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Mapping Patient Complexity to Educational Needs: Proof-of-Concept for a Data-Driven Framework

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ABSTRACT

Purpose: This study aimed to determine whether routinely collected clinical data from a university dental clinic could be translated into a coherent framework for organizing competency-based clinical training. By examining patterns of patient complexity, the study sought to generate an evidence-informed set of educational care lines to guide case allocation, support competency development, and strengthen assessment practices.

Methods: A total of 331 anonymized patient records from 2023 to 2025 were extracted from the institutional database. Variables included demographic information, reasons for appointments, treatment duration, number of visits, procedure codes, and completion status. After data cleaning, relevant variables were selected based on their educational relevance. A multivariate K-means clustering model (K = 2–7) was applied using standardized numerical variables and one-hot-encoded categorical variables. The optimal solution ($K = 2$) was identified through silhouette analysis. Cluster profiles were examined and interpreted pedagogically to generate educational care lines.

Results: Two distinct macro-clusters emerged, reflecting low and high clinical complexity. Low-complexity patients (n = 282) typically underwent short, straightforward treatments with high completion rates. High-complexity patients ($n = 49$) demonstrated longer treatment trajectories, multiple procedures, and a higher risk of interruption. These patterns informed the derivation of five educational care lines: preventive care, simple restorative care, complex chronic care, prosthodontic care, and critical adherence care. For each line, corresponding competencies, learning objectives, assessment criteria, and autonomy expectations were defined.

Conclusions: This proof-of-concept study demonstrates that clinical data can be transformed into a structured educational framework capable of informing competency-based curriculum design. The resulting care-line model offers a practical method for aligning case complexity with student readiness, improving consistency in clinical exposure, and supporting more reliable assessment practices. Further validation in larger or multicenter cohorts is warranted.

1 | Introduction

Clinical training in dentistry constitutes one of the most complex and widely debated aspects within international academic literature [1, 2]. Despite numerous curricular reforms introduced over recent years, many university dental clinics continue to rely on traditional operational models. These models are frequently characterized by non-systematic patient allocation, a resulting heterogeneity in clinical exposure among students, and significant challenges in reliably assessing competencies [3]. Evidence in dental education has long established how the randomness of clinical case distribution can compromise learning quality, generate inequitable educational experiences, and impede the development of an equitable, transparent assessment culture focused on competency progression [4].

In parallel, international standards (ADEA, CODA, and AMEE) are increasingly promoting a transition toward competency-based education, assessment for learning, and entrustable professional activities (EPAs). These frameworks posit that students must be progressively exposed to cases of increasing complexity, that clinical learning pathways should follow an intentional pedagogical logic, and that assessment should rely on measurable, reliable indicators linked to clearly defined professional tasks [5, 6].

Within this context, the availability of structured clinical databases represents a highly promising, though underutilized, opportunity. Patient-related information—such as reasons for access, duration of treatment, number of visits, treatment completion or dropout status, and sociodemographic characteristics—can be leveraged as a powerful educational tool. This data is capable of generating training pathways that are aligned with real clinical needs and the actual complexity of the cases managed by students. The literature indicates that integrating clinical data into educational design enhances curricular coherence and contributes to the development of replicable and scalable instructional models [7, 8].

Building upon these premises, this study proposes an innovative educational model predicated on the analysis of real patient data sourced from the dental clinic of the University of Caxias do Sul, Brazil.

The objective of this study was to analyze patient records from the institutional clinical database of a university dental clinic in order to identify patterns of patient management complexity using data-driven clustering analysis. A second objective was to translate the identified patterns into a structured educational framework consisting of clinically meaningful care lines designed to support case allocation, competency development, and supervision levels in the undergraduate clinical training environment.

2 | Materials and Methods

The study adhered to ethical principles for educational and clinical research and involved no procedures that placed patients at risk. Ethical approval was granted by the local Ethics Committee (protocol no. 93026125.4.0000.5341). All data were anonymized prior to analysis, with no identifiable information retained at any stage of the research.

2.1 | Study Setting

The study was conducted at the Dental Clinic of the University of Caxias do Sul. Patient-related information was extracted from the institution's official clinical database and included demographic data, medical history, reasons for appointments, total number of visits, overall treatment duration, treatment completion status, and procedure codes.

2.2 | Study Design

A descriptive and analytical observational design was employed, utilizing retrospective clinical data extracted from the institutional clinical database of the university dental clinic.

2.3 | Data Collection and Management

A total of 331 patient records were selected using a simple random sampling method from the institutional clinical database. Random selection was performed using Excel software (Excel version 16.84, Microsoft Office, 2024) from patients who attended the clinic between 2023 and 2025. The sample size was determined by the number of eligible records available in the institutional clinical database during the study period.

To provide an indication of statistical precision, the margin of error associated with this sample size was estimated using standard formulas for prevalence studies recommended by the World Health Organization for observational datasets with a 95% confidence level, resulting in an approximate precision of ±5.4% [9]. The following variables were included in the analysis:

- age
- sex
- profession
- nationality
- reasons for appointments
- total number of procedures
- total treatment duration (days)
- treatment completion status
- procedure codes (extractions, restorations, endodontics, prosthodontics, hygiene procedures, etc.)

Data cleaning comprised the removal of inconsistent values and the recoding of non-informative categories into an "NA" field.

2.4 | Selection of Relevant Variables for Clustering

Consistent with a competency-based educational framework, variables were selected according to their relevance in characterizing patient management complexity within the educational clinical setting, including not only procedural demands but also treatment duration, care continuity, and adherence patterns that influence how cases are managed by students and supervisors. These included:

- clinical complexity: treatment duration, number of visits, and types of procedures;

- reasons for access: diagnostic, preventive, restorative, referral, and aesthetic;
- treatment adherence: completion versus non-completion;
- demographic profile: age, sex, and socioprofessional background.

These dimensions were considered critical for defining the level of competency required of students and for constructing an educational model aligned with the progression of autonomy.

2.5 | Construction of Data-Driven Clinical Clusters

To identify natural groupings within the patient population, an unsupervised machine learning procedure was implemented. A multivariate *K*-means clustering model was applied using both:

- numerical variables: age, total treatment duration, and number of visits;
- categorical variables: reasons for appointments, procedure codes, and treatment completion.

Numerical variables were standardized (*z*-score), while categorical variables were one-hot encoded to ensure their correct integration into the model. This preprocessing strategy enables categorical variables to be incorporated into distance-based clustering algorithms such as *K*-means by converting them into binary indicator variables. The combination of *z*-score standardization and one-hot encoding is commonly adopted in exploratory machine-learning pipelines to analyze mixed-type healthcare datasets and to identify underlying structural patterns within heterogeneous clinical populations.

Models with $K = 2$–7 clusters were generated and evaluated using the silhouette coefficient, which assesses cluster cohesion and separation. The model with $K = 2$ demonstrated the highest silhouette score and was selected as the optimal solution. Although the resulting silhouette coefficient indicated moderate cluster separation, the two-cluster solution was retained due to its clear clinical interpretability and its suitability for supporting the pedagogical objective of distinguishing broad levels of patient complexity relevant to clinical training.

Each patient was therefore allocated to one of two clusters (low- and high-complexity) based on their multivariate clinical and behavioral profile. These clusters represent two distinct macro-levels of clinical complexity emerging objectively from the dataset.

2.6 | Statistical Comparison of Cluster Profiles

To further characterize the profiles of the clusters identified through the clustering analysis, additional statistical comparisons were conducted between the two groups. Continuous variables (age, treatment duration, and number of visits) were compared using the Mann–Whitney *U* test due to the non-normal distribution of treatment duration and visit counts. Effect sizes were estimated using rank-biserial correlation to provide an indication of the magnitude of the observed differences between clusters.

2.7 | Derivation of Educational Care Lines

The clustering analysis was used to identify broad macro-levels of patient management complexity within the dataset. The subsequent definition of educational care lines was conducted through an interpretive step aimed at translating these complexity patterns into pedagogically meaningful clinical pathways. Specifically, the distribution of procedures, treatment duration, visit frequency, and adherence characteristics observed within each cluster was examined to identify recurrent treatment trajectories relevant to student training. Following cluster identification, a structured educational interpretation was applied:

A. Cluster characterization: Each cluster's clinical profile (treatment duration, number of visits, procedure mix, and adherence) was analyzed.

B. Pedagogical alignment: Cluster characteristics were compared with the educational needs associated with competency progression.

C. Macro-complexity levels: The two clusters were interpreted as low- and high-complexity macro-groups.

D. Generation of educational care lines: Within these two macro-levels, five educational care lines were defined to structure student learning and supervision:
   1. Preventive care
   2. Simple restorative care
   3. Complex chronic care
   4. Prosthodontic care
   5. Critical adherence care

These care lines were derived from cluster-informed patterns rather than predetermined categories, ensuring full coherence between clinical evidence and the pedagogical organization of the curriculum.

2.8 | Definition of Educational Protocols

For each care line, the following components were established:

a. expected clinical competencies

b. educational objectives

c. recommended clinical activities

d. student assessment criteria

e. appropriate levels of autonomy and supervision

This framework allows for competency-based assignment of cases, reinforcing equity, standardization, and longitudinal assessment across the clinical curriculum.

TABLE 1 | Summary of clinical activity indicators.

Variable	Range	Mean	Median	Notes
Number of clinical visits	0–29	3.76	2	High variability; majority with few visits
Total treatment duration (days)	0–899	83.5	14	Coexistence of short and extended pathways

TABLE 2 | Most frequent procedure codes.

Procedures	Frequency (n)
Miscellaneous/minor administrative codes	79
Tooth extraction	63
Professional oral hygiene	47
Dental restoration	21
Combined hygiene + restoration	14

3 | Results

3.1 | Sample Characteristics

A total of 331 patient records were included in the analysis. The mean age of the population was 38.4 years (median: 36; range: 3–95). The distribution of appointment reasons was highly concentrated in three categories:

- diagnostic access: 210 cases (63.4%)
- initial assessment: 77 cases (23.2%)
- specific referral: 40 cases (12.1%)

Treatment completion status was almost evenly divided, with 50.4% of cases finalized and 49.6% not completed.

Tables 1 and 2 highlight distribution of variables among the sample.

3.2 | Data Processing and Variable Preparation

All selected variables were successfully incorporated into the multivariate preprocessing pipeline.

Numerical variables were standardized (z-score), and categorical variables were transformed using one-hot encoding.

No information loss occurred during preprocessing; all included variables contributed to the clustering model.

3.3 | Cluster Model Selection

Clustering models with $K = 2$–7 were generated and evaluated via the silhouette coefficient. The two-cluster solution demonstrated the highest silhouette value (0.3825), indicating the best balance between internal cohesion and external separation. While the silhouette value reflects moderate cluster separation, the resulting groups exhibited consistent differences in treatment duration, number of visits, and procedural profiles, supporting their interpretability for the purposes of educational modeling.

Thus, two distinct macro-groups of patients emerged naturally from the dataset:

Cluster 0 (high complexity): 49 patients

Cluster 1 (low complexity): 282 patients

These clusters represent the dominant structural pattern in the population and were used as the foundation for subsequent educational interpretation.

3.4 | Cluster Profiles

Table 3 summarizes the cluster characteristics.

Statistical comparisons confirmed significant differences between the two clusters across the main indicators of patient management complexity. Patients in the high-complexity cluster presented significantly longer treatment durations and a greater number of visits compared with those in the low-complexity cluster ($p < 0.001$). Age differences were also observed, with patients in the high-complexity cluster being older on average. The magnitude of these differences was substantial, with large effect sizes observed for treatment duration and number of visits, supporting the interpretability of the clusters as distinct levels of patient management complexity within the dataset.

Patients in Cluster 1 underwent short, simple procedures, with higher rates of treatment completion. Most procedures belonged to hygiene, simple restorative, or diagnostic categories. Cluster 0 contained patients with long, multi-step, and frequently multidisciplinary treatment plans, often involving combinations of extractions, restorations, endodontic procedures, prosthodontic steps, and higher rates of non-completion. The high-complexity cluster also exhibited greater internal variability in terms of treatment duration, number of visits, and combinations of procedures, suggesting the presence of heterogeneous treatment trajectories within this group.

3.5 | Cluster-Based Educational Interpretation

The two clusters were interpreted at the pedagogical level according to their clinical and behavioral characteristics, forming two macro-levels of patient management complexity relevant to clinical training:

TABLE 3 | Comparison of cluster characteristics.

Variable	Cluster 1–Low complexity	Cluster 0–High complexity	p value	Effect size
Patients (n)	282	49		
Mean age (years)	37.2	45.6	0.02	Moderate
Mean treatment duration (days)	31.4	382.8	< 0.001	Large
Median treatment duration (days)	7	367	< 0.001	Large
Mean number of visits	2.49	11.08	< 0.001	Large
Median number of visits	2	10	< 0.001	Large
Visit range	0–8	2–29		

TABLE 4 | Mapping of clusters to educational care lines.

Macro-cluster	Educational care lines derived	Characteristics
Low complexity	(1) Preventive care (2) Simple restorative care	Short duration, few visits, high completion, and simple procedures.
High complexity	(3) Complex chronic care (4) Prosthodontic care (5) Critical adherence care	Long duration, multiple visits, combined procedures, and interruption risk.

a. Low-complexity cluster: early and intermediate student training
b. High-complexity cluster: advanced and senior student training

The descriptive patterns of each cluster directly informed the derivation of the five educational care lines, which represent subdivisions within the two complexity tiers (Table 4). These care lines were not generated by the clustering algorithm itself but were derived through pedagogical interpretation of the procedural profiles observed within the clusters. This step aimed to translate statistical patterns into clinically recognizable categories that could structure student learning and supervision within the academic clinic. Within the high-complexity cluster, two distinct dimensions of complexity were identified. The Complex Chronic Care line refers primarily to cases characterized by clinical and therapeutic complexity, typically involving long treatment pathways, multiple procedures, and multidisciplinary management. In contrast, the Critical Adherence Care line represents cases in which the main source of complexity is related to patient adherence and continuity of care, such as irregular attendance, treatment interruptions, or difficulties completing planned treatment (Table 5).

3.6 | Definition of Educational Protocols

Based on the cluster-derived care lines, structured educational protocols were developed for each category, including:

- expected competencies;
- learning objectives;
- recommended clinical activities;
- assessment criteria;
- autonomy levels appropriate to student progression.

This framework supports equitable case distribution, enhances consistency of clinical exposure, and strengthens longitudinal assessment of student performance.

4 | Discussion

This exploratory study aimed to determine whether real clinical data from an academic dental clinic could be systematically analyzed to produce a coherent educational structure capable of informing competency-based teaching, case allocation, and assessment practices. Consistent with this objective, the sample size of $n = 331$ is considered appropriate and methodologically aligned with similar single-center exploratory studies commonly used in health professions education [10]. The intention was not to generate population prevalence estimates but rather to identify meaningful patterns of complexity that could guide pedagogical design. Within this scope, the results provide a clear and interpretable framework grounded in authentic clinical activity. In academic dental clinics, case complexity from an educational perspective often emerges from the interaction between procedural requirements, longitudinal treatment pathways, patient adherence, and organizational aspects of care delivery. Consequently, variables such as treatment duration, number of visits, and treatment completion status were considered indicators of patient management complexity, which directly affect supervision needs, continuity of care, and the educational value of clinical encounters.

TABLE 5 | Educational structure associated with the cluster-derived care lines.

Care line	Core competencies	Learning objectives	Typical clinical activities	Assessment methods
Preventive care	Risk assessment; patient communication; preventive planning	Perform preventive examination; provide oral hygiene instruction; apply preventive measures	Professional hygiene procedures; preventive counseling; risk assessment	Direct observation checklists; supervisor feedback; reflective case discussion
Simple restorative care	Diagnosis of caries; operative skills; material selection	Diagnose simple lesions; perform cavity preparation; restore with appropriate materials	Direct restorations; basic operative procedures	Procedure-based evaluation; rubric-guided assessment of restorations
Complex chronic care	Comprehensive treatment planning; longitudinal patient management	Develop multi-visit treatment plans; coordinate sequential procedures	Management of complex treatment pathways over multiple visits	Longitudinal case evaluation; portfolio documentation
Prosthodontic care	Prosthetic planning; interdisciplinary coordination	Plan and evaluate prosthetic rehabilitation; integrate diagnostic information	Prosthodontic treatments and follow-up visits	Structured supervisor feedback; case presentation evaluation
Critical adherence care	Patient management; adherence monitoring; communication	Manage interrupted treatments; implement strategies to improve adherence	Follow-up planning; management of treatment discontinuation	Reflective case review; supervisor entrustment decision

The clustering analysis yielded two distinct macro-groups of patients that effectively captured low and high levels of clinical complexity. These clusters demonstrated alignment with well-documented patterns in the literature, which typically describe the caseload of academic dental clinics as predominantly composed of preventive and simple restorative care, accompanied by smaller but significant proportions of prosthodontic, endodontic, or chronic cases [11–13]. This convergence with existing evidence reinforces the validity of the observed patterns and their suitability as a basis for educational structuring.

The derivation of five educational care lines from these clusters (preventive care, simple restorative care, complex chronic care, prosthodontic care, and critical adherence care) offers a structured narrative through which learning experiences can be intentionally sequenced. This approach responds directly to long-standing concerns in dental education regarding the variability and unpredictability of student case exposure, issues highlighted by key authors such as Hendricson, Formicola, and Licari [14–18]. The care-line framework proposes a strategy to transition from opportunistic clinical learning to a more purposeful approach that supports progressively increasing autonomy and skill development.

The educational implications of this model are substantial. The alignment between case complexity and learner readiness strengthens the validity of assessment practices, thereby enabling instructors to evaluate student performance on tasks that correspond to their stage of development. This concept resonates strongly with the literature on EPAs, supervision levels, and entrustment decisions, as articulated by Ten Cate and collaborators [19–21]. By associating each care line with specific competencies, expected autonomy levels, and procedural demands, the framework supports the creation of targeted rubrics, calibrated rating scales, checklists, and entrustment scales that reflect the appropriate degree of supervision.

Moreover, the structure provides a practical foundation for implementing programmatic assessment. As advocated by Van der Vleuten and colleagues, meaningful assessment relies on the accumulation of multiple low-stakes data points across time rather than isolated high-stakes evaluations. The graded complexity inherent in the care lines facilitates the longitudinal monitoring of student progression, allowing data from multiple encounters to be combined into a coherent picture of competence development [22–24].

Furthermore, the model cultivates significant opportunities to enhance self-assessment and reflective practice. As emphasized within the research of Eva and Regehr, learners require explicit reference standards to accurately judge their own abilities [25]. The care-line structure furnishes these essential benchmarks, thereby enabling students to contextualize their performance within a developmental continuum, identify areas requiring improvement, and engage proactively in their progression toward greater autonomy. This framework aligns with contemporary perspectives on assessment for learning, fostering a more active role for learners in directing their educational trajectories [26, 27].

The proposed structured approach holds particular relevance for faculty calibration, a historically persistent challenge in dental education. By establishing a shared taxonomy of care lines and expectations, the model serves as a concrete referential baseline for clinical instruction [28–30]. This common frame of reference is instrumental in mitigating inter-rater variability regarding supervision and grading, thereby enhancing the overall reliability of evaluative decisions. The cultivation of such shared mental models constitutes a prerequisite for ensuring fairness and transparency across the clinical teaching team. Interpretation of the current findings, however, requires recognition of specific study limitations.

4.1 | Study Limitations

Data acquisition was restricted to a single institution, inevitably reflecting the specific clinical, demographic, and organizational characteristics of that environment. Although the sample size of $n = 331$ suffices for an exploratory analysis aimed at detecting macro-patterns of complexity, the integration of expanded datasets would facilitate greater refinement of the clusters and a more robust estimation of procedural trends. In addition, the clustering procedure was conducted as an exploratory analysis and did not include formal stability testing, sensitivity analyses, or feature contribution metrics. While these techniques may provide further insights into cluster robustness, the present study prioritized interpretability and pedagogical applicability of the resulting patient complexity profiles. Future research using larger datasets and multicenter samples should incorporate stability analyses and feature importance metrics to strengthen the methodological robustness of the framework. Future investigations employing larger cohorts (e.g., ≥ 500–800 patients) or multicenter designs would serve to stabilize cluster centroids, potentially unveiling additional substructures within the high-complexity group and improving generalizability across diverse educational settings.

A related methodological constraint pertains to the variables utilized in the clustering procedure, which relied solely on data readily available within the institutional dataset. Additionally, the clustering procedure relied on *K*-means combined with preprocessing techniques that allowed the integration of categorical variables. While this approach is widely adopted for exploratory pattern detection, alternative algorithms specifically designed for mixed-type data (e.g., *k*-prototypes or hierarchical clustering) may be explored in future studies to further refine the identification of patient complexity profiles. Although these variables captured essential dimensions of complexity—treatment duration, number of visits, procedure mix, and adherence—future research should incorporate complementary data such as diagnostic categories, radiographic indicators, socioeconomic variables, or patient-reported outcomes to enrich the model's predictive power. The imbalance observed between the two clusters likely reflects the natural distribution of clinical demand in dental school clinics, where preventive and relatively simple procedures constitute the majority of patient encounters. Nevertheless, the smaller high-complexity cluster displayed considerable internal variability, suggesting that additional substructures may exist within this group. Future studies using larger datasets or multicenter samples may allow further stratification of complex cases and the identification of additional complexity levels. Furthermore, while the present study establishes the feasibility of deriving educational care lines from clinical data, the model requires extensive empirical validation. It is important to note that the educational care lines were derived through pedagogical interpretation of the cluster profiles rather than through an independent statistical validation procedure. Future studies should evaluate the educational validity of this framework by testing its implementation in clinical training environments and assessing its impact on student learning outcomes and case allocation practices. As well, future research must assess the direct impact of this structure on student learning outcomes, assessment validity, patient care metrics, and clinic workflow. Longitudinal studies tracking students across care lines could rigorously evaluate improvements in competency acquisition, readiness for independent practice, or performance on external assessments. Experimental or quasi-experimental designs are also necessary to test whether structured case allocation effectively improves student confidence, reduces variability in learning experiences, or enhances patient care continuity.

The model may ultimately benefit from integration with digital tools. Machine learning algorithms, dashboard systems, or automated case-allocation platforms could significantly extend the utility of the care lines, enabling real-time mapping of patient complexity to student readiness, supporting faculty calibration, and facilitating continuous quality improvement.

4.2 | Implications for Dental Education

The care-line structure developed in this study offers several actionable benefits for dental education. By linking clinical complexity to developmental expectations, it supports more equitable case distribution and enhances the validity of competency assessments. The graded organization of care lines facilitates the longitudinal tracking of skills, improves opportunities for formative feedback, and provides clearer benchmarks for student self-assessment. Furthermore, the model promotes faculty calibration by offering shared expectations and structured categories. As dental schools continue to transition toward competency-based and programmatic approaches, data-driven frameworks such as the one proposed here can serve as valuable instruments for improving coherence, fairness, and educational outcomes within the clinical environment [31, 32].

5 | Conclusion

This exploratory study demonstrates the potential for systematically converting clinical data from a university dental clinic into a structured, pedagogically meaningful framework for organizing clinical education. The two macro-level clusters of complexity and the five educational care lines derived from the analysis establish a coherent system designed to guide case allocation, competency progression, and assessment practices. Although further validation in larger or multicenter cohorts is required, this model provides a feasible and scalable foundation for aligning real patient needs with competency-based educational design, thereby strengthening both instructional coherence and patient care quality.

Author Contributions

Francesca Zotti: conceptualization, methodology, investigation, data curation, writing. **Rozendo Luiz Corso**: conceptualization, methodology, investigation, formal analysis, writing. **Bruna Orlandin**: methodology and data curation. **Leandro Corso**: methodology and data curation. **Thiago Oliveira Gamba**: methodology, investigation, formal analysis, supervision, writing. All authors read and approved the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The dataset analyzed in this study was obtained from the institutional clinical database of the university dental clinic. Due to institutional and ethical regulations governing patient records, the dataset is not publicly available. Aggregated data supporting the findings of this study are available from the corresponding author upon reasonable request.

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