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Teaching Reform and Practice of the Asset Valuation Course Enabled by Digital Intelligence

Hua Zhang

School of Accounting, Chongqing Technology and Business University, Chongqing 400067, China

Abstract: Digital intelligence technologies have profoundly reshaped the methodologies and operational paradigms of the asset valuation industry, driving higher education to transform asset valuation teaching from traditional knowledge delivery toward fostering students' data-driven thinking and competencies in applying intelligent technologies. Against this backdrop, this study systematically examines the major challenges facing the current Asset Valuation course, including outdated curriculum content, limited pedagogical approaches, insufficient practical training, and inflexible assessment methods. Building on this analysis, a four-dimensional digital-intelligence-enabled teaching reform framework is proposed, encompassing curriculum reconstruction, blended instruction, simulation-based learning, and intelligent assessment. Two representative teaching cases-the *Virtual Simulation Experiment for Mass Real Estate Valuation* and the *Data Asset Valuation Simulation*-are employed to demonstrate the implementation process and evaluate students' learning outcomes. Quantitative comparisons between an experimental class and a control class across multiple performance dimensions reveal that the proposed teaching model significantly reduces valuation errors, enhances students' ability to integrate and analyze multisource data, and strengthens their confidence in handling complex valuation scenarios. These findings provide a replicable pedagogical framework and empirical evidence to support the digital transformation of core business and economics curricula.

Keywords: Digital Intelligence–Enabled Education, Asset Valuation, Case-based Data Analysis, Teaching Reform.

1. Introduction

With data being recognized as a new factor of production, the scope of asset valuation has expanded beyond traditional tangible assets to encompass data assets, algorithmic models, and ecosystem service values. Correspondingly, valuation methodologies have evolved from manual estimation to automated valuation models (AVMs), multisource data integration, and visual analytics. In response to these developments, the China Appraisal Society has issued new professional guidelines, including the *Guidelines for Data Asset Valuation*[1], which explicitly require practitioners to possess competencies in data acquisition, processing, modeling, and algorithm interpretation. Nevertheless, the teaching of Asset Valuation courses in many universities remains largely confined to the conventional paradigm of lecture-based instruction combined with static textbook exercises. As a result, students have limited opportunities to engage with real-world market data and intelligent valuation tools, leading to a prolonged transition period when entering professional practice.

To advance the digital transformation of higher education, China's Ministry of Education has promoted a national strategy encouraging the integration of virtual simulation, artificial intelligence, and other digital technologies into curriculum design[2]. Although some universities have introduced automated valuation models (AVMs) and big-data cases into classroom instruction, these initiatives are often limited to the isolated adoption of technological tools, lacking systematic pedagogical redesign and rigorous empirical evaluation of learning outcomes[3]. Against this background, this study develops an integrated framework for digital intelligence–enabled teaching reform. Furthermore, two comprehensive teaching cases, together with evidence on students' learning performance, are embedded into the reform process to provide quantifiable and replicable evidence for advancing curriculum innovation in asset valuation education.

2. Challenges in Traditional Asset Valuation Education

2.1. Misalignment between Course Content and Industry Practice

Current Asset Valuation textbooks continue to focus primarily on traditional asset categories, such as machinery and equipment, real estate, and business valuation, while emerging valuation domains-including data assets, carbon assets, and environmental, social, and governance (ESG) valuation-receive limited attention[4]. Moreover, advanced valuation technologies, such as automated mass appraisal, random forest algorithms, and neural networks, as well as recently issued professional standards, including the Guidelines for Data Asset Valuation, have yet to be systematically incorporated into classroom instruction.

2.2. Misalignment between the Teaching Process and Real-World Decision-Making

Teaching cases are typically based on highly simplified and static datasets that fail to capture market volatility and information asymmetry encountered in professional practice[5]. For example, when applying the income approach, students are often provided with key parameters-such as the discount rate and perpetual growth rate-by instructors, leaving little opportunity to develop critical thinking regarding parameter estimation and model assumptions. In addition, most experimental software operates as standalone applications that emphasize procedural calculations and formula-based data entry, rather than authentic valuation workflows involving data cleaning, comparable-case selection, and risk quantification.

2.3. Misalignment between Assessment Methods and Competency Development

Current assessment practices place excessive emphasis on memorizing valuation formulas and performing accounting-related calculations, while largely overlooking essential professional competencies, including data literacy, proficiency in digital valuation tools, teamwork, and professional judgment[6]. Consequently, existing evaluation methods are insufficient to distinguish students who merely perform well in examinations from those who possess the practical competencies required for professional asset valuation.

3. Systematic Design of Digital Intelligence–Enabled Teaching Reform for the Asset Valuation Course

Guided by the principle of technology as an enabler and competency development as the core objective, the teaching team of the Asset Valuation course developed a four-dimensional teaching reform framework (Figure 1). The framework integrates digital intelligence technologies throughout the entire teaching process and translates abstract valuation theories into hands-on learning tasks through authentic teaching cases.

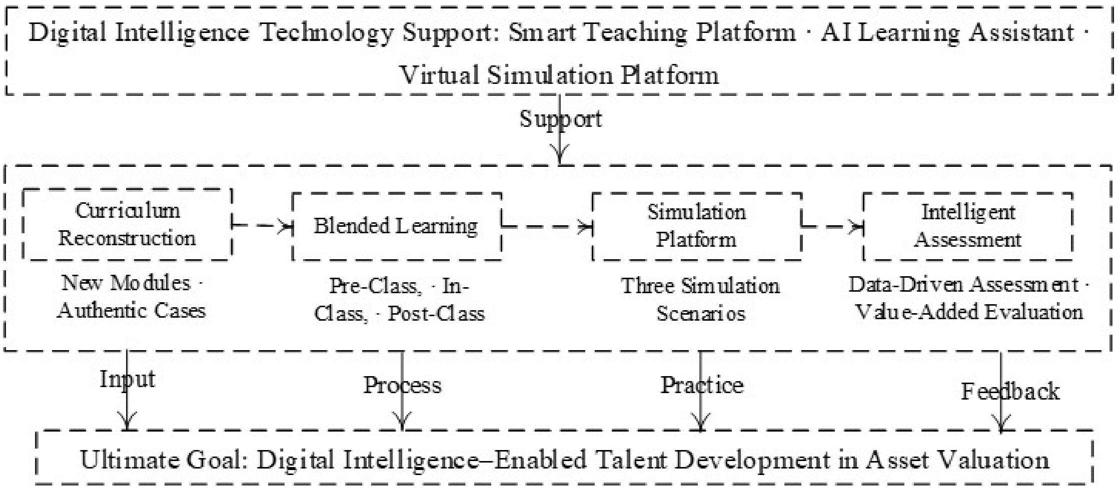

Figure 1. Four-Dimensional Digital Intelligence Teaching Reform Framework for the Asset Valuation Course

3.1. Reconstructing the "Digital Intelligence + Asset Valuation" Curriculum

To overcome the fragmentation of the traditional curriculum, three new instructional modules were introduced.

(1) Data Assets and Emerging Asset Valuation (6 class hours). This module covers data asset ownership verification, revenue-sharing ratio estimation, privacy-preserving computing, and the implications of blockchain-based data authentication for asset valuation. Seminar-based cases are designed in accordance with the Guidelines for Data Asset Valuation to familiarize students with emerging valuation standards and practices. (2) Intelligent Valuation Methods (8 class hours). This module introduces the principles of Automated Valuation Models (AVMs). Using Python scripts, instructors demonstrate the application of hedonic pricing models and random forest algorithms to mass real estate appraisal. The instructional emphasis is placed on understanding how algorithmic parameters influence valuation outcomes rather than on programming skills.(3) Dynamic Market Case Repository. A web crawler automatically collects publicly available transaction data from judicial auction platforms and property exchanges on a weekly basis, generating continuously updated "live" cases aligned with individual course topics. For example, the repository supporting the income approach contains financial data from approximately 200 listed companies over the previous three years together with industry beta coefficients. Each student receives a different combination of companies for analysis, ensuring both novelty and uncertainty in learning tasks.

3.2. Developing a Blended Smart Teaching Model

Supported by a smart teaching platform, the traditional instructional process was redesigned into an integrated pre-class–in-class–post-class learning cycle.

(1) Pre-class. Students are provided with 5–8-minute micro-lectures together with a diagnostic quiz based on a deliberately flawed valuation example, such as an incorrect procedure for determining the discount rate. The objective is to reveal students' misconceptions before formal instruction. The platform automatically records completion rates and response distributions, enabling instructors to adjust classroom teaching accordingly. (2) In-class. Interactive functions such as real-time bullet comments and word clouds are used to visualize students' viewpoints and facilitate structured valuation debates. For example, during the income approach module, one student group presents its valuation results together with the supporting assumptions, while another group challenges these assumptions using real-time industry databases and financial information integrated into the platform. The instructor then provides focused explanations based on the major points of disagreement. (3) Post-class. An AI learning assistant generates personalized exercises according to each student's learning weaknesses identified through classroom assessments. Individual diagnostic reports are automatically produced, and supplementary cases of appropriate difficulty are recommended from the dynamic case repository to support continuous learning.

3.3. Developing a Virtual Simulation Platform for Asset Valuation Training

A virtual simulation platform for digital intelligence–enabled asset valuation was jointly developed through university–industry collaboration. The platform simulates authentic professional practice by assigning students to three roles-client, valuation firm, and review expert-and incorporates three core simulation experiments. The following section illustrates the implementation process through representative teaching cases.

Case 1: Virtual Simulation Experiment for Mass Real Estate Valuation

The case is based on 150 residential property transactions completed during the third quarter of 2024 in the Cuihuyuan residential community of a Chinese city. The dataset contains 12 property attributes, including transaction price per square meter, floor area, floor level, orientation, interior decoration, and distance to the nearest metro station. Students work in groups of three, assuming the roles of valuation professionals and review experts.

Task A (Traditional Market Approach). Students manually select three comparable transactions from the dataset, perform adjustment analyses for relevant valuation factors, estimate the market value, and prepare a written valuation report explaining their assumptions and procedures.

Task B (Intelligent Valuation). Students import 120 observations into the platform as the training dataset and construct a random forest model by adjusting key parameters, including the number of trees (n_estimators = 100, 200, and 300) and maximum tree depth. The remaining 30 observations are used as the testing dataset to generate batch valuation results, which are then compared with the actual transaction prices. Students further interpret feature importance rankings to evaluate model performance and the rationality of the valuation results. The platform automatically records all operational logs throughout the experiment. Table 1 summarizes the key performance outcomes of the two instructional groups.

Table 1. Comparison of Student Performance in the Virtual Simulation Experiment for Mass Real Estate Valuation (n = 29 groups)

Indicator	Traditional Market Approach Group	Automated Valuation Model (AVM) Group	Statistical Test
Mean Absolute Percentage Error	8.57%	3.21%	$t=6.74$, $p<0.01$
Proportion of Students Using Two or More Data Sources	10.3%	89.7%	$\chi^2=34.2$, $p<0.01$
Average Task Completion Time (min)	52.4	38.9	$t=4.12$, $p<0.01$
Proportion of Students Correctly Interpreting Feature Importance	—	86.2%	—

As shown in Table 1, the student groups employing the Automated Valuation Model (AVM) based on the random forest algorithm achieved significantly lower valuation errors than those using the traditional market approach. Moreover, the proportion of multisource data incorporated into the valuation process increased substantially. Notably, although the AVM groups completed the tasks in less time, the use of intelligent valuation tools did not diminish students' professional judgment. Specifically, 86.2% of the groups correctly identified distance to the nearest metro station and floor level as the two most influential variables and were able to critically discuss the potential risk of model overfitting.

Case 2: Simulation Experiment for Data Asset Valuation

The second case focuses on the valuation of a desensitized maternal and infant consumer profiling dataset to be transferred by an e-commerce platform. The dataset contains one year of user information for 100,000 consumers, including purchasing preferences and product-category association tags. Students were required to estimate the value of the data asset by comprehensively applying the cost, income, and market approaches, while incorporating valuation discounts to account for data quality and ownership risks. The platform provided detailed information on data acquisition and storage costs, probabilistic forecasts of incremental advertising revenue generated through targeted marketing, and three anonymized transaction cases involving comparable data assets completed within the previous year. Each student independently prepared a professional valuation report.

Under the income approach, future incremental revenues were estimated using three scenarios-low, medium, and high-with assigned probabilities of 30%, 50%, and 20%, respectively. Students were required to determine an appropriate discount rate by considering the specific risks associated with data assets. Although the platform supplied the parameter ranges required by the risk buildup method, the final discount rate was determined independently by each student. The platform also automatically generated a data quality score based on completeness, accuracy, and consistency, yielding a score of 82 for this case. In addition, students were informed of a potential ownership risk arising from incomplete user authorization and were required to determine an appropriate valuation discount factor based on their professional judgment. Table 2 summarizes the distribution of valuation results obtained from the 58 participating students.

Table 2. Summary Statistics of Student Valuation Results in the Data Asset Valuation Simulation Experiment (n = 58)

Valuation Method	Valuation Range (RMB 10,000)	Median (RMB 10,000)	Relative Deviation from the Expert Benchmark (RMB 1.20 million)
Cost Approach	42-78	61.5	-48.75%
Income Approach	98-156	128.4	+7.0%
Market Approach	75-138	109.2	9.0%
Integrated Valuation (Weighted Average)	82-147	118.6	-1.17%

As reported in Table 2, valuations derived using the cost approach were generally substantially lower than those obtained using the other methods, indicating that this approach inadequately captures the future economic benefits embodied in data assets. In contrast, the income approach produced relatively higher valuation results with considerable dispersion, primarily attributable to differences in students' subjective judgments regarding scenario probabilities and risk-adjusted discount rates. Valuations based on the market approach also exhibited substantial variability because of the limited availability of comparable transactions and the subjectivity involved in adjustment procedures. In the final integrated valuation stage, students were required to determine the weighting assigned to each valuation approach and provide a justification for their decisions. The median comprehensive valuation reached RMB 1.186 million, deviating by only 1.17% from the expert benchmark value of RMB 1.20 million. However, the interquartile range (IQR) was RMB 245,000, suggesting that some students had yet to develop strong competencies in synthesizing evidence from multiple valuation approaches. Further analysis revealed that 34.5% of the students applied a valuation discount of 8%–15% to account for data ownership risks, whereas 47.0% adopted a discount rate between 3% and 7%. The remaining 18.5% failed to incorporate any ownership-risk discount into their valuations. These findings provide clear diagnostic evidence for targeted instructional interventions and subsequent curriculum refinement.

3.4. Establishing a Data-Driven Multidimensional Assessment System

The assessment system for the Asset Valuation course consists of five components: pre-class online learning and diagnostic assessment (10%), in-class participation and valuation debate performance (15%), virtual simulation experiments and technical reports (30%), stage-based case analysis and oral presentation (20%), and a final comprehensive competency assessment (25%). The smart teaching platform automatically captures students' digital learning traces throughout the instructional process and generates a Data Application Competency score based on indicators such as the frequency of multisource data utilization, the appropriateness of parameter selection and adjustment, and compliance with data-cleaning procedures. In addition, a value-added assessment mechanism is incorporated to emphasize learning progress rather than solely final performance. Students whose post-test valuation error rates rank among the top 20% in terms of improvement relative to their pre-test results receive an additional two bonus points. This incentive mechanism encourages continuous learning, reinforces competency development, and promotes sustained improvement in professional valuation performance.

4. Quantitative Evaluation of the Teaching Reform

The proposed teaching reform was implemented during the Fall Semester of the 2024–2025 academic year in two parallel Asset Valuation classes at an application-oriented university specializing in business and economics. Class A (n = 29) served as the experimental group and adopted the digital intelligence–enabled teaching model described above, whereas Class B (n = 30) served as the control group and continued with the conventional instructional approach. Prior to the intervention, no statistically significant differences were observed between the two groups in their academic performance in foundational disciplinary courses.

(1) Student Learning Engagement

Learning analytics collected through the smart teaching platform indicated a 98.3% completion rate for pre-class micro-lectures and a 94.7% submission rate for AI-generated personalized post-class exercises in the experimental group. During classroom instruction, the average number of real-time interactive comments submitted by each student increased from 2.1 at the beginning of the semester to 5.6 by the end, representing a 167% increase in classroom engagement. Comparable learning analytics were unavailable for the control group because the traditional teaching model did not employ a digital learning platform. Nevertheless, classroom observations suggested substantially lower levels of voluntary participation and independent information retrieval among students in the control group.

(2) Comparison of Comprehensive Competency

To evaluate students' ability to integrate valuation knowledge and professional judgment, a comprehensive case-based assessment was administered at the end of the semester. Students were provided with anonymized financial statements of an environmental protection enterprise, together with an industry report and relevant market transaction information, and were required to independently complete a valuation report and justify the selection of key valuation parameters. All examination scripts were evaluated using a double-blind marking procedure conducted by two independent assessors. The comparative performance of the experimental and control groups is presented in Table 3.

Table 3. Comparison of Final Case Analysis Performance Between the Experimental and Control Groups

Group	Mean Score (Maximum = 50)	Excellence Rate (≥ 40)	Score Rate for Parameter Justification	Score Rate for Disclosure of Special Valuation Issues
Experimental Group(n=29)	42.3±4.1	72.4%	88.5%	81.6%
Control Group(n=30)	34.5±5.8	26.7%	59.2%	42.5%
t/χ^2	t=5.92, p<0.01	χ^2=12.4, p<0.01	—	—

As reported in Table 3, the experimental group achieved a mean score of 42.3 (SD = 4.1), whereas the control group obtained a mean score of 34.5 (SD = 5.8), representing a difference of 7.8 points. An independent-samples t-test ($t = 5.92$, $p < 0.01$) confirmed that this difference was statistically significant. Notably, the experimental group exhibited a smaller standard deviation, indicating a more homogeneous distribution of student performance and suggesting that the digital intelligence–enabled teaching model mitigated the polarization in learning outcomes commonly observed under conventional instruction. Using 40 points as the threshold for excellent performance, 72.4% of students in the experimental group achieved the excellence criterion, compared with only 26.7% in the control group. A chi-square test further demonstrated that this difference was highly significant ($\chi^2 = 12.4$, $p < 0.01$). These findings indicate that more than two-thirds of the students receiving the reformed instruction were able to competently address authentic, complex, and information-imperfect valuation tasks, whereas only about one-quarter of the students receiving traditional instruction reached a comparable level of performance. Furthermore, although the experimental group outperformed the control group in overall scores, the most pronounced advantages were observed in the higher-order assessment dimensions of parameter justification and consideration of special valuation issues, where score rates were higher by 29.3 and 39.1 percentage points, respectively. These results suggest that digital intelligence–enabled instruction substantially strengthened students' evidence-based reasoning and their awareness of risk identification and disclosure.

(3) Changes in Students' Self-Assessed Competencies

Students completed the same five-point Likert-scale questionnaire before and after the course to evaluate three dimensions of professional competence: data-driven thinking (the ability to identify and solve problems through data analysis), digital tool application (the ability to operate at least one intelligent valuation tool), and professional judgment (the ability to critically evaluate valuation results). In the experimental group, the mean pre-test scores for these three dimensions were 2.31, 1.97, and 2.52, respectively, increasing to 4.19, 4.28, and 4.05 after the intervention. Paired-samples t-tests indicated statistically significant improvements across all three dimensions ($p < 0.01$). By comparison, the corresponding post-test means for the control group were 2.85, 2.10, and 3.12, reflecting substantially smaller gains than those observed in the experimental group.

(4) Student Satisfaction

The anonymous course evaluation survey revealed that 93.1% of students in the experimental group agreed that the virtual simulation activities enhanced their confidence in addressing complex valuation scenarios, while 89.7% believed that the digital intelligence–enabled teaching model improved their understanding of abstract valuation principles. Some students also reported that the AI learning assistant effectively reduced their reluctance to ask questions by providing timely feedback and guidance. At the same time, they suggested incorporating a larger volume of authentic anonymized industry data into the teaching platform to further enhance the realism and immersive quality of the learning experience.

5. Conclusion

Despite the encouraging outcomes, three boundary conditions warrant careful consideration in future implementation.

Firstly, an appropriate balance must be maintained between the application of digital technologies and the cultivation of professional judgment. A small proportion of students tended to rely excessively on the outputs generated by Automated Valuation Models (AVMs) while overlooking the verification of underlying model assumptions. To address this issue, dedicated instructional activities featuring deliberately designed “AI valuation pitfalls” should be incorporated into the curriculum to strengthen students' critical thinking and model validation capabilities.

Secondly, greater emphasis should be placed on data security and ethics education. Because the virtual simulation platform utilizes large volumes of anonymized datasets, instruction on legal and regulatory compliance should precede practical training, particularly with respect to the Data Security Law and the Personal Information Protection Law. In addition, an ethical evaluation component should be integrated into the assessment system to evaluate students' compliance and responsible data practices throughout the experimental process.

Thirdly, the digital intelligence competencies of the teaching team require continuous enhancement. Some instructors remain hesitant to adopt algorithm-driven teaching because of limited familiarity with computational models. A collaborative lesson-planning mechanism involving instructional designers, industry technology experts, and asset valuation faculty has proven effective in alleviating these challenges. However, its long-term sustainability depends on complementary institutional reforms in workload recognition, professional development, and incentive mechanisms.

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