

Differentiated Teaching Model for Data Analysis Courses in Higher Education Continuing Education: A Comprehensive Exploration

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Abstract: Within the context of higher education continuing studies, students exhibit significant heterogeneity in disciplinary foundations, technical experience, and learning motivation. The traditional model of uniform textbooks, uniform pacing and uniform assessment has resulted in low learning efficacy for data analytics courses. This research, grounded in differentiated instruction theory, constructs a pedagogical model featuring tiered objectives, graded content and diversified assessment. Leveraging an online learning platform, it enables data-driven precision decision-making and dynamic adjustments. Practice demonstrates that this model significantly enhances students' sense of learning achievement and project completion rates, with student satisfaction exceeding 90%. Differentiated instruction effectively alleviates the challenge of teaching homogenisation in continuing education, providing a replicable paradigm for personalised talent development within this sector.

Keywords: Differentiated Instruction; Data Analysis; Higher Education; Continuing Education

1. Introduction

Driven by the digital revolution, data analytics proficiency has become a critical competency for enhancing the professional competitiveness of students in higher education continuing programs. However, continuing education classrooms predominantly adhere to the traditional model of standardised textbooks, uniform pacing and identical assessments, overlooking the significant variations in students' disciplinary backgrounds, professional experiences, and learning requirements. This approach results in low learning satisfaction within data analytics courses. Differentiated instruction, emphasising teaching according to individual aptitude, offers a novel solution to this predicament. This study takes data analysis courses as its entry point to explore how to construct a differentiated teaching model within continuing education settings. This model features tiered learning objectives, graded content, and diverse assessment methods. Leveraging data from online platforms, it enables precise decision-making and dynamic adjustments. The aim is to provide a replicable and scalable practical paradigm for enhancing the quality of continuing education and promoting students' personalised development.

2. The Theoretical Foundations of Differentiated Instruction

2.1. The Origins and Significance of Differentiated Instruction

Global trends, such as the increasing number of pupils from diverse backgrounds and those formerly educated in special needs schools, have heightened diversity within student populations^[1]. Variations among pupils may influence their learning and educational requirements, encompassing yet not limited to differences in ability, prior knowledge, interests, learning preferences, native languages, and personality traits^[2]. Historically, it was believed that teachers should treat all pupils equally, ensuring identical learning opportunities regardless of their differences. Today, it is recognised that a one-size-fits-all approach does not yield optimal learning outcomes for most students^[3]. This necessitates a shift from teaching the average pupil towards addressing individual learning needs. Differentiated Instruction (DI) is an educational methodology designed to enhance equity in learning opportunities.

Although DI is regarded as pivotal to delivering high-quality education, considerable inconsistencies

exist in its definition and operationalisation^[4]. Tomlinson's framework states, 'In diverse classrooms, teachers proactively plan and implement varied content, processes, and products in response to students' differences in learning readiness, interests, and learning needs^[5].' Consequently, DI constitutes a learner-centred approach where educators flexibly adapt elements within the learning environment to maximise educational opportunities for all pupils. For instance, this involves offering diversity in the complexity of teaching content, student grouping during instructional processes, and the presentation of learning outcomes^[6].

Although DI constitutes a heterogeneous and multifaceted teaching approach^[7], prior research has identified general principles underpinning effective differentiated instruction. These principles may take varied forms to meet specific contextual needs. Based on cognitive task analyses of mathematics teachers, five principles for high-quality DI have been established^[8, 9]. The primary principle of goal orientation emphasises the selection of teaching activities that can effectively achieve predetermined objectives, whilst continuous monitoring requires teachers to gather timely feedback on pupils' progress towards these objectives. By tailoring teaching to individual needs and making personalised adjustments to teaching plans, learning outcomes can be effectively enhanced. Finally, the principle of self-regulation and motivation advocates guiding pupils, under the teacher's supervision, to take the initiative in their own learning^[8,9].

2.2. Differentiated Requirements for Data Analysis Courses

The differentiated requirements for data analysis courses within higher education continuing education are concentrated across three dimensions: disciplinary foundations, technical experience, and learning motivation.

Firstly, variations in students' disciplinary backgrounds determine their capacity to absorb teaching content. Those from liberal arts backgrounds exhibit weaker statistical concepts, whereas science students possess prior knowledge of probability distributions and hypothesis testing^[10]. Students with foundational knowledge in advanced mathematics and linear algebra can swiftly grasp model derivations, whereas those with weaker foundations often encounter difficulties with such derivations, necessitating instructors to translate abstract symbols into relatable real-world examples.

Secondly, disparities in programming proficiency necessitate differentiated teaching content. Learners with prior programming experience may bypass foundational Python syntax and proceed directly to data cleansing and modelling. Students lacking basic programming skills, however, require transitional approaches such as visual drag-and-drop tools or Excel functions to progressively develop computational thinking^[11].

Finally, the significant heterogeneity in learning motivations dictates distinct learning demand categories, manifesting as three types: certification, skill acquisition, and interest. Among these, utilitarian learners prioritise earning credits or certificates, exhibiting a tendency towards minimal learning investment. They rely more on fragmented, low-cognitive-load microtasks and instant feedback mechanisms to reduce time and psychological costs. Career advancement-driven learners focus on immediate application, emphasising highly realistic industry scenarios and preferring case studies based on real corporate datasets to enhance practical transferability. Interest-driven learners focus more on the underlying logic of algorithmic principles and result interpretability, being willing to undertake high cognitive investment while pursuing project complexity and knowledge completeness. Significant differences exist among these three groups in task difficulty thresholds, evaluation dimension weightings, and feedback frequency requirements. Developing differentiated teaching content and personalised resource recommendation strategies to accommodate students' varying learning levels and needs can effectively enhance both learning engagement and programming proficiency^[12].

3. The Logical Framework for Constructing Differentiated Teaching Models in Data Analysis Courses

3.1. Tiered Learning Objectives

Tiered learning objectives form the core foundation of differentiated teaching approaches. Addressing the diverse backgrounds and varied needs of continuing education learners, data analytics courses may establish three-tiered objectives: foundational, advanced, and extension. The foundational tier targets learners with no prior knowledge, requiring mastery of descriptive statistics, data cleansing and

visualisation using Excel or drag-and-drop tools, interpretation of common business charts, and development of preliminary data literacy. The advanced tier targets learners with higher mathematics and basic programming experience. It requires proficiency in Python or R for data integration, inferential statistical analysis, and regression modelling, alongside the independent completion of medium-scale project reports to meet technical requirements for career advancement. The extension tier caters to students with programming backgrounds seeking algorithmic depth. It demands the implementation of feature engineering, machine learning model tuning, and interpretable analysis of results, enabling the proposal of data-driven decision-making solutions in real industry scenarios, alongside the capacity for ongoing research into new algorithms. The three tiers correspond to distinct credit weightings and assessment criteria. Students may flexibly select based on their foundational knowledge and developmental aspirations, while teaching staff provide differentiated resources and guidance pathways. This approach achieves personalised cultivation through same course, different standards; each finding their place.

3.2. Teaching Content Grading

The teaching content is modularised into three tiers—Foundational, Advanced and Extended—corresponding to tiered learning objectives. Firstly, the foundational module covers introductory statistics, Excel and visualisation, and business metric interpretation. It employs case-based micro-lectures combined with online practical training to help learners with no prior knowledge rapidly develop data literacy. Secondly, the advanced module focuses on Python or R programming, data cleansing, inferential statistics, and regression modelling. Project-driven tasks are supported by tiered code templates and automated assessment to meet workplace competency requirements. Finally, the extension module covers feature engineering, machine learning, deep learning, and cutting-edge industry case studies, enabling capable learners to tackle complex scenarios.

3.3. Diversified Teaching Assessment

Teaching assessment has been diversified, moving away from reliance on a single end-of-term examination paper. Instead, it comprehensively evaluates process performance, project outcomes, and developmental progress. The process dimension incorporates platform logs, automatically generating radar charts for learning engagement and knowledge mastery based on video viewing, online quizzes, and discussion interaction data, accounting for 30% of the assessment. The outcomes dimension features tiered project assessments: the foundational group primarily submits visualised reports; the advanced group must provide complete modelling code and result validation, while the extension group additionally completes algorithm optimisation and explainability analysis, accounting for 50% of the assessment. The growth dimension measures progress in statistical thinking, programming proficiency, and problem-solving confidence through pre- and post-course questionnaires, contributing 20% to the overall assessment.

3.4. Teaching Effectiveness Evaluation and Continuous Improvement

The core of evaluating teaching effectiveness and achieving sustained enhancement resides in the adoption of a data-driven and bidirectional feedback methodology. It tracks student performance leaps, project completion rates, and the number of skills certificates obtained. Concurrently, through teacher self-assessment and student satisfaction questionnaires, it gathers information on task difficulty, timeliness of feedback, and classroom engagement. This establishes a systematic mechanism for monitoring student learning outcomes, thereby forming a continuous improvement cycle of ‘assessment, diagnosis, adjustment, and reassessment’. This ensures the iterative optimisation of differentiated teaching models, enabling steady and sustained progress.

4. Practical Pathways and Institutional Safeguards

4.1. Teacher professional development mechanism

The teacher professional development framework is driven by two main strands: the first is to help teachers improve their data analysis skills, and the second is to enhance their ability to deliver differentiated teaching. Firstly, the school organises training courses at different levels: the basic course teaches how to interpret common charts on the platform; the advanced course uses students’ pre-test

results to conduct live demonstrations on setting sub-goals and selecting tasks; and the advanced course organises seminars in collaboration with businesses to explore the use of algorithms for identifying learning risks. Secondly, following the training, data coaches are appointed; these pre-trained teachers mentor their colleagues, working together weekly to refine lessons, modify code and adjust groupings. Thirdly, small grants for action research are allocated to encourage teachers to undertake short-term semester projects focusing on topics such as tiered teaching and value-added assessment. At the end of the term, a case study competition is held, with successful cases incorporated into the school's repository. Finally, a criterion measuring student progress and satisfaction is added to the professional title and performance evaluation metrics, incentivising teachers to continuously refine their data literacy and teaching strategies, thereby achieving simultaneous improvements in professional development and teaching quality.

4.2. Teaching Management and Institutional Safeguards

Academic management and institutional safeguards operate in tandem through three measures: a flexible academic system, process supervision and performance incentives. Credits are flexibly structured. The maximum duration of study may be extended to five years, and students are permitted to pause or accelerate their progress due to work commitments, ensuring that the pace of study is tailored to individual circumstances. A teaching supervision group, comprising both academic staff and industry mentors, is responsible for reviewing and approving tiered teaching plans at the start of each term. Mid-term monitoring involves classroom observations and analysis of platform data to assess implementation, whilst end-of-term evaluations take into account students' progress, thereby forming a comprehensive quality control cycle. The effectiveness of teachers' differentiated teaching is incorporated into performance appraisals and academic promotion reviews, with particular emphasis on the extent of student progress and project completion. Teachers who demonstrate effective tiered teaching and high student satisfaction are rewarded with additional teaching hours and research funding.

4.3. Evaluation of Teaching Outcomes and Continuous Improvement

The evaluation of teaching effectiveness and continuous improvement are centred on data-driven evidence and two-way feedback. Each term, the platform generates learning value-added reports to track academic progress, project completion rates and the number of skills certificates obtained across all student cohorts. At the same time, it collects information on task difficulty, the timeliness of feedback and classroom engagement through teacher self-assessments and student satisfaction surveys, thereby establishing a systematic mechanism for monitoring student learning outcomes. Research has also confirmed that feedback from both teachers and students validates the effectiveness of differentiated teaching methods, highlighting their potential in meeting diverse learning needs and improving academic performance^[13]. Accordingly, the college convened a debriefing meeting, attributing the completion rate of advanced content below 60% to insufficient foundational programming training. Consequently, in the following semester, a Python Beginners' Warm-up Camp was introduced, and the scale of initial project data was reduced. Simultaneously, advanced-level students were presented with industry competition challenges to intensify the learning experience, and student feedback was collected regularly to dynamically optimise teaching strategies and content design. After the revised plan was reviewed and approved by the supervisory group, it was incorporated into the system, forming a continuous improvement cycle of 'assessment, diagnosis, adjustment, and reassessment'. This ensures the iterative optimisation of the differentiated teaching model, enabling it to progress steadily and sustainably.

5. Conclusions and Outlook

This study, taking data analytics courses in higher continuing education as its context, has developed and implemented a differentiated teaching model characterised by tiered objectives, graded content and diversified assessment. Findings indicate that differentiated instruction not only mitigates teaching challenges arising from varying foundational knowledge and fragmented time commitments but also provides a replicable and scalable paradigm for personalising continuing education curricula. Moving forward, we shall focus on educational large-scale models to advance differentiated teaching towards greater precision, intelligence, and openness. Concurrently, we will broaden disciplinary coverage and explore transferability across different fields, thereby providing robust support for building a lifelong learning society.

Acknowledgements

This research was supported by Beijing Higher Education Undergraduate Teaching Reform and Innovation Project "Exploratory Research on Differentiated Teaching Models for Data Analysis Courses in Higher Continuing Education"(202410037005) and Key Project for Innovation in Undergraduate Education and Teaching Reform at Beijing Wuzi University "Research and Practice on the Construction and Functioning Mechanism of Virtual Teaching and Research Rooms"(054250050803).

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