Intelligent Accounting and Financial Innovation from the Perspective of New Productivity: On-Balance Sheet and Disclosure Practices Based on Large Models

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ABSTRACT Large-language-model applications in intelligent accounting generate new technical assets whose recognition, measurement, and disclosure are difficult to handle under conventional static accounting frameworks. To address ambiguous asset-recognition standards, uncertain value measurement, and insufficient disclosure of model-related risks, this study constructs an LLM-based intelligent accounting asset-entry and disclosure framework. A three-layer asset identification model is developed to evaluate technical substance, expected economic benefit, and cost measurability. A dual-track measurement system combining cost approach and income approach is then established, with lifecycle cost tracking, excess-return estimation, amortization-period updating, and recoverable-amount testing. An intelligent disclosure template is further designed to report model architecture parameters, training-data sources, application performance, and risk-control indicators. Empirical analysis using 12 pilot enterprises over an 18-month period shows that the framework increases financial-statement readability from 62.3 to 85.7, improves audit efficiency by 42.3%, reduces substantive test samples by 42.4%, and increases investor decision relevance to 0.638. The study provides a structured information-system framework for technical asset measurement, model-risk disclosure, and data-driven financial decision support.

INDEX TERMS large language model, intelligent accounting, asset measurement, model disclosure, decision support

I. INTRODUCTION

DIGITIZATION has completely transformed the process of transforming factors of production. As artificial intelligence technology is no longer a supplementary means but also a factor of production, it has affected the way enterprises create value. Due to the current logic of industrial accounting standards not recognizing intelligent assets with self-learning ability, continuous iteration and upgrading, and constantly changing value [1,2], it makes it difficult for enterprises to identify asset attributes, distinguish between capitalization and current period deduction of R&D expenditures, and select unclear subsequent measurement methods. Intelligent accounting investment cannot be reflected in financial statements, and information users cannot measure the true value and risk of enterprises, which affects the process of capitalizing new productive forces. At home and abroad, literature has accumulated rich experience in the accounting of intangible assets, but it is based on static assets such as patents and trademarks, and there is no research on the special characteristics of dynamic and evolving technological assets [3,4]. Some literatures have put machine learning systems into the internal software processing, but did not fully consider the data dependence, algorithm black box and ethical risks of large language models. The current disclosure framework emphasizes presenting financial results, and there is no description of the model's technical architecture, training data sources and effectiveness of application scenario, which causes the information disclosure to be scattered and comparability poor [5,6]. This paper constructs an asset identification and confirmation model, dual-track measurement system and intelligent disclosure framework of intelligent accounting system from the perspective of new quality productivity theory, and studies the mechanism and practical effect of improving the quality of financial information, increasing audit efficiency and enhancing the relevance of investor decision.

II. RELATED WORK

Based on the new productivity theory, technological innovation will change the way production factors combine. AI as the new production factor will change the business operation model and value creation of enterprises. Research on intelligent accounting has evolved from rule-driven to data-driven. Expert systems use rules to complete simple classification. Machine learning uses features to complete the abnormal detection and risk analysis. Deep learning overcomes the limitation of manual designed features [7,8]. With the emergence of large language models, intelligent accounting has entered the stage of semantic understanding. It can understand unstructured financial text, understand complex business logic and generate audit opinions. rational. However, this study is more technical implementation level research, less research on the economic connotation of intelligent accounting as an enterprise asset.

Current research on the accounting treatment of intangible assets focuses on the cost model and revaluation model. Standard formulation follows the principle of prudence. That is, the intangible assets generated by enterprises internally must meet the conditions for capitalization. The accounting treatment of software assets makes a distinction between assets purchased from others and assets developed by themselves. The capitalization judgment of development stage expenditure follows the criteria such as technical feasibility, willingness to use and the possibility of economic benefits flowing in. Some scholars have studied the accounting recognition of data assets. They believe that data has the characteristics of identifiability, controllability and future economic benefits. However, in the existing literature, simply use the intelligent model to understand the software processing or database processing. Disclosure research focuses on the expansion of financial indicators, lacks a specific disclosure framework for artificial intelligence technology characteristics [9,10].

III. METHODS

A. ASSET IDENTIFICATION AND CONFIRMATION MODEL OF INTELLIGENT ACCOUNTING SYSTEM

This paper constructs a three-layer progressive asset identification model. The bottom layer is the technical substance determination layer. The three variables of parameter size of LLM model, training dataset size and inference response time are used to determine resource controllability. If the enterprise has model weight files deployed in its own data center, it is considered to be self-controlled; if it only calls third-party model via API, the asset is removed. The middle layer is the economic benefit assessment layer. The Monte Carlo simulation system is used to calculate the probability of future cash inflow. The expected net present value is calculated after 10,000 iterations. The economic benefit inflow condition is met when the lower limit of the 95% confidence interval is greater than zero, ensuring a statistically significant positive net present value (NPV). The simulation assumes a log-normal distribution for future cash flows and a triangular distribution for R&D volatility, with cross-variable correlations calibrated to historical industry volatility. The final layer is the cost measurability layer. A full lifecycle cost tracking mechanism is adopted to record computing power consumption cost, labeled data procurement cost, engineer salary amortization in the process of model development, and server depreciation, electricity, version iteration investment in the process of operation and maintenance. If it is a joint development project, the cost is weighted according to the amount of training samples provided by each party, algorithm contribution and capital investment ratio. Finally, after cross validation of the three-layer determination results, asset confirmation decision matrix is obtained and binary classification result and confidence score are output.

B. DESIGN OF AN ASSET MEASUREMENT SYSTEM BASED ON LLM

This paper constructs two tracks: The cost track takes cumulative direct cost method, constructs categorized accounts to track the whole life period cost of the model. The capitalized items of cost track during developing period include: rental fee for GPU cluster, licensing fee of pre-training corpus, cost of cleaning and labeling domain data, man-hours of designing model architecture, and hyperparameter tuning experiment cost included in original asset cost value. The expensed items of cost track during operation and maintenance period include: daily computing power maintenance for self-deployed clusters, engineering optimization expenditure of Prompt, and security audit maintenance fees included in profit and loss. The threshold of capitalization is triggered by updating model, if the parameters of new version updated by developer are increased more than 15% compared with old version or the accuracy of task improves more than 8 percentage points, the development cost increment should be added to the book value of asset.

The revenue track takes excess return discount model, constructs control group to track the benefits brought by intelligentization in accounts of whole life period. Taking the company which hasn't applied LLM as example, the turnover days of target company's accounts receivable, time to approve expense reimbursement, and tax compliance risk loss should be used as control group. The excess return = (turnover days - control group) * (unit time value coefficient of money). The discount rate = weighted average cost of capital of company + 300 basis points technology risk premium, the prediction period = the smaller value of technology life cycle of model and statutory maximum amortization period. The results of two tracks are compared by test of recoverable amount, taking the lower value of two as the amount of asset measured at the end of period, the difference is recorded in account of asset impairment loss.

C. CONSTRUCTION OF INTELLIGENT DISCLOSURE FRAMEWORK AND TEMPLATE DEVELOPMENT

Technical architecture module: Enterprises need to disclose 4 basic information points of LLM: the number of Transformer layers, the number of attention heads, the hidden layer dimension, and the vocabulary size.

They also need to disclose their customized information: name of the pre-trained base model, type of finetuning method, LORA rank parameter, and number of quantization bits. Data source module: Designs a 3-level traceability template. Displays the total number of tokens of training set, the proportion of domain corpus data, and the data update deadline. Requires an explanation of data collection channels. Divides the proportion of publicly available financial reports, internal business documents, and third-party data providers. The third level contains granularity of temporal generalization, numerical perturbation amplitude and sensitive information anonymization rules, entity replacement rules.

Application performance includes task-indicator mapping table. For voucher verification tasks, it follows Table 1 and reports accuracy, recall, F1 score and confusion matrix; for financial forecast tasks, it follows Table 2 and reports mean absolute percentage error, root mean square error and prediction interval coverage; for anomaly detection tasks, it follows Table 3 and reports true positive rate, false positive rate and area under the ROC curve. For each indicator, we report the size of test dataset, the time window of evaluation and the comparison with state-of-the-art methods.

Risk control adopts a quantitative scoring card. It scores the model on four indicators output illusion rate, bias test score, adversarial sample robustness and privacy leakage risk in a quantitative way from 0 to 100. If the model scores less than 70—a threshold derived from the industry-standard 'Grade C' in financial risk maturity models—we report the rectification measures and expected completion time. To ensure comparability, scoring for hallucination and bias follows the standardized Benchmarking Framework for Financial AI (BFAI), utilizing a unified testing dataset for cross-enterprise evaluation.

D. EMPIRICAL RESEARCH DESIGN AND DATA ACQUISITION SCHEME

A quasi-natural experiment method was adopted. We constructed an experimental group consisting of 12 listed companies from Shanghai and Shenzhen stock exchanges who started to build intelligent accounting systems. We selected 12 control companies according to the category of industry, size of assets and level of revenue in a 1:1 ratio. The experimental group should satisfy the following three conditions: ILM model parameter size > 7 Billion RMB, time to develop financial scenario >18 months, and monthly voucher quantity >5,000 on average. We collected full text data from annual report, semi-annual report, quarterly report, intangible asset information from financial notes, R&D expenditure capitalization explanation and disclosure information of important accounting policy changes from CNINFO; and we got stock trading data from Wind financial terminal to calculate 5-day, 10-day and 20-day cumulative excess return. We distributed questionnaires to the participating companies to get model training time, deployment cost, number of personnel and business process change information. A total of 91.7% of the responding companies returned the questionnaires. We signed data sharing agreement with 4 accounting firms to get process indicator information such as size of working paper's test sample, time spent on performing substantive procedures, and number of adjusting entries.

TABLE 1. Comparative Analysis of Financial Statement Information Transparency

Evaluation Dimensions	Experimental group (before framework application)	Experimental group (after framework application)	control group	Increase
Readability Index	62.3	85.7	63.1	37.6%
Specific scoring	71.8	98.4	72.5	37.0%
Integrity Coverage (%)	68.4	94.2	69.1	37.7%
Disclosure level depth	Level 2.4	Level 3.8	Level 2.5	58.3%
Data granularity (items)	147	216	152	46.9%

IV. RESULTS AND DISCUSSION

A. ANALYSIS OF IMPROVED TRANSPARENCY IN FINANCIAL STATEMENT INFORMATION

This paper uses text analysis method to measure financial statement transparency and constructs readability, specificity and completeness indicators to measure transparency from readable, detailed and comprehensive three aspects. The readability index is a composite score weighted by the Flesch Reading Ease (40%), Gunning Fog Index (30%), and the average length of financial terminology (30%). To ensure consistency, the same panel of three raters conducted a blind, longitudinal evaluation of the same 12 companies' reports from both the pre-application period (2022) and the post-application period (2024). Specificity indicator measures granularity of financial data and depth of disclosure levels. Completeness indicator measures the coverage of mandatory and voluntary disclosure items. The experimental and control groups' eight periods of financial statements from the first quarter of 2023 to the fourth quarter of 2024 are coded and analyzed. The review panel consists of two certified public accountants and one finance professor to score the statements, and the Cronbach's Alpha coefficient is 0.89, which reflects that the statements have a good reliability.

Table 1 shows that after applying this framework, the readability index of the experimental group increased from 62.3 to 85.7, an increase of 37.6%. In terms of specificity score, the experimental group improved by 26.6 percentage points to 98.4, and the completeness coverage rate jumped from 68.4% to 94.2%, both significantly higher than the control group's 72.5 and 69.1, respectively. The 1.4-level increase in disclosure hierarchy depth reflects that the intelligent disclosure template supported by LLM can automatically generate multi-level structured information. The 69-item increase in data granularity proves that the model

TABLE 2. Multi-dimensional evaluation results of audit efficiency improvement

Enterprise Group	Substantive test sample size (number of samples)	Total audit duration (person-hours)	Audit fees (ten thousand yuan)	Risk rating of material misstatement	Time efficiency improvement rate (%)
Mean values of A1-A6 in the experimental groups (before application)	3842	1847	156.3	Medium and high	-
Mean values of experimental groups A1-A6 (after application)	2214	1065	118.7	medium to low	42.3
Mean values of B1-B6 in the control group (during the same period)	3791	1832	153.8	Medium and high	1.2
Significance of differences between groups (t-value)	4.83***	5.26***	3.91***	-	-

TABLE 3. Results of Regression Analysis on the Relevance of Investor Decisions

Variable	Model 1 (Benchmark)	Model 2 (with LLM disclosure)	Model 3 (Experimental Group)	Model 4 (Control Group)
Earnings per share (EPS)	3.247***(0.418)	2.983***(0.392)	3.156***(0.401)	3.221***(0.445)
Net asset value per share (BVPS)	0.876***(0.103)	0.794***(0.098)	0.812***(0.095)	0.869***(0.108)
LLM asset disclosure variables	-	1.532***(0.287)	1.847***(0.312)	0.243 (0.196)
Adjust R^2	0.524	0.638	0.675	0.531
F-statistic	87.34	118.67	132.45	89.12
Sample size	192	192	96	96

Note: *, 1, and 10% indicate significance at the 1%, 5%, and 10% levels, respectively; the standard error is in parentheses.

can effectively identify and supplement subdivided subject data. The paired t-test results all showed p-values less than 0.001, indicating that the improvement in transparency is statistically significant.

B. ASSESSMENT OF THE RELEVANCE OF AUDIT EFFICIENCY TO INVESTOR DECISIONS

Audit efficiency tracking records four indicators: audit team working hours and test sample size changes such as hour of substantive procedure execution time, cycle of confirmation send and receive time, analytical review time, audit adjust entry process time. Stock price and earnings per share, net assets per share, and LLM asset disclosure information selected as dependent variable to test investor decision relevance with value relevance model. Ohlson regression analysis implemented to collect audit report issue date, audit fee, audit opinion type information from experimental group and control group. Total audit time and audit time unit asset calculated. Stock closing price selected as event study window, abnormal investor trading volume, analyst attention, institutional research times after financial statement announcement.

Table 2 shows that after applying the framework, the number of substantive test samples in the experimental group was reduced from 3842 to 2214, a decrease of 42.4%. The total audit time was correspondingly reduced to 1065 person-hours, resulting in a 42.3% improvement in time efficiency and a 24.1% saving in audit costs to RMB 1.187 million. In contrast, the control group showed only a slight improvement of 1.2%. Table 3 shows that the model adjustment R^2 increased from 0.524 to 0.638 after adding the LLM asset disclosure variable. The R^2 for the experimental group subsample reached 0.675, 27.1% higher than the 0.531 in the control group. The coefficient of the LLM asset disclosure variable was 1.847 in the experimental group and significant at the 1% level, while the coefficient in the control group was only 0.243 and not significant. The Chow test F-value was 12.83 ($p<0.001$), confirming that intelligent disclosure information has a significant incremental explanatory power for investors' pricing decisions. The 28.8% increase in investor decision relevance is both economically and statistically significant.

V. CONCLUSION

This paper focuses on the problems of ambiguous recognition, difficult value measurement and lack of disclosure standards of assets in the intelligent accounting system under the background of new quality productivity. According to the large language model, the framework of asset entry and disclosure are established. Based on the three-layer progressive asset identification model, it determines the judgment basis of technical substance, economic benefits and measurable costs. A parallel measurement way of cost and income approach solves the problem of dynamic value measurement. Structured disclosure template transfers the information of technical parameters, data traceability, application effectiveness and risk control. The empirical results show that the framework improves financial statement transparency, improves the efficiency of audit, makes investors decision-making relevant, and improves regulatory compliance. The framework establishes a theoretical framework and implementation path of standardized application of intelligent accounting technology. It promotes the new quality productivity factors from technological black box value to explicit value, improves the accounting standards system under digital economy.

AUTHOR CONTRIBUTIONS

Wang Jing designed, collected and analyzed the data, and drafted the manuscript. Wang Jing conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Wang Jing participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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