then performed a pairwise comparison between clusters using the Wilcoxon Rank Sum test, correcting for multiple comparisons via a Benjamini-Hochberg (BH) procedure. The results of the pairwise comparisons are displayed in Table III).

Interestingly, profiles *B* and *C* are the profiles that have most statistical differences with other profiles. The apprentices assigned to profile *B* have significantly lower grades than apprentices from profiles *A*, *C*, *D*, *E*, *F*, *G*, and *I*. Conversely, the apprentices assigned to profile *C* have significantly higher grades than apprentices from profiles *B*, *H*, *J*, *K*, *L*, and *M*. Profiles *B* and *C* have contrasting characteristics for Effort, Quality and Consistency: profile *B* has *Low* Quality, *Low* Effort, and *Increasing* Consistency, while profile *C* has *High* Quality, *High* Effort and *Decreasing* Consistency.

Furthermore, while profile *F* shows a significantly higher academic performance than profile *B*, their main difference lies in the Consistency dimension: profile *B* has an *Increasing* Consistency pattern whereas profile *F* shows a *Normal* pattern. An *Increasing* Consistency means that apprentices worked

Profile	**Effort**	**Quality**	**Consistency**	**Help Seeking**	**Regularity**
A	High	High	Increasing	Low	Low Peaks
Sem. 1	***	*	*		***
Sem. 4	***	**		**	+
B	Low	Low	Increasing	Low	Low Peaks
Sem. 1	***	***	**	***	***
Sem. 2	+		+	+	***
Sem. 4	**	**	***	***	***
Sem. 6	*	***	***	***	+
C	High	High	Decreasing	Low	Low Peaks
Sem. 1	***	***	***		
Sem. 3	***		***	**	
D	Low	High	Decreasing	Low	High Peaks
Sem. 2		**	***		
E	High	High	Normal	Increasing	Low Peaks
Sem. 2	**	***	+		***
F	Low	Low	Normal	Low	Low Peaks
Sem. 3	***		***	***	***
Sem. 5	***	***		**	**
G	Low	Medium	Normal	Low	Low Peaks
Sem. 3	***		***	***	***
H	Low	Low	Decreasing	Low	Low Peaks
Sem. 4	**	**	**	***	**
I	High Increasing	Medium	Normal	Low	Alt. Peaks
Sem. 5		+		***	
J	High Increasing	High	Normal	High	Low Peaks
Sem. 5		***		**	*
K	High	High	Normal	Low	Low Peaks
Sem. 6			**	**	*
L	High	High	Increasing	High	Low Peaks
Sem. 6		**	***	***	+
M	High Increasing	Medium	Increasing	Low	Low Peaks
Sem. 6		**	**	***	*

*** $\geq$ 90%, ** $\geq$ 80%, * $\geq$ 75%, + $\geq$ 65%

TABLE II: Interpretation of apprentice profiles. Overall, we observe 13 distinct profiles. The italic text denotes the semesters a profile was present in (*Sem. 1 - Sem. 6*) and indicates the reliability of the interpretation for each dimension based on the percentage of apprentices of the profile conforming to the interpretation label.

	B	C	D	E	F	G	H	I	J	K	L	M
A	***											
B		***	**	**	*	***		***				
C							**		**	**	*	**
H								*				
I										*		*

* ≤ 0.05, ** ≤ 0.01, *** ≤ 0.001

TABLE III: Lower triangular matrix of significant differences in academic performance between profiles.

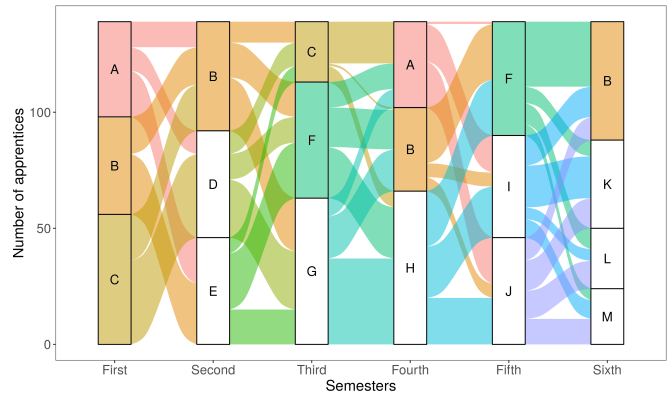


Fig. 3: Profiles over semesters for `VS1`. Each letter denotes a profile of Table II. The boxes of the profiles occurring in more than one semester are colored (e.g., profiles *A*, *B*, *C*, and *F*).

more towards the end of the semester (see Fig. 6), which might be due to some form of *procrastination*. However, it is important to treat the different dimensions in combination to reason about academic performance. For example, in the case of profiles C and K, the *Normal* Consistency pattern of profile K does not lead to significantly better academic performance (profile C outperforms profile K).

In summary, this analysis confirms hypothesis **(H1)** by showing distinct SRL profiles. Using their cluster centroids, we were able to interpret the profiles and find meaningful differences in their composition. Significant differences in academic performance were found between profiles. Moreover, academic performance is influenced by the combination of dimensions rather than a single dimension **(RQ1)**.

Profile Evolution. In a second analysis, we studied how different profiles form, merge and divide over time. Throughout their three-years apprenticeship, apprentices' workplace, and school context would change and the apprentices would also grow personally. Based on our user-centered characterization of SRL [39], following the findings of previous work on apprentice learning [35], [36] and on the influence of the environment on SRL [47], [49], we hypothesized that apprentices' SRL behavior would evolve over time **(H2)**.

Fig. 3 shows the evolution of the profiles previously discussed over the six semesters of the apprenticeship. Certain profiles (e.g., profile *D* in semester 2) are formed from other profiles splitting a semester before. Other profiles, such as profile *B* in semester 1 and 2, appear in consecutive semesters. A group of apprentices remains in the same profile.

In the transition between semesters 1 and 2, we see examples of profiles dissolving and forming. Profile *B* is split into two with 40% of the apprentices remaining in cluster *B* during the semester 2. A larger part of the apprentices (60%) move to profile *E*: they spend more time on the platform, provide documentation of higher quality, and work more consistently during the semester. This change is of educational relevance because it shows that not all the *Low* Effort apprentices show *Low* Effort or Quality over the apprenticeship. Conversely, in this same transition, profile *C* with *High* Effort dissolves into profile *B* and *D*; one-third of the apprentices in the *High* Effort group move to the *Low* Effort profile in semester 2.

Between semesters 3 and 4, there are some examples of more stable flows of apprentices. For example, 60% of the apprentices in profile *G* move to profile *H*; both profiles are

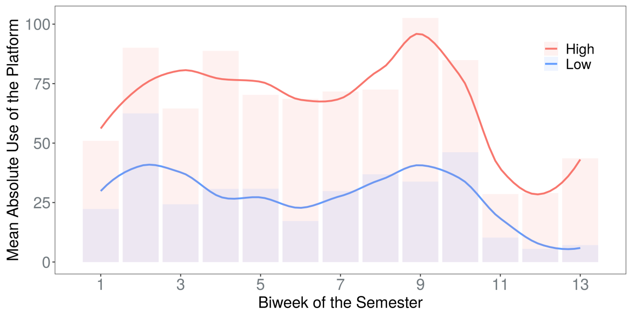


Fig. 4: **Effort** for semester 1.

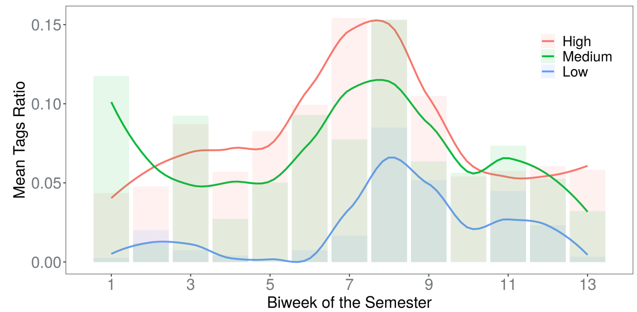


Fig. 5: **Quality** for semester 5.

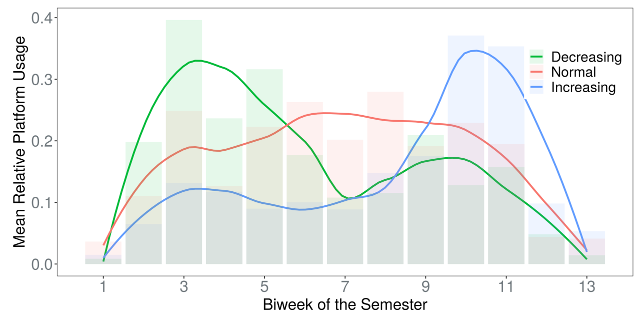


Fig. 6: **Consistency** for semester 2.

alike in the meaningful dimensions except for Consistency. Another example is the flow from profile *C* to *A*; the majority (70%) of the apprentices in profile *C* move to profile *A*. Both profiles have similar characteristics: *High* Effort and *Low* Help-Seeking. Finally, 60% of the apprentices from profile *F* move to profiles with *Low* Effort and Quality (profiles *B*, *H*).

In summary, this exploration confirms our hypothesis **(H2)** that apprentices' SRL behavior would evolve over the six semesters. Overall, there is a considerable movement between the profiles across the semesters. However, as shown with the transition from semester 3 to 4, apprentices tend to move to profiles similar to those they were in before **(RQ2)**.

Distinct Behavior Patterns. In a third analysis, we investigated apprentices' behavioral patterns per dimension and semester. Based on [17], [31], we expected some learners to show higher engagement (Effort) than others and learner engagement to vary over the semester (**H3.1**). For Quality, we hypothesized that it would mainly be dominated by magnitude (*High* vs. *Low*) [1] (**H3.2**). For Consistency, prior findings suggest that some apprentices would exhibit high consistency [19], while others would increase [20] or decrease engagement over time [20], [51] (**H3.3**). For Help-Seeking Behavior, we hypothesized that we would observe patterns of higher and lower activity [16] as well as changes over time, e.g., apprentices stopping to ask for help at some point or exhibiting an increased number of feedback requests over time (**H3.4**). Finally, based on [13], we expected that Regularity would be dominated by magnitude (*High* vs. *Low*) (**H3.5**).

In the following, we discuss each dimension for a selected semester. Note that not all the dimensions are relevant for all the semesters. For each dimension, we have therefore selected a semester where this dimension can be considered relevant for all profiles (i.e., the interpretation labels were significant ($\geq$ 65%) for each profile in that semester). In Figs. 4, 5, 6, and 7, the x-axis denotes the biweeks of the semester and the y-axis the explored feature of the respective dimension.

In terms of ***Effort***, Fig. 4 shows the platform usage in terms of the number of writing events for semester 1. We obtain two clusters of similar shape, with one cluster (*Low*) spending considerably less time on the platform than the other cluster (*High*). In semester 1, profiles *A* and *C* have a *High* Effort pattern, whereas profile *B* has a *Low* Effort pattern. We obtain similar patterns for the other features in this dimension.

As an example for the ***Quality*** dimension, Fig. 5 shows the average tags ratio per group (*High*, *Medium*, and *Low*) and biweek. Analogously to Effort, the difference in the three patterns stems from the magnitude rather than the shape: apprentices in cluster *High* add on average more tags per event than the apprentices from the other groups. Again, we obtain similar patterns for the other features in this dimension.

In terms of ***Consistency***, Fig. 6 shows the mean relative platform use per biweek for semester 2. In contrast to the dimensions Effort and Quality, Consistency patterns differ in shape. We obtain one cluster working more towards the end of the semester (*Increasing*), a second cluster working more at the beginning of the semester (*Decreasing*), and a third cluster working consistently (*Normal*). The other two features in this dimension exhibit similar patterns.

Regarding ***Help-Seeking Behavior***, we obtain two different clusters in semester 3, : *High* and *Low*. Fig. 7 shows the mean feedback request ratio per biweek for the two groups. The feedback response ratio was generally low for both groups, but relatively higher for the group with *High* feedback requests.

Finally, Fig. 8 illustrates features Peak on the Biweek (a) and Periodicity of Day Hour (b) for ***Regularity*** in semester 5. We observe three different groups: *High Peaks*, *Low Peaks*, and *Alternate Peaks*. The *High Peaks* group represents apprentices that work mostly on specific days and hours, while apprentices in the *Low Peaks* cluster tend to work on the platform on different days and hours. Cluster *Alternate Peaks* contains apprentices that work mainly on the same days per biweek, but do not have a preferred day hour. Fig. 9 shows the average platform use per day of the biweek for two example apprentices, one apprentice belonging to cluster *Low Peaks* and the other one belonging to cluster *High Peaks*. The days marked in red are the days apprentices go to school. The

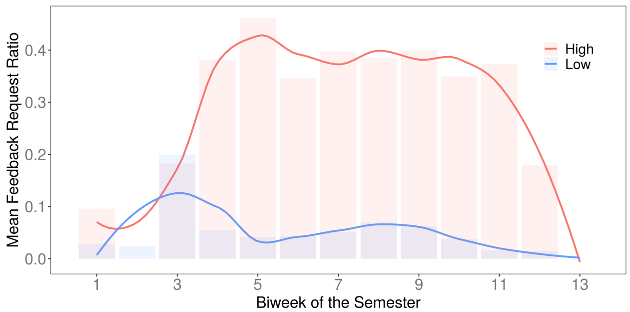
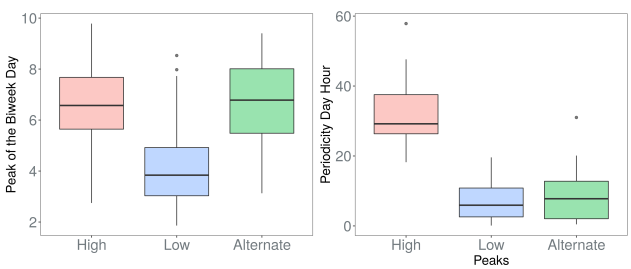


Fig. 7: **Help-Seeking Behavior** for semester 3.



(a) Peak of the Biweek Day (b) Periodicity Day Hour

Fig. 8: **Regularity** for semester 5.

apprentice of the *High Peaks* cluster has a strong preference for working on school days. The apprentice from the *Low Peaks* cluster tends to work every day of the biweek.

While we observe distinct patterns for Regularity at the dimension level, those differences get lost at the profile level. For example, for semester 1, the label *Low Peaks* for profile *C* is not reliable as only 55% of the apprentices belong to cluster *Low Peaks*. Similarly, in semester 5, only 45% of the apprentices in profile *I* belong to cluster *Alternate Peaks*; 34% of the apprentices are assigned to cluster *High Peaks*. Thus, it seems that the four other dimensions dominate the cluster solution of *K-Modes*. The pattern *Low Peaks* occurs more often than the two other patterns, which might confirm this observation. For example, in semester 5, cluster *Low Peaks* contains 80 apprentices, cluster *High Peaks* contains 28 apprentices, and cluster *Alternate Peaks* contains 61 apprentices.

In summary, we observe distinct behavioral patterns within each dimension. Contrary to our hypothesis **(H3.1)**, absolute student engagement does not vary over the semester. It seems that highly engaged learners spend more time on the platform in general. For Quality, we observed three levels of magnitude (*High*, *Medium*, *Low*), confirming our hypothesis **(H3.2)**. For Consistency, our hypothesis **(H3.3)** is also confirmed as we observe *Normal*, *Increasing*, and *Decreasing* patterns. Regarding Help-Seeking Behavior **(H3.4)**, our hypothesis is partially confirmed: we observe low and high activity as well as *Increasing* patterns (see profile *E*), but no *Decreasing* patterns. Similarly, our hypothesis **(H3.5)** can be partially confirmed for Regularity. We indeed observe apprentices with high (*High Peaks*) and low (*Low Peaks*) Regularity. However, we also obtain a third group of students, who prefer specific days, but not hours (*Alternate Peaks*) **(RQ3).**

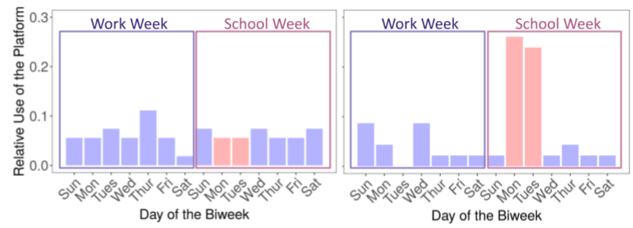


Fig. 9: Examples of intra-biweek Regularity for semester 5.

B. Profile Comparison

In our second experiment, we compared SRL profiles across different contexts. The learning process is influenced by the learning environment and context [35], [36]. Moreover, the latter can be characterized as expansive (e.g., having time off the job for college attendance and reflection) or restrictive (e.g., being all-on-job), and the position of these characteristics in the spectrum has an impact on the learning environment. Despite following the same national training plan, some apprenticeship characteristics differ between the two schools. since they are geographically located in two different regions, have different teachers, dissimilar attendance, and periodicity. We hence hypothesized that a dissimilar learning environment would influence apprentices behavior and lead to different profiles in `VS2` (**H4**).

To test this hypothesis, we applied our pipeline to data from the second vocational school `VS2`. Since the curriculum of the apprentices at `VS2` is organized in weeks, we used weeks as a basis for computing the time series. Table IV presents the obtained profiles for `VS2`. We identified 12 distinct profiles, with five of them (*B, C, F, H*, and *K*) present also in `VS1`. Fig. 10 shows the evolving apprentice profiles over time.

As observed for `VS1`, some profiles are repeated in several semesters. Profiles *B, F, P*, and *T* appear more than once. A key difference between the two populations is that the profiles in `VS2` seem more stable, in particular between semesters 2 and 4. In the transition between semesters 3 and 4, profile *S* dissolves almost completely to form profile *T*; both profiles have *High* Effort, *Low* Quality, and *High Peaks* in Regularity. From semester 4 to semester 5, profile *P* is formed out of profile *T*. Profiles *P* and *T* both have a *Decreasing* Consistency pattern, *Low* Help-Seeking Behavior, and *Low Peaks* in Regularity. Different from the profiles in `VS1`, `VS2` exhibits more variability between the Effort and the Quality dimensions. For `VS1`, most profiles with *High* effort also have *High* Quality. In contrast, six of the new seven profiles of `VS2` (i.e., profiles not present in `VS1`) have mismatches on the levels in these dimensions (i.e. *Low* Effort, but *High* Quality and vice-versa).

Furthermore, compared to `VS1`, more dimensions in the profiles appear to be meaningful. Exploring each dimension in detail, we identified that a big difference is that the dimensions have mostly two patterns each. For example, Quality is simply *High* and *Low*; whereas in `VS1`, Quality in most semesters is formed by three groups: *High*, *Medium* and *Low*. A possible explanation is the number of apprentices in each group. In `VS2`, there are only 44 apprentices, while there are 139

Profile	Effort	Quality	Consistency	Help Seeking	Regularity
B	Low	Low	Increasing	Low	Low Peaks
Sem. 1	**	***	**	***	+
Sem. 3	***	**	***	***	***
Sem. 6	***	***	*	***	*
C	High	High	Decreasing	Low	Low Peaks
Sem. 4	***	***		***	***
F	Low	Low	Normal	Low	Low Peaks
Sem. 4	***	***	+	***	***
Sem. 5	***	***		***	**
H	Low	Low	Decreasing	Low	Low Peaks
Sem. 6	***	***	***	***	***
K	High Increasing	Medium	Normal	Low	Alt. Peaks
Sem. 1	***	+	+	***	+
P	Low	High	Decreasing	Low	Low Peaks
Sem. 1	**	**	***	***	**
Sem. 4	***		***	***	
Q	Low	Low	Decreasing	Decreasing	Low Peaks
Sem. 2	**	***		***	+
R	Low	High	Normal	Decreasing	Low Peaks
Sem. 2	+	*	*	**	***
S	High	Low	Normal	Decreasing	High Peaks
Sem. 2	**	***	***	***	*
T	High	Low	Decreasing	Low	High Peaks
Sem. 3	+	**	***	***	*
Sem. 5	***	*	*	**	+
W	High	Low	Normal	Low	Low Peaks
Sem. 5	***	+	***	***	***
X	High	Low	Decreasing	Low	Low Peaks
Sem. 6	+	**	***	***	

*** $\geq$ 90%, ** $\geq$ 80%, * $\geq$ 75%, + $\geq$ 65%

TABLE IV: Interpretation of apprentice profiles based on the dimensions for the `VS2`. Overall, we observe 12 distinct profiles, 5 shared with the `VS1` (profiles *B, C, F, H* and *K*).

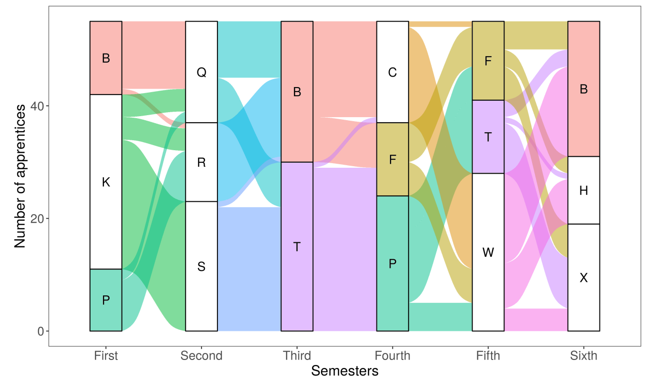


Fig. 10: Apprentice profiles over semesters for `VS2`. Each letter denotes an apprentice profile described in Table IV. The boxes of the profiles occurring in more than one semester (e.g., profiles *B*, *P*, *F*, and *T*) are colored.

apprentices in `VS1`. As a consequence of following more generations of apprentices in time, there is more variability in `VS1`. A higher number of categories in the dimensions leads to more possibilities and, therefore, profiles.

Apart from shared profiles, we also observe similarities in some dimensions across all profiles. For both `VS1` and `VS2`, Help-Seeking Behavior and Regularity are dominated by one cluster label (*Low* and *Low Peaks*, respectively).

This second experiment supports our hypothesis **(H4)**, showing that only a subset of profiles is shared across contexts. The differences in the data sets include the number of apprentices and generations followed through time, the organization of the apprenticeship (weekly versus biweekly), the different locations, languages, teachers, companies, and school **(RQ4)**.

VI. Discussion

In this paper, we aimed at identifying apprentices' SRL profiles as a basis for adaptive guidance. Specifically, we were interested in answering the following four research questions: Can we identify interpretable profiles of apprentices integrating different behaviors, and are these profiles related to academic performance (**RQ1**)? How do these profiles evolve throughout the apprenticeship (**RQ2**)? What type of behavioral patterns (in terms of effort, quality, consistency, help-seeking behavior, and regularity) can we observe during a semester (**RQ3**)? How do the emerging learner profiles compare across schools (**RQ4**)?

A. Lessons Learned

Our findings show that it is possible to identify interpretable multi-dimensional profiles (**RQ1**). However, not all dimensions are meaningful to the same extent. For example, effort appears to be constant in several profiles (e.g., *A, C, E, K, L* have a *High* effort and *B, D, F, G, H* have a *Low* effort). Profiles with the same effort magnitude differ based on other dimensions (e.g., Consistency). This is in line with [18], where three groups showed the same effort but a different consistency. Interestingly, a profile with a *Low* or *Decreasing* pattern in all dimensions (profile *H*) was also found among university students [31]. However, in that case, this type of profile included dropping students.

Compared to prior work profiling learners based on individual SRL aspects (e.g., [19], [17], [16]), we integrated five dimensions into a combined profile. This resulted in a larger number of multi-dimensional profiles, though the patterns of a single dimension were limited to three or four, as in the above prior work. Our study better reflects the diverse nature of learning. These differences could be attributed to internal factors (e.g., individual differences [39]) or external factors (e.g., differences in the CoP [34] or characteristics of the learning environment [49]). Though the school segments, teachers, structure, and design of the apprenticeship are the same for all apprentices, the *participative memory* and the tradition of apprenticeship of the CoP (people and relationships at the restaurant) varied. The behavioral differences may also be the result of the work and inclusion culture of the CoP [34], [49].

Our analyses also confirmed that there were some significant differences in academic performance between the profiles

(**RQ1**). These results are coherent with findings from prior work (e.g.,[19], [13], [20], [16]) showing that achievement was significantly higher for students with high SRL skills (focusing on a single dimension). Our results are also in line with [17] and [1], who demonstrated that apprentices in high performing profiles often exhibit either *High* Effort, *High* Quality, or both. However, our results also show that it is important to take into account the dependencies between SRL dimensions and analyze them in combination rather than focusing on an isolated dimension. While prior work [20], [19] for example found that students who worked consistently exhibited a higher academic performance, our findings demonstrate that working consistently is not enough: profile *C* (Increasing Consistency) for example shows a significantly better performance than profile K (Normal Consistency). Moreover, differently from [16], Help-Seeking Behavior did not appear to have much weight in our profiles. And while regularity was demonstrated to be a predictor for academic performance in MOOCs [13], in our case Regularity was often overruled by other dimensions.

We then showed that the profiles considerably change and evolve throughout the apprenticeship (**RQ2**). Similarly to [14], we found that the number of clusters and cluster size varies over time. One reason why the clusters in [14] are more stable than ours might be that they did not study the flow of learners across clusters, but mainly the evolution of the number and the size of the clusters. They also dealt with cluster evolution over short sessions in an intelligent tutoring system, whereas our evolution covers a much longer time frame (three years) where personal development and changes in the learning environment are likely to influence the SRL behavior. The influence of the time frame on the cluster stability was already observed in the MOOCs [20], which shows a good extent of transition between clusters in subsequent course weeks.

In a third analysis, we investigated the apprentices' distinct behavioral patterns separately for each dimension in a single semester (**RQ3**). The shapes of the *Increasing* and *Decreasing* patterns found for the Consistency dimension are very similar to the ones found by [19]. At a first glance, an *Increasing* Consistency pattern could be a sign that the apprentices are procrastinating [51]. However, [19] hypothesized that the increasing pattern could be a consequence of active delay (i.e. learners deliberately delaying tasks because they prefer to work under pressure). The latter interpretation might explain why there are no significant differences in the academic performance between the following pairs of profiles differing only in the Consistency dimension: *B* (*Increasing*) and *H* (*Decreasing*) , and *A* (*Increasing*) and *C* (*Increasing*).

Moreover, our results are in line with [17] and [1], showing that patterns in the Effort and Quality dimensions are mainly driven by magnitude (*High*, *Medium*, *Low*). Coherent with [16], we also found patterns of high and low help-seeking activity. However, in contrast, to [16], we also observed behavioral changes over time (*Increasing* Help-Seeking Behavior). [13] found that in the case of MOOCs, students can be divided into highly regular students (working on specific weekdays and hours) and low regulators (not showing a preference for specific days and hours). While we also found these two patterns (*High Peaks*, *Low Peaks*), in our case a third pattern emerged, describing apprentices who work on specific days but do not have a preference of the hour (*Alternate Peaks*).

We also showed the learner profiles emerged from an independent population of a different vocational school (**RQ4**). We found that apprentices' SRL behavior is influenced by the learning environment, as only a subset of the obtained profiles appeared for both populations. This is in line with prior research, which showed 1) the influence of the learning context and CoP on apprentices' learning process [35], [36], 2) the influence of the learning environment (i.e. expansive versus restrictive) on apprentice learning [49], and 3) the significant association between workplace context and SRL behavior [47].

Despite the different environments, the two populations share common profiles (*B, C, F, H, K*). Notably, two of the profiles appearing for both data sets showed significant differences to all other profiles in terms of academic performance (on `VS1`). Profile *C* describes apprentices with optimal SRL behavior, while apprentices in profile *B* exhibit a suboptimal behavior in every dimension. We also observed that the Help-Seeking Behavior and Regularity dimensions were the same across context. Given that the platform is a tool that is steered from the school in both locations, it has been proved difficult to involve apprentices' in-company trainers (leading to generally low feedback ratios). Furthermore, platform usage is dependent on the structure of apprentices' work week, potentially leading to a lower impact of the Regularity dimension. Finally, the proposed pipeline can be extended to other (VET) contexts.

B. Limitations

While our results are promising, some limitations should be considered. First, learning is a complex phenomenon, and our analysis was restricted to log data from the learning journal. This reduces the analysis to a few yet relevant dimensions, and other learning aspects (e.g., time spent in school, conversations with supervisors) might not be covered. Moreover, the absence of pre- and post-test data is a challenge for the interpretation of the obtained results. For example, apprentices with *High* Effort generally had good grades, but that does not necessarily mean that spending more time on the platform will increase the academic performance of another apprentice.

Second, identifying interpretable multi-dimensional learner profiles may come at the expense of added complexity. However, other methods that are computationally less expensive and still valid like latent class analysis (e.g., [33], [20]) are not able to take the temporal aspect into account or to represent the dependencies between different learning dimensions.

Third, our analysis is influenced by the underlying numerical assumptions of the clustering methods chosen (Spectral Clustering and K-Modes). Both are hard clustering methods, requiring to assign every apprentice to exactly one cluster. Soft clustering methods (e.g., Gaussian Mixture Models and Latent Class Analysis), which instead output the probability of belonging to each cluster, can be explored. Further research is needed to integrate such approaches into our pipeline and evaluate them in comparison to the advantages of the current methods (identification of outliers and non-convex clusters).

C. Implications and Recommendations

Our analysis describes how apprentices use the platform through different lenses. With this information, teachers, in-company trainers, and program designers can reflect on whether these are the desired patterns and, if not, what can be done to intervene and improve the apprentices' learning experience. For instance, Profile *B* exhibited significantly worse academic performance than other profiles. Thus, if we identify the apprentices that would be in Profile *B* early in the semester, we could intervene to improve their learning experience and performance. More generally, the findings can suggest possible platform modifications tailored to individual learner profiles. Another implication is that the learners have different behavioral patterns and profiles. Future work on online learning journals and future interventions must acknowledge this diversity. For example, learners in profiles with *Low* Regularity could receive personalized reminders on specific days of the week to encourage them to work more regularly. A possible platform modification for learners in platforms with *Low* Consistency would be to add a dashboard where they can visualize their consistency patterns and to award badges for the desired patterns. Furthermore, reflection prompts could be personalized to encourage learners that struggle with the quality of their reflective entries to reflect deeper. Moreover, we could show peer examples to the apprentices to get inspired. Another option could be to use immediate auto-generated feedback or show apprentices' work of their peers as examples in order to increase the feedback response rate for learners in profiles that struggle with help-seeking behavior. A dashboard could allow teachers to monitor the patterns and profiles of the apprentices. The last important implication is the prominence of the environment and context. Future work must study apprentices together with their CoP, and interventions should recognize its critical role and look for support within their CoP.

To conclude, this work contributes to the ongoing research of reusable analytics. To study SRL behavior, we proposed a new generalizable pipeline that can be re-used across contexts and settings, contributing to the generality of theories and to support and evaluate transfer or SRL patterns. Our work finally showcases the huge potential learning analytics has in VET, serving as a starting point for data-driven learning journal explorations in VET.

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