Research on the Reshaping Path of Professional Competence of Accountants in the Era of Artificial Intelligence: Dynamic Optimization Perspective Based on Competency Model

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Abstract: With the rise of the AI (Artificial intelligence) era, as AI technology deeply reshapes the accounting industry, and traditional accounting functions and work models are undergoing revolutionary changes. This research explores the new connotations and components of professional competencies for accountants in the AI era from the perspective of dynamic optimization of competency models. It constructs a four-dimensional competency framework: core competency-professional ability-technical capability-strategic thinking. Using literature review, case studies, and structural equation modeling, the research examines the status and gaps in the competencies of accountants. Besides，the research proposes three targeted approaches to reshape the professional competencies of accountants: improving the education and training system, establishing a dynamic evaluation mechanism, and optimizing the career advancement system. This research aims to provide theoretical support for revising accounting talent development programs in universities, enhancing corporate accounting talent development mechanisms, and promoting the self-improvement of accounting professionals, thereby assisting accounting practitioners in achieving sustainable career development in the AI era.

Keywords: Artificial Intelligence Era; Accountants; Competence; Reshaping Path; Dynamic Competency Model

1. Introduction

In recent years, with the rapid advancement of artificial intelligence technology, its applications across various industries have deepened, and the accounting industry is no exception. AI is reshaping the accounting industry's ecosystem, business processes, and functional roles at an unprecedented pace. International accounting firms like PwC and KPMG have taken the lead in introducing financial robots to boost efficiency, while major domestic enterprises are accelerating the deployment of intelligent financial shared service centers. According to the KPMG Global Financial Intelligence Survey Report, 71% of companies have already implemented AI in their financial operations [1]. The role of accounting has shifted from simple financial calculations to more advanced strategic decision-making. Based on this, this research constructs a four-dimensional competency framework that includes core competencies, professionalability, technical capability, and strategic thinking. This framework not only covers traditional accounting skills but also integrates new capabilities required in the AI era, which is providing a reference for the transformation of accounting professionals in the AI era. The research employs methods such as bibliometric analysis and structural equation modeling to examine the impact of the AI era on the accounting industry, the construction of the accounting personnel competency model, the current status and gaps in the accounting personnel's competencies, and the pathways for reshaping the professional competencies of accounting personnel carry on research.

2. Literature Review

2.1 Accounting: AI Application Status

The application of AI technology in the accounting field is expanding, which reflecting the industrys transformation and efficiency gains driven by technological advancements.

Currently, AI is widely used in repetitive and rule-based accounting tasks, such as voucher entry, account reconciliation, and report generation. Financial Robots (RPA) automate operations like invoice recognition and bank reconciliation through predefined rules, significantly reducing human error and boosting efficiency [2]. For instance, numarics as a fintech company, which has successfully integrated AI with expertise in accounting, auditing, and digitalization to develop an integrated intelligent digital financial management application [3]. It demonstrates that the potential for AI technology development remains significant, and it is expected to further transform the way the accounting industry operates in the future.

2.2 Traditional Accounting: Function & Mode Reform

Under the influence of artificial intelligence technology, the functions and working models of traditional accounting have undergone a significant transformation. Fundamentally, AI is reshaping the accounting profession, and transforming accountants from traditional data processors into strategic business advisors [4]. It is evident that the basic accounting functions are becoming less prominent, while the analytical and decision-making roles are being strengthened. In fact, AI can perform large-scale data analysis, predict user behavior, and analyze user actions [5]. A prime example is Sage Copilot, launched by Sage, which uses AI to analyze budget variances and provide decision support for businesses [6]. AI technology will further shift the role of accounting from post-event recording to pre-event prediction and in-process control.

2.3 Accounting Competence: Professional Challenges

The rapid advancement of artificial intelligence technology has placed significant pressure on accounting professionals, which compelling them to evolve from specialized roles into versatile talents [7]. Future accountants will need to have a broad knowledge base in finance, management, and information technology [8], and sometimes even integrate knowledge across multiple disciplines. For example, trullions leasing accounting tool requires accountants to set up the algorithm structure, which involves the logic of rent allocation. If accountants are not familiar with the AI systems parameter settings, it could lead to errors in data processing [9].

3. Methodology

3.1 Research Philosophy

The theoretical foundation of competency models primarily stems from the classic theories in psychology, management, and human resource management [10,11]. At its core, it involves establishing quantifiable capability standards by identifying the key competencies of high performers. A key function of competency models is to translate organizational strategies into employee behaviors [12], and then transforming abstract strategic goals into actionable guidelines for employees. For instance, the goal of digital transformation can be broken down into specific business objectives like accountants using AI systems for business processing, which can then be further refined into specific standards such as a 30% increase in the efficiency of reviewing AI-generated financial data [13]. From a behavioral science perspective, the behavior theory studies and explains human behavior through incentives and punishments, which is crucial for understanding the behavior of accounting professionals at work [14]. Therefore, in the accounting field, understanding the behavioral patterns of accounting professionals can help optimize the design of management accounting systems, thereby improving the quality and utilization efficiency of accounting information [15].

3.2 Research Design

The professional competence system for financial personnel, a crucial component of modern enterprise human resource management, encompasses four core dimensions: core competencies (C), professional skills (P), technical capabilities (T), and strategic thinking (S). This system is divided into three levels—beginner, intermediate, and advanced—based on the career development stage, forming a systematic and tiered framework for evaluating capabilities (Table 1).

3.2.1 Research methods

(1) Based on the direct effect model (Direct Effects Model), the following hypotheses are

proposed:

H1: Core quality (C) has a positive impact on comprehensive competence (Y).

H2: Professional ability (P) has a positive impact on comprehensive competence (Y).

H3: Technical ability (T) has a positive impact on comprehensive competence (Y).

H4: Strategic thinking (S) has a positive impact on comprehensive competence (Y).

(2) Based on the mediation model (Mediation Model), the following hypotheses are proposed:

H5: Data-driven decision-making ability (M1) plays a positive mediating role between technical ability (T) and strategic thinking (S).

H6: The proficiency of intelligent tool application (M2) plays a positive mediating

H7: Technical ability (T) has a positive impact on data-driven decision-making ability (M1).

H8: Data-driven decision-making ability (M1) has a positive impact on strategic thinking (S).

Table 1. Four-Dimensional Competency Model

Core dimensions	Concrete ability	Entry-level requirements	Intermediate requirements	High requirements
Core Competencies (C)	Professional ethics and conduct	Understand basic professional ethics and abide by company rules and regulations	Take the initiative to maintain your professional image and deal with simple moral dilemmas	Establish a model of professional ethics and guidance Others deal with complex moral issues
	Communication and collaboration skills	Be able to complete basic work communication and participate in team collaboration	Coordinate work within the department effectively and express professional opinions clearly	Cross-departmental communication is efficient and promotes recovery Cross-project collaboration
	Learning and adaptability	Receive training and guidance to adapt to the basic requirements of the post	Take the initiative to learn new things and adapt to changes in your job	Lead change and promote organizational learning culture
Professional Ability (P)	Financial accounting knowledge	Master basic accounting treatment and be able to complete simple accounting	Independently handle complex business accounting and prepare financial statements [16]	Design and optimize accounting process, guidance Application of significant accounting policies
	Management accounting skills	Understand basic cost concepts and assist in cost accounting	Conduct cost analysis independently and participate in budget preparation	Lead overall budget management and provide Strategic cost decision support
	Tax processing ability	Understand basic taxes and assist in tax returns	Handle the regular tax matters of the enterprise independently and carry out simple planning	Lead the strategic planning and processing of tax Complex cross-border tax issues
Technical Capability (T)	Information system operations	Proficient in basic financial software	Master the core modules of ERP system and be able to conduct data analysis	Lead the selection and implementation of financial systems to promote digital transformation
	Data analysis capability	Use Excel for basic data processing	Use professional tools for financial analysis and produce visual reports	Build predictive models and support data Drive decisions
	Smart tool applications	Understand basic office automation tools	Proficient in using RPA and other tools to automate processes	Evaluate the introduction of AI technology to optimize finance Intelligent application of services
Strategic Thinking (S)	Business insight	Understand the companys basic business model [17]	Analyze industry trends and identify business opportunities and risks	Anticipate industry change and plan for the long term financial strategy
	Risk management capability	Identify basic financial risks	Establish risk early warning mechanism and formulate response plan	Building a comprehensive risk management system, Ensure the implementation of the strategy
	Resource integration capability	Complete the assigned resource coordination tasks	Optimize the allocation of resources and improve efficiency	Coordinate cross-departmental resources to support the war Achieve sub-goals [18]

3.2.2 Data Sources

This study employed a questionnaire survey method to collect data, utilizing the Questionnaire Star platform to design and distribute the survey. The survey was widely distributed among students in the accounting department and accounting professionals. The survey was conducted over a one-month period, resulting in a total of 250 completed questionnaires. After excluding invalid responses, 212 valid questionnaires were obtained, achieving an effective recovery rate of 84.8%. The questionnaire used a five-point Likert scale as the measurement tool to assess respondents opinions and attitudes toward specific issues, with scores ranging from 1 to 5, where 1 indicates strongly disagree and 5 indicates strongly agree, for quantitative evaluation. The questionnaire comprised 20 questions, covering various dimensions of competence, presented in a closed-ended format to ensure practicality and data comparability.

3.3 Data Analysis

The reliability and validity of the questionnaire were evaluated using SPSS26.0.

3.2.1 Reliability analysis

According to the reliability analysis results (Table 2), the Krummbach Alpha coefficient of each dimension is above 0.7, indicating that the reliability of the data is good. Moreover, the Krummbach Alpha coefficient after deletion is smaller than that of each dimension, indicating that each item is appropriate.

3.2.2 Validity analysis

Meanwhile, a validity analysis was conducted. The results of the validity analysis (Table 3) indicate that the KMO value of the data is 0.868, and it has passed the Bartletts test of sphericity, indicating that the data is suitable for factor analysis. The total variance explained (Table 4) shows that a total of 7 factors were extracted, with 79.869% of the total variance explained, suggesting that the information extraction is quite thorough. The rotated component matrix (Table 5) indicates that the dimensions of the extracted factors align with the original questionnaire, indicating good data validity.

Table 2. Reliability Analysis

	The mean of the scale after deletion	Standard deviation after deletion	Revised items and their correlation to the total	Clone Bach Alpha after deletion	Cloning Bach Alpha
C1	6.54	4.685	0.716	0.8	0.852
C2	6.52	4.308	0.746	0.77	
C3	6.6	4.336	0.707	0.809	
P1	6.47	5.426	0.726	0.83	0.866
P2	6.54	5.074	0.757	0.8	
P3	6.38	4.558	0.759	0.801	
T1	6.11	4.518	0.714	0.807	0.854
T2	6.19	4.912	0.73	0.793	
T3	6.21	4.488	0.735	0.786	
S1	6.56	4.731	0.74	0.752	0.843
S2	6.58	4.625	0.703	0.785	
S3	6.5	4.64	0.682	0.807	
DDMA1	6.32	5.156	0.745	0.827	0.871
DDMA2	6.34	4.965	0.754	0.818	
DDMA3	6.38	4.844	0.762	0.811	
PITA1	6.47	5.473	0.726	0.83	0.866
PITA2	6.54	5.197	0.775	0.784	
PITA3	6.58	5.26	0.736	0.821	
CC1	3.25	1.357	0.661		0.796
CC2	3.24	1.34	0.661	.	

Table 3. Validity Analysis

KMO and Bartlett test		
KMO sample adequacy index.		0.868
Bartlett sphericity test	Approximate chi-square	2422.069
	free degree	190
	conspicuousness	0.000

Table 4. Total Variance Interpretation

ingredient	Initial eigenvalues			Extract the squared load			Square sum of repeated loads		
	amount to	variance percentage	accumulate %	amount to	variance percentage	accumulate %	amount to	variance percentage	accumulate %
1	7.700	38.500	38.500	7.700	38.500	38.500	2.462	12.311	12.311
2	1.693	8.466	46.966	1.693	8.466	46.966	2.410	12.048	24.359
3	1.473	7.365	54.331	1.473	7.365	54.331	2.390	11.952	36.312

4	1.436	7.178	61.509	1.436	7.178	61.509	2.383	11.915	48.227
5	1.413	7.063	68.572	1.413	7.063	68.572	2.359	11.795	60.021
6	1.258	6.291	74.863	1.258	6.291	74.863	2.322	11.611	71.633
7	1.001	5.006	79.869	1.001	5.006	79.869	1.647	8.236	79.869
8	0.49	2.449	82.318						
9	0.438	2.191	84.509						
10	0.385	1.927	86.436						
11	0.375	1.874	88.310						
12	0.339	1.693	90.003						
13	0.32	1.599	91.602						
14	0.293	1.467	93.069						
15	0.289	1.444	94.513						
16	0.256	1.28	95.793						
17	0.236	1.179	96.972						
18	0.227	1.136	98.108						
19	0.209	1.045	99.153						
20	0.169	0.847	100.000						

Table 5. The Rotated Component Matrix

	ingredient						
	1	2	3	4	5	6	7
C1	0.043	0.181	0.841	0.087	0.096	0.126	0.208
C2	0.128	0.158	0.826	0.107	0.157	0.167	-0.055
C3	0.167	0.078	0.82	0.176	0.11	0.151	0.199
P1	0.128	0.198	0.134	0.194	0.169	0.76	0.188
P2	0.112	0.133	0.104	0.159	0.128	0.818	0.117
P3	0.14	0.15	0.219	0.102	0.113	0.812	0.095
T1	0.178	0.041	0.158	0.128	0.84	0.14	0.131
T2	0.121	0.169	0.073	0.142	0.814	0.055	0.139
T3	0.119	0.192	0.134	0.152	0.793	0.219	0.097
S1	0.134	0.081	0.184	0.799	0.145	0.15	0.116
S2	0.178	0.195	0.035	0.824	0.152	0.161	0.087
S3	0.126	0.102	0.139	0.848	0.12	0.124	0.1
DDMA1	0.847	0.179	0.101	0.094	0.154	0.109	0.153
DDMA2	0.827	0.111	0.124	0.175	0.074	0.127	0.181
DDMA3	0.855	0.078	0.103	0.171	0.191	0.133	0.012
PITA1	0.09	0.828	0.149	0.14	0.157	0.123	0.105
PITA2	0.175	0.818	0.122	0.093	0.183	0.091	0.135
PITA3	0.104	0.824	0.144	0.143	0.053	0.266	0.084
CC1	0.199	0.106	0.19	0.174	0.154	0.221	0.815
CC2	0.143	0.218	0.136	0.129	0.221	0.163	0.819

3.2.3 Distinguish between validity analysis

In addition, the discriminant validity test was also conducted. According to the discriminant validity results (Table 6), the square root of AVE value of each factor is greater than the coefficient with other factors, and all are above 0.7, indicating that the discriminant validity of the data is good.

According to the results of the factor loading coefficient table (Table 7), the factor loading of each item is above 0.7, indicating that the correlation between the factors and items is high, and the factors can represent the items. The CR value is above 0.8, and the AVE value is above 0.6, indicating that the data has good aggregation validity, which indicates that the questionnaire has strong discriminant validity.

3.2.4 Correlation analysis

According to the results of correlation analysis (Table 8), it is found that there are significant positive correlations between core competency, professional ability, technical Capability strategic thinking, data-driven decision-making ability, proficiency in intelligent tool application, comprehensive competence and other indicators, and the correlation coefficients are all below 0.5, which is relatively low.

Table 6. Discriminatory Validity

	Core competencies	Professional ability	Technical Capability	Strategic thinking	Data-driven decision-making ability	Proficiency in intelligent tool application	Comprehensive competencies
Core competencies	0.825						
professional ability	0.502	0.801					
technical competence	0.428	0.494	0.813				
Strategic thinking	0.413	0.502	0.465	0.821			
Data-driven decision making ability	0.385	0.440	0.459	0.460	0.844		
Proficiency in intelligent tool application	0.452	0.535	0.443	0.438	0.413	0.823	
Comprehensive competencies	0.510	0.569	0.526	0.470	0.490	0.482	0.842

Table 7. Factor Loadings Table

			Estimate	S.E.	C.R.	P	CR	AVE
C3	<---	Core qualities	0.854				0.865	0.681
C2	<---	Core competencies	0.777	0.074	12.408	***		
C1	<---	Core competencies	0.842	0.073	13.463	***		
P3	<---	professional ability	0.801				0.843	0.642
P2	<---	professional ability	0.773	0.08	11.359	***		
P1	<---	professional ability	0.828	0.09	12.059	***		
T3	<---	technical competence	0.834				0.854	0.661
T2	<---	technical competence	0.758	0.075	11.683	***		
T1	<---	technical competence	0.845	0.07	12.935	***		
S3	<---	Strategic thinking	0.828				0.861	0.674
S2	<---	Strategic thinking	0.849	0.079	13.066	***		
S1	<---	Strategic thinking	0.784	0.075	12.158	***		
DDMA1	<---	Data-driven decision-making ability	0.864				0.881	0.712
DDMA2	<---	Data-driven decision making ability	0.823	0.071	13.928	***		
DDMA3	<---	Data-driven decision-making ability	0.844	0.068	14.328	***		
PITA3	<---	Proficiency in intelligent tool application	0.845				0.863	0.678
PITA2	<---	Proficiency in intelligent tool application	0.804	0.073	12.72	***		
PITA1	<---	Proficiency in intelligent tool application	0.821	0.07	12.993	***		
CC1	<---	Comprehensive competencies	0.857				0.830	0.709
CC2	<---	Comprehensive competencies	0.827	0.087	10.792	***		

Table 8. Correlation Analysis

	Core competencies	professional ability	technical competence	Strategic thinking	Data-driven decision-making ability	Proficiency in intelligent tool application	Comprehensive competencies
Core competencies	1						
professional ability	0.430**	1					
technical competence	0.367**	0.414**	1				
Strategic thinking	0.362**	0.428**	0.404**	1			
Data-driven decision-making ability	0.338**	0.380**	0.395**	0.404**	1		
Proficiency in intelligent tool application	0.394**	0.451**	0.393**	0.375**	0.362**	1	
Comprehensive competencies	0.418**	0.473**	0.449**	0.399**	0.419**	0.414**	1

3.2.5 Competency gap analysis (structural equation model)

The AMOS 24 software was used to construct the model diagram (Figure 1), and the overall goodness of fit of the model was tested and analyzed (Table 9). The $\chi 2$ value of the overall fit index is significantly influenced by the sample size. The results from the structural equation modeling indicate that the CMIN/DF ratio is 1.257, which is less than 3, indicating a good fit of the model. The RMR is 0.053, and the RMSEA is 0.035. Additionally, indicators such as GFI, AGFI, IFI, TLI, and CFI are all above 0.8, suggesting a good fit of the model.

According to the results of the path coefficient table (Table 10), it is known that core quality can significantly affect data-driven decision-making ability (β=0.116, $p<0.05$), Proficiency in the application of intelligent tools ($\beta=0.177$, $p<0.05$) Comprehensive Competence ($\beta=0.179$, $p<0.05$), all coefficients are positive, indicating that core competencies positively promote data-driven decision-making ability, proficiency in intelligent tool application, and comprehensive competence; professional competence can significantly influence data-driven decision-making ability ($\beta=0.3$, $p<0.05$), Proficiency in the application of intelligent tools ($\beta=0.16$, $p<0.05$), Comprehensive Competence ($\beta=0.225$, $p<0.05$), all coefficients are positive, indicating that professional competence positively promotes data-driven decision-making ability, proficiency in intelligent tool application, and comprehensive competence; technical competence significantly influences data-driven decision-making ability ($\beta=0.226$, $p<0.05$), Proficiency in the application of intelligent tools ($\beta=0.154$, $p<0.05$),Comprehensive Competence ($\beta=0.185$, $p<0.05$), all coefficients are positive, indicating that technical ability positively promotes data-driven decision-making, proficiency in intelligent tool application, and comprehensive competence; strategic thinking significantly influences data-driven decision-making ($\beta=0.229$, $p<0.05$),Proficiency in the application of intelligent tools ($\beta=0.147$, $p<0.05$), Comprehensive Competence ($\beta=0.082$, $p<0.05$) showed positive coefficients, indicating that strategic thinking positively promoted data-driven decision-making ability, proficiency in intelligent tool application, and comprehensive competence; Data-driven decision-making ability ($\beta=0.158$, $p<0.05$),Proficiency in the application of intelligent tools ($\beta=0.098$, $p<0.05$) has a positive impact on comprehensive competence. The analysis of the mediation effect (Table 11) shows that in the path from core competencies to data-driven decision-making ability and then to comprehensive competence, the indirect effect confidence interval is 0.001-0.053, excluding 0, indicating a significant mediation effect, suggesting that data-driven decision-making ability mediates the relationship between core competencies and comprehensive competence. Similarly, in the path from professional skills to data-driven decision-making ability and then to comprehensive competence, the indirect effect confidence interval is 0.005-0.075, excluding 0, indicating a significant mediation effect, suggesting that data-driven decision-making ability mediates the relationship between professional skills and comprehensive competence. In the path from technical skills to data-driven decision-making ability and then to comprehensive competence, the indirect effect confidence interval is 0.011-0.081, excluding 0, indicating a significant mediation effect, suggesting that data-driven decision-making ability mediates the relationship between technical skills and comprehensive competence. In the path from strategic thinking to data-driven decision-making ability and then to comprehensive competence, the indirect effect confidence interval is 0.013-0.094, excluding 0, indicating a significant mediation effect, suggesting that data-driven decision-making ability mediates the relationship between strategic thinking and comprehensive competence. In the path from core competencies to proficiency in intelligent tool application and then to comprehensive competence, the indirect effect confidence interval is 0.006-0.067, excluding 0, indicating a significant mediation effect, suggesting that proficiency in intelligent tool application mediates the relationship between core competencies and comprehensive competence. There is a mediating effect between competencies; in the path from professional ability to intelligent tool proficiency and then to comprehensive competence, the indirect effect confidence interval is 0.009-0.119, excluding 0, indicating that the mediating effect is valid, meaning that the proficiency in using intelligent tools acts as a mediator between professional ability and comprehensive competence. Similarly, in the path from technical ability to intelligent tool proficiency and then to comprehensive competence, the indirect effect confidence interval is 0.002-0.069, excluding 0, indicating that the mediating effect is valid, meaning that the proficiency in using intelligent tools acts as a mediator between technical ability and comprehensive competence. Lastly, in the path from strategic thinking to intelligent tool proficiency and then to comprehensive competence, the indirect effect confidence interval is 0.004-0.081, excluding 0, indicating that the mediating effect is valid, meaning that the proficiency in using intelligent tools acts as a mediator between strategic thinking and comprehensive competence.

Table 9. Key Indicators

metric	standard	numeric value
CMIN		188.515
CMIN/DF	<3	1.257
RMR	<0.05	0.053
GFI	>0.9	0.925
AGFI	>0.9	0.895
IFI	>0.9	0.984
TLI	>0.9	0.979
CFI	>0.9	0.983
RMSEA	<0.05	0.035

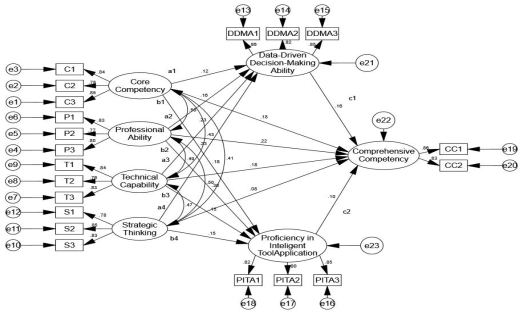

Figure 1. Structural Equation Model of the Factors Influencing the Revision

Table 10. Path Coefficient Table

			β	B	S.E.	C.R.	P
Data-driven decision-making ability	<---	Core competencies	0.116	0.121	0.088	2.366	0.017
Proficiency in intelligent tool application	<---	Core competencies	0.177	0.188	0.09	2.089	0.037
Proficiency in intelligent tool application	<---	professional ability	0.3	0.346	0.11	3.136	0.002
Proficiency in intelligent tool application	<---	technical competence	0.154	0.161	0.091	2.075	0.038
Proficiency in intelligent tool application	<---	Strategic thinking	0.147	0.155	0.091	2.703	0.008
Data-driven decision making ability	<---	professional ability	0.16	0.18	0.107	2.682	0.009
Data-driven decision-making ability	<---	technical competence	0.226	0.232	0.09	2.565	0.01
Data-driven decision making ability	<---	Strategic thinking	0.229	0.236	0.091	2.609	0.009
Comprehensive competencies	<---	Data-driven decision-making ability	0.158	0.154	0.08	2.14	0.035
Comprehensive competencies	<---	Proficiency in intelligent tool application	0.098	0.094	0.082	2.143	0.035
Comprehensive competencies	<---	Core competencies	0.179	0.181	0.085	2.142	0.032
Comprehensive competencies	<---	professional ability	0.225	0.248	0.107	2.319	0.02
Comprehensive competencies	<---	technical competence	0.185	0.186	0.087	2.125	0.034
Comprehensive competencies	<---	Strategic thinking	0.082	0.083	0.087	2.057	0.039

Table 11. Mediation Effect Analysis

way	The effect size	standard error	95% confidence interval	
			lower limit	superior limit
Core quality-> data-driven decision-making ability-> comprehensive competence	0.018	0.016	0.001	0.053
Professional ability-> data-driven decision-making ability-> comprehensive competence	0.025	0.02	0.005	0.075
Technical ability-> data-driven decision-making ability-> comprehensive competence	0.036	0.021	0.011	0.081
Strategic thinking-> data-driven decision-making ability-> comprehensive competence	0.036	0.022	0.013	0.094
Core quality-> proficiency in intelligent tool application-> comprehensive competence	0.017	0.019	0.006	0.067
Professional ability-> proficiency in intelligent tool application-> comprehensive competence	0.029	0.032	0.009	0.119
Technical ability-> proficiency in intelligent tool application-> comprehensive competence	0.015	0.017	0.002	0.069
Strategic thinking-> proficiency in intelligent tool application-> comprehensive competence	0.014	0.016	0.004	0.081

4. Discussion

4.1 Improve the Education and Training System

The key to reshaping the professional competence of accounting personnel lies in enhancing the education and training system to adapt to the rapidly evolving global economy and emerging technologies. [18] Schools can align their curricula with real-world accounting scenarios to develop students problem-solving skills. For example, by analyzing financial scandals, students can gain a deeper understanding of the importance of professional ethics. At the same time, schools can integrate information technology into teaching to enhance students ability to use technology to solve accounting problems [19]. Information technology instruction should emphasize student participation, self-directed learning, and the development of critical thinking [19]. Additionally, it is crucial to strengthen the integration of artificial intelligence (AI) into accounting education. This includes developing students skills in using AI accounting information systems to improve work efficiency and data analysis capabilities.

4.2 Establish a Dynamic Evaluation Mechanism

To reshape the professional competence of accounting personnel, it is crucial to establish a dynamic evaluation mechanism. This mechanism must adapt to the rapidly changing business environment and technological advancements, ensuring the continuous development of accounting professionals and maintaining their professional capabilities while optimizing career advancement systems. The dynamic evaluation mechanism should be based on a clearly defined competency framework that includes technical skills, critical thinking, communication skills, leadership, and ethical and professional values [20]. Additionally, the dynamic evaluation mechanism should provide ongoing feedback and guidance to help accounting personnel understand their strengths and weaknesses and develop improvement plans.

4.3 Optimize the Career Promotion System

To optimize the career advancement system for accounting professionals, it is essential to start by identifying the weaknesses in the current system and then reshape it according to the characteristics and trends of the accounting industry. First, companies should provide employees with clear career development paths, aligning personal goals with corporate strategies, and helping them understand the conditions and requirements for promotion. Second, for different levels of accounting positions (such as junior accountant, supervisor, financial manager, and financial director), clearly define the required competencies and link these standards to career advancement. These standards should be quantifiable where possible, and if not, they should have clear descriptive requirements [21]. Finally, use a variety of evaluation methods (such as 360-degree feedback, scenario simulations, written tests, and interviews) to comprehensively assess the competencies of accounting personnel, and use the evaluation results as a key basis for promotions.

5. Conclusion and Prospect

5.1 Research Conclusion

This research sets against the backdrop of artificial intelligence reshaping the accounting industry, constructs a four-dimensional competency framework: core qualities, professional skills, technical skills, and strategic thinking. It reveals new dimensions of professional competence for accountants. The study confirms that the advancement of AI will drive the transformation of accounting functions from mere record-keeping to strategic decision-making. Traditional accounting methods can no longer meet the industrys needs, and the four key dimensions—core competency, professional ability, technical caoability, and strategic thinking—will become the critical factors in distinguishing accounting professionals. Empirical tests further validate the models guiding value for the development of accounting personnels capabilities. The study also proposes pathways for reshaping these competencies from the perspectives of the education system, evaluation mechanisms, and career development, providing theoretical and practical references for university curriculum reform, corporate talent cultivation, and the self-improvement of accounting practitioners.

5.2 Insufficient and Prospects

The data for this research primarily comes from students in the accounting department and accounting professionals. The sample is concentrated in specific fields, with insufficient coverage of specialized sectors such as finance and government, which may affect the general applicability of the research findings. Additionally, artificial intelligence technology evolves rapidly, and the competency model developed in this study has limitations in its forward-looking analysis of emerging technologies, failing to fully meet the demands of future accounting scenarios.

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