

# Can AI Improve the Nominal Validity of Empirical Research in Modern Financial Accounting?

Wang S\*

*School of Finance and Economics, University of Sanya, No. 191 Xueyuan Road, Jiyang District, Sanya City, Hainan Province, China*

\*Corresponding author: Wang S, School of Finance and Economics, University of Sanya, No. 191 Xueyuan Road, Jiyang District, Sanya City, Hainan Province, China; E-mail: [fw107@foxmail.com](mailto:fw107@foxmail.com)

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## Abstract

The application of empirical regression analysis in the field of accounting and finance has become increasingly widespread. Today, empirical research has already become one of the main academic research paradigms. However, among the numerous empirical research studies in accounting and finance, the similarity of research models, the arbitrariness in the logic of research questions, and the looseness in the argumentation of research problems have affected the scientific and rational nature of the empirical research results. This is an academic issue that few have paid attention to, yet it exists abundantly in current accounting and finance literature. This paper takes empirical accounting articles published in *\*Accounting Research\** in 2024 as samples, collecting 1,140 data points. Using logistic regression analysis and introducing the concept of nominal validity in empirical research, these samples were subjected to quantitative analysis. The study found that about 30% of the empirical research content is nominally valid, while approximately 70% of empirical research is invalid. This academic state conceals significant operational risks, which are highly probable to exist. One of the main reasons for the publication of so many similar research articles lie in the imitation of writing forms and the neglect of strict logical argumentation in research questions, resulting in an academic ecosystem of superficially similar but fundamentally flawed research articles, whose negative impact is difficult to estimate. In the current accounting and finance research landscape, the introduction of AI technology cannot change the ongoing prevalence of this situation. Through variance analysis and the calculation of information entropy, it is further verified from another perspective that the nominal validity of empirical research is robustly around 30%.

**Keywords:** Financial accounting; Empirical research; AI; Nominal validity; Information entropy

## Introduction

Empirical regression analysis has become one of the fundamental paradigms in contemporary financial accounting research. In recent years, the vast majority of articles published in *\*Accounting Research\** have conducted empirical studies on data samples through the establishment of econometric models, following this basic research model. With the expansion of applications of artificial intelligence (AI), its use in modern financial accounting empirical regression analysis is gradually increasing and is bound to become a powerful research tool. The penetration and impact of AI technology in financial decision-making, data analysis and forecasting, automated processing and intelligent decision-making,

intelligent decision support systems, and AI accounting education have become a rapidly growing trend. It can thus be said that the application of AI in financial accounting is an unavoidable and significant subject. However, research analysis shows that the underlying logic of AI technology applications in modern accounting empirical research follows already widely adopted modeling methods and research paradigms and does not exceed existing research norms. Based on this analysis, we conclude the following logical finding: AI technology in modern financial accounting empirical research follows the same underlying logic as that followed by existing financial accounting research. Based on this judgment, the traditional empirical research paradigm of financial accounting can be seamlessly applied to the context of AI

technology, with no essential distinction. The remainder of this article is structured as follows: Section 2 provides a literature review and research hypotheses; Section 3 presents the research design; Section 4 offers the empirical regression analysis; Section 5 discusses AI application models; Section 6 covers results and discussion; and Section 7 concludes the paper.

## Literature Review and Research Hypotheses

In the research literature published in *\*Accounting Research\**, it is rare to see articles that rely entirely on AI technology; however, this does not hinder the smooth introduction of AI technology. In financial accounting research, empirical analyses using econometric models cover a wide and diverse range of topics, reflecting a certain degree of depth and breadth in the research. This can be glimpsed from the following eight research perspectives.

**Regarding the digital transformation of enterprises:** the digital transformation of enterprises improves the symmetry of information within the company, reduces the risk of credit default and the cost of credit financing [1], suppresses management from manipulating the tone of annual reports [2], and can also reduce corporate debt financing costs through financial shared services [3]. The resulting economic effects can be predicted using an internal model to forecast internal control deficiencies based on recurrent neural networks [4].

**From the perspective of corporate management:** The absence of a controlling shareholder can influence the excess returns of management stock trading [5]. In fact, the executive compensation claw back system can effectively curb corporate misconduct [6]. Corporate executives, such as the chairman, due to emotional ties like hometown sentiment and familial relationships, tend to be stricter in corporate supervision, thereby reducing the occurrence of violations [7].

**In terms of corporate information disclosure:** the comparability of accounting information can not only improve analysts' accuracy in predicting stock market trends [8], but may also reduce the likelihood of stock exchanges issuing annual report inquiry letters [9]. This information, whether related to the company's financial assets or the technical background of directors, in addition to potentially enhancing corporate social responsibility [10], is greatly beneficial for improving the firm's total factor productivity [11].

**Regarding state-owned enterprises and participation or control of state-owned equity:** Participation of state-owned equity can effectively reduce the financial risks of family businesses [12]. In fact, compared to non-state shareholders, governance can not only increase the share of employees' labor income in competitive industry state-owned enterprises [13], but

also optimize the strategic decisions of state-owned enterprises, promote research and development innovation of products and services, and enhance the efficiency and effectiveness of state-owned enterprise operations [14].

**Publicly Listed Companies and Their Regulation:** The regulation of publicly listed companies involves market transparency and the choice of corporate strategies. For example, relaxing short-selling regulations exacerbates companies' behavior of short-term borrowing for long-term investments [15]; encouraging listed companies to participate in targeted poverty alleviation projects stimulates their expansion into businesses in other regions and the establishment of new subsidiaries [16]; strengthening regulatory measures prompts listed companies with implicit related-party relationships to improve their real earnings management levels [17]. Even if accounts receivable accounting policies are strengthened, the expected credit loss model can still detect their earnings levels through the bad debt provisions made by listed companies [18]. In practice, using different evaluation methods results in varying assessments of the operational performance of listed companies. For instance, achievement-oriented ESG ratings cannot identify signs of stock price collapses, whereas risk-oriented ESG evaluations can predict the risk of stock price crashes [19].

**Audit supervision:** Conducting audit supervision over listed companies has a significant impact on the operational status of enterprises, and vice versa. Companies are keen on mergers and acquisitions (M&A), which, besides being closely related to normal business expansion and the implementation of diversified development strategies, are sometimes used by companies to cover up abnormal operational behaviors. Government audit supervision can curb such M&A activities that are not necessary for business development [20]. Regarding the operation of a company, it faces real challenges concerning audit quality and audit fees [21]. If a company implements a "fuzzy consolidation" strategy, it must face higher audit fees [22]. If a company attempts to attract investment by promising higher performance returns, it will face rigorous audits from major accounting firms such as the Big Four [23]. Even if some accounting firms are willing to provide audit cover for a company's operational behavior, this cooperation will be greatly suppressed once the firm is subject to inspection [24]. In the digital era, audit work is greatly impacted and also uncertain [25]. The development of the internet can not only significantly improve audit correction quality [26] but also, the CPA examination system can significantly enhance audit quality [27].

**Corporate supervision, management, and operations:** After the rollout of the Golden Tax Phase III system, companies increasingly manipulate core performance through profit and loss classification [28]. This demand driven by 'risk transfer' and 'goal selection' makes distant acquirers more willing to sign contracts and commit

higher amounts [29]. However, companies that secure government procurement contracts benefit from the supervisory governance associated with such procurement [30]. Equity pledges are also a financing activity in corporate operations. Exercising shareholder center rights can effectively curb shareholders' equity pledge behavior and prompt companies to increase cash dividend payments [31]. Greater stability in cash dividends can increase a company's financial leverage [32].

**Other related aspects:** The operational efficiency of government-backed foundations is high [33]; cross-industry diversification of loans may increase systemic risks for banks [34]; and equity internationalization helps enhance a company's value creation capability in mergers and acquisitions [35]. Based on the in-depth analysis and review of the above literature, it is found that a common characteristic of all empirical studies on the topic is that they primarily focus on testing the statistical significance of parameters, while paying little attention to the goodness of fit. A fundamental reason for this situation is the pursuit of expanding sample size, which, in a statistical sense, masks the validity of the model itself by increasing the number of sample points, resulting in a nominally valid conclusion. This method is highly misleading. Therefore, the hypotheses of this paper are as follows:

H1: Are existing financial accounting empirical studies nominally valid?

The way to answer this question is to estimate the probability of empirical analysis being valid.

H2: Can AI improve the validity of such empirical research?

This hypothesis mainly discusses whether AI can autonomously transcend the existing paradigms of financial accounting empirical research to make up for the shortcomings of current empirical studies.

## Research Design

In empirical regression analysis of financial accounting, the modeling methods used are basically consistent, namely

Dependent variable = Intercept + Explanatory variables (group) + Control variables (group) + Random error term

The sample involves collecting relevant data around these variables, and the sample size is expanded as much as possible, following the principle that the larger, the better. Additionally, there is work on modifying the raw data, that is, the original samples, if the researcher considers it necessary. Then, a series of supplementary empirical regression analyses are conducted on the basic regression results, such as robustness tests, endogeneity tests, unit root tests, mechanism tests, and fixed effects tests, among others, in order to demonstrate that the research conducted is robust and reliable. The common characteristic of these studies is that tests are conducted for the sake of testing; all possible tests are

carried out without arguing for the necessity or sufficiency of these tests. These tests are mainly based on subjective assumptions. Naturally, such research brings about an obvious problem: Are these studies valid? Is it possible that a large number of invalid studies are being regarded as valid? Answering these questions, circling back to the earlier research hypothesis, is the purpose of this study. In order to study these fundamental issues, this paper will conduct the corresponding research using logistic regression analysis. The reason for choosing the logistic regression analysis method is that it meets the requirements of the collected samples necessary for this study. The samples collected in this paper all come from the empirical research content of 35 research papers published in Accounting Research, totaling 1,140 sample points. These sample points are sufficient to support the needs of this study. Considering the completeness of the article, the data obtained from each empirical model in the article are regarded as independent samples, because these data are independent. Although there is a certain subjective correlation between these models in a certain sense, they are actually relatively independent and lack a strictly logical necessary connection.

Why is it said that these data in the same article are independent of each other?

The main reason is that, on the surface, every empirical model exhibits a certain degree of correlation, and these correlations are based on subjective speculation. For example, after conducting a benchmark model test, if there is a subjective suspicion of possible multicollinearity, a multicollinearity test is carried out; if there is a subjective suspicion of autocorrelation, an autocorrelation test is then conducted, and so on. From a research perspective, such work is considered to be ineffective, or even a deliberate attempt to increase the length of the paper, and some may engage in this type of research under the mindset of 'doing more can't hurt.' However, as rigorous research, conducting unnecessary excessive tests is a waste of resources. From the perspective of precise and efficient strategy, any correlation between empirical models that is not pre-justified by a sound logical relationship, but based merely on 'subjective suspicion,' is regarded as having no necessary connection with each other within an article, even if the article claims there may be some 'correlations' between them. The sample collected in this study consists of the goodness-of-fit for each empirical model. The 1,140 goodness-of-fit measures correspond to 1,140 empirical regression reports, and their random statistical distribution is shown as follows:

The arrangement of the 1,140 sample points shown in Figure 1 is random, and the overall distribution appears to be stable. In order to conduct more precise scientific research on this sample, it is necessary to establish an appropriate econometric model and adopt suitable research methods.

Definition 1: For a certain positive number  $\vartheta \in (0,1)$ , define the dummy variable as follows:

$$1, R^2 \geq \vartheta \\ D = \{0, R^2 < \vartheta,$$

where  $\vartheta$  is the nominal measurement parameter,  $R^2$  represents the goodness of fit.

According to econometric theory, for every empirical regression model, there exists a corresponding goodness-of-fit, which reflects how well the empirical model fits the sample data. A higher goodness-of-fit indicates that the corresponding empirical model has stronger explanatory power for the population; conversely, a lower goodness-of-fit suggests weaker explanatory power for the population. For an empirical model, its ability to explain the data exists at least on two levels. The first level is the measurement of the model's explanatory power for the population, i.e., the goodness-of-fit. The second level is the explanatory power of the independent variables for the dependent variable or the overall population. The former serves as the foundation, providing a description of the overall framework, while the latter mainly manifests in the specific functional performance. Based on the literature referenced, numerous empirical studies focus on the significance testing of the latter, while the attention to the former is often consciously or unconsciously neglected. The general strategy is basically to use it if it fits, discard it if it does not, leaving it in a somewhat optional and awkward position. This situation mainly arises from insufficient understanding of goodness-of-fit. The relationship between goodness-of-fit and the independent variables is like the relationship of "without the skin, how can the hair attach?" Here, the "skin" corresponds to the goodness-of-fit, which measures the effectiveness of the empirical model, and the "hair" corresponds to the independent variables. The magnitude of the goodness-of-fit is naturally positively correlated with the empirical model's explanatory power for the population. In this paper, the nominal effectiveness of an empirical regression model in explaining the population is consistently measured by the value of its goodness-of-fit. To this end, the established testing model is shown as follows:

$$Di = a + bR^2 + \varepsilon_i, \quad (1)$$

where  $a$  and  $b$  are parameters,  $\varepsilon$  serving as random disturbance terms.  $i=1,2,\dots,n$ .

**Definition 2:** Suppose  $R^2$  the goodness of fit of an empirical regression model,  $\rho \in (0,1)$  is a nominal measurement parameter. If  $R^2(R^2 \geq \rho)$  the empirical regression model is said to be nominally valid; otherwise, the empirical regression model is said to be nominally invalid.

$R^2(R^2 < \rho)$  is referred to as the nominal validity and nominal invalidity of the corresponding empirical regression model.

The empirical regression model corresponding to the goodness-of-fit of nominal invalidity is also nominally invalid. For the convenience of study, whether it has nominal validity or nominal invalidity, both are referred to as nominal validity. The distinction is expressed through probability; for example, a nominal validity of 60% indicates that 60% of the empirical models are nominally valid, while 40% of the empirical models are nominally invalid.

Therefore, Model (1) is a basic model for measuring the empirical validity of regression models, studied using Logistic regression analysis, and characterized in the form of a probability distribution to represent the nominal validity of empirical regression analysis.

**Proposition:** With a given sample size, the nominal validity of empirical regression analysis can be obtained through model (1).

The conclusion of the proposition can be derived from the proof process of the theorem by Sheng Wang [36].

## Empirical Regression Analysis

Based on the analysis of the actual situation, the nominal measurement parameter can be assumed to be 0.5. According to Definition 1, the 1,140 sample points are calculated one by one to form the required sample set. Then, performing a Logistic regression analysis on model (1) yields the following results: (Table 1).

According to the formula for calculating the expected probability  $E(p)$  given by Sheng Wang, it is concluded that:

Where  $a = -37.1069$ ,  $b = 75.06112$ , a total of 1,140 probability estimates were calculated, and their distribution is shown in (Figure 1,2).

For the probability distribution in Figure 2, the expected probability estimate is obtained after calculation, that is

$$E(p) = 0.2913$$

This result indicates that in modern empirical research on financial accounting, its nominal validity is less than 30%. The empirical conclusion drawn from the sample reveals a harsh reality: a large number of empirical research articles on financial accounting published in core journals are nominally unreliable, with 70% of their research conclusions being dubious, even though each academic paper claims its results are reliable, that is, the parameter t-tests are significant. This phenomenon can tentatively be called the illusion of empirical research.

## AI Application Models

The way AI functions is achieved through three domain approaches: the model domain, the data domain, and the algorithm domain, as illustrated in the diagram below:

Figure 3 illustrates that the boundary where AI technology exerts its function is defined by the common area jointly determined by the three domains. This 'common area' is formed through the



integrated linking of AI, and AI can only play its application role within it. Within the area where AI operates, the model domain plays a crucial role. Considering the application of current AI in empirical regression analysis in financial accounting, it is mainly reflected in the following five dimensions, as shown in (Table 2): The paths for improving the validity of empirical regression analysis with the help of AI technology, as described in Table 2,

still follow the three-domain framework, as shown in Figure 3. Since the model domain followed by AI technology does not surpass the level and concept of modeling before the introduction of AI technology, it is determined that structurally, the errors or overlooked issues in empirical research in financial accounting that existed before the introduction of AI technology still persist afterward.

Table 1: Logistic Regression Analysis of Model (1).

Variable	Coefficient	Standard Error	Z-statistic	Probability
intercept	-37.1069	5.31208	-6.98538	0
R <sup>2</sup>	75.06112	10.62619	7.063785	0
Note: The probability of 0 in Table 1 means that the corresponding probability is very small, rather than an actual probability of 0.				

Table 2: The Pathways Through Which AI Enhances the Validity of Empirical Research in Financial Accounting.

Data processing and analysis	Big Data Analysis
	Automated data cleaning
Predictive Modeling	Predictive Model
	Risk Management
Automated Report Generation	Automatically generate report
	Visualization tool
Intelligent Decision Support	Intelligent Decision-Making System
	Automated data cleaning
Natural Language Processing	High-quality translation
	Text Analysis
Source: Public network	

Table 3: List of Methods Suggested by AI to Improve Model Significance.

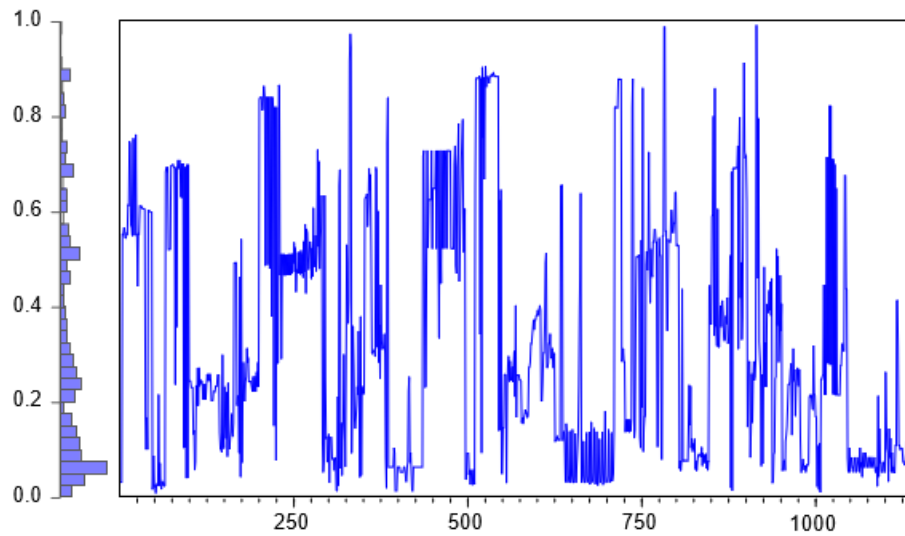
Check whether the variable calculation is correct	Optimize data quality	Variable transformation calculation method	Convert Data	Adjust regression model
Improve the model	Consider other factors	Optimize control variables	Check for multicollinearity	Try other statistical methods
Using a nonlinear regression model	Check model assumptions	Remove abnormal data	Switch to another data source	Select samples under specific conditions
Increase the number of samples		Select specific salient samples		

These problems are not resolved and, with the widespread application of AI technology, there is a real possibility that these issues could be further amplified, enlarging the self-reinforcing loop of errors and causing enduring negative impacts.

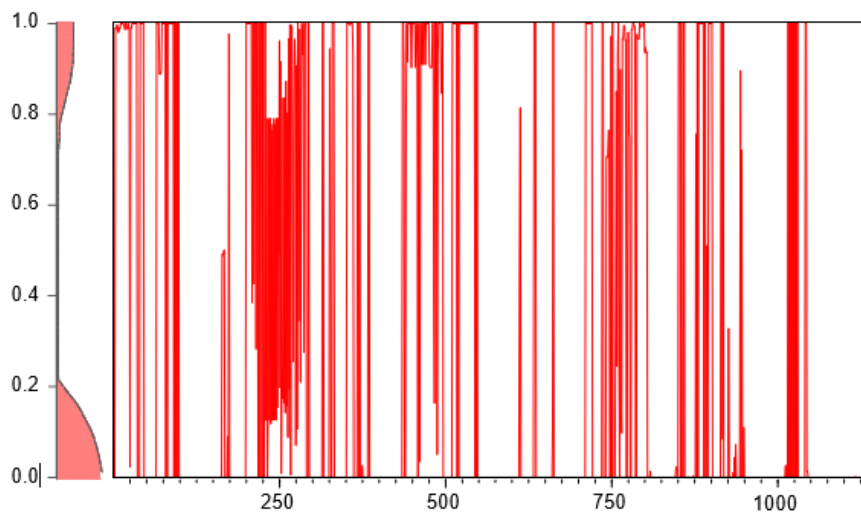
The work that AI technology can currently accomplish is mainly improving work efficiency, but it cannot guarantee the effectiveness of the work. The main reason for this situation is that AI is still unable to establish adaptive models for specific problems or consciously select the appropriate models from the model

domain to handle these related issues, forming optimized solutions. These are technical gaps that AI cannot autonomously overcome at

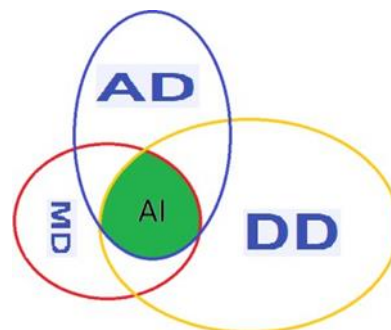
present, and they represent the "bottleneck" problems faced by the development of AI technology.



**Figure 1:** Probability distribution diagram of the sample space.

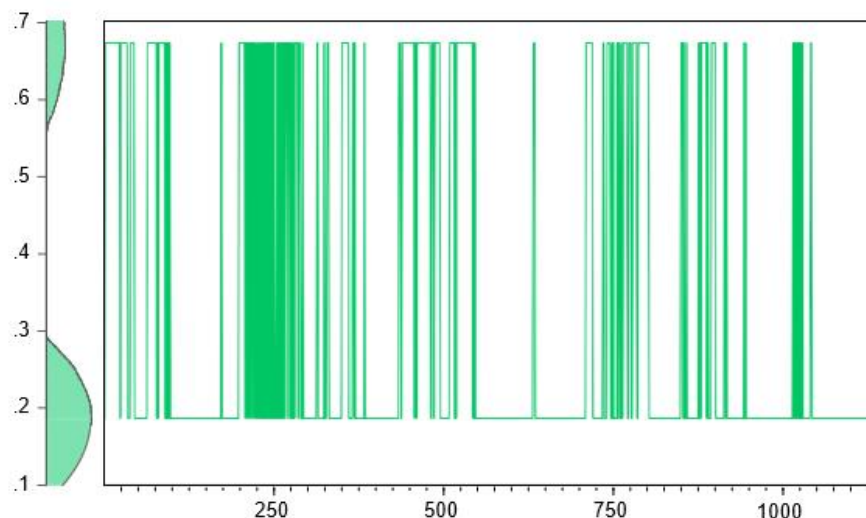


**Figure 2:** Probability Distribution of the Validity of Accounting Empirical Analysis.

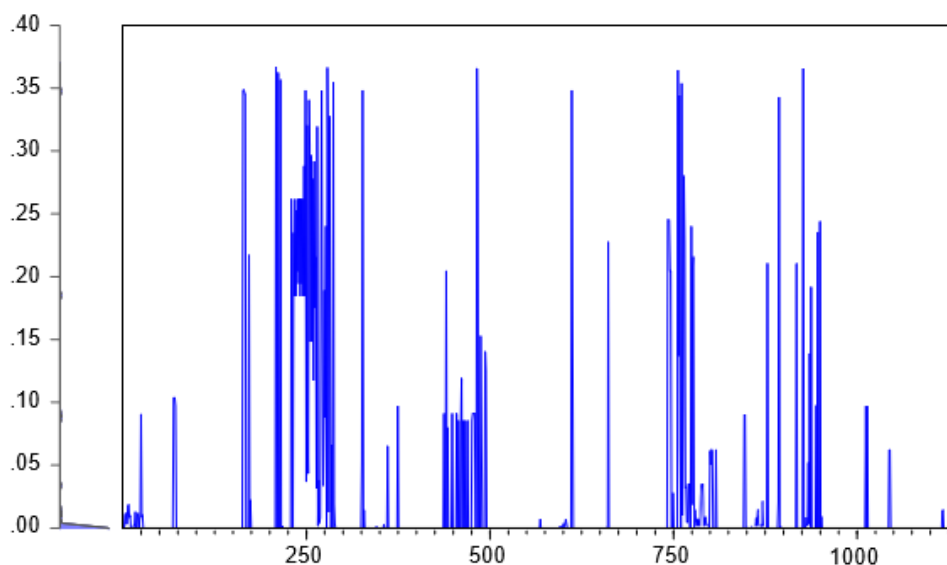


**Figure 3:** Areas Where AI Plays a Role.

**Note.** AD: Algorithm domain, MD: model domain, DD: data domain.



**Figure 4:** Probability Distribution of the Validity of Empirical Regression Analysis in Financial Accounting.



**Figure 5:** Information probability distribution used to calculate information entropy.

According to the analysis above, even if AI technology were fully applied to the study of related issues, the validity of empirical regression analysis would not be better than the current research situation. AI technology is parasitic on the foundation of human civilization, and in the foreseeable future, it cannot develop independently or surpass the level of human civilization without this foundation. Therefore, AI cannot fundamentally improve the validity of modern financial accounting empirical research, but it is still a useful auxiliary tool for promoting the enhancement of research in modern financial accounting. (Table 3) below illustrates this situation.

From the content presented in Table 3, it is clear that the framework for the role of AI still follows the scope shown in Figure 3, and its

deductive path is also constrained by the framework displayed in Figure 3. Any extraordinary expectations regarding the role of AI technology in empirical research in financial accounting will fall into a myth of AI technology, with little benefit to be expected!

## Results and Discussion

The above research analysis indicates that H1 is likely to be rejected with a probability of about 70%, and the conclusion of H2 is similar to that of H1. The current development trend of AI technology falls within the framework standardized in (Figure 3). Even if AI technology exhibits surprising performance in certain aspects, it merely represents a moderate expansion of the overlapping areas of the three domains. Its outer boundaries are

extremely solid, and in the foreseeable future, it will be difficult for AI technology to break through this formidable barrier. Although AI cannot currently significantly enhance the validity of empirical research in financial accounting, the previous conventional analysis also suggests that the nominal validity of current empirical research in accounting is approximately 30%. This conclusion can be corroborated as reasonable from the perspective of variance distribution. Based on a measurement parameter of 0.5, through variance analysis, the probability distribution of validity from the following empirical regression analysis is obtained:

The expected probability estimate of the validity of the empirical regression analysis derived from this is 0.3248. This estimate demonstrates that the validity of the empirical regression analysis obtained through Logistic regression analysis is reliable, as the difference in expected probabilities between them is 0.0335, with an error of less than 5%. From a statistical perspective, this conclusion is significant, meaning that this difference is acceptable. According to the analysis of the samples collected in this study, only about 30% of the empirical regression models are nominally valid. One of the main reasons for this outcome is that the establishment of the empirical regression models is largely disconnected from the relationship between the models and the samples, preventing them from forming effective explanatory power. This has led to the phenomenon of 'model illusion,' where the selection of empirical regression models lacks logical theoretical relationships or empirical real-world associations; instead, there is a tendency to simply expand the sample size as much as possible or artificially manipulate existing sample data. Some methods, as shown in (Table 2), are aimed at achieving the statistical significance of parameter estimates for explanatory variables. Such research concepts and methods weaken or disregard the objectivity of the data, which in turn affects the objectivity of the conclusions and results in a loss of their explanatory power, assuming such power exists at all.

Unfortunately, a large number of empirical analyses that appear to be seemingly significant, reliable, and robust are actually invalid, or their effects are far smaller than expected. Such empirical regression illusions are rampant in academic journals and other scholarly publications. The practical significance of these research results is merely the pretense of science, while the operational risks are concealed within. These academic risks have evolved into systemic risks, and only time will be their ultimate judge.

The contents listed in Tables 2 and 3 basically reflect the fundamental approaches and handling models of empirical research on AI technology in financial accounting, and do not exceed the norms of the current model domain, data domain, and algorithm domain; they are simply confined to the norms shown in (Figure 3). This reality indicates that using AI technology to overcome the current dilemma in empirical financial accounting

research—in which only about 30% of nominal validity is achieved—is an impossible task. This empirical conclusion is reliable, which can be argued from the perspective of information entropy.

According to Shannon's definition of information entropy [37], the calculated information entropy is 0.022133. This result indicates that the validity of empirical research in financial accounting is reliable at about 30%. The information probability distribution used to calculate the information entropy is shown in (Figure 4,5) below:

The probability distribution shown in Figure 5 indicates that the validity of current empirical accounting research is around 30%, objectively reflecting that the state of academic research in empirical studies is not very optimistic. If practical departments formulate corresponding work plans or policies based on these research recommendations, the operational risks they face are likely to be significant.

## Conclusion

The main conclusions of this study are summarized as follows:

**First**, it provides, for the first time, a definition of the validity of empirical regression analysis and expresses it in terms of probability.

**Second**, through the logistic regression analysis method and with the help of Sheng Wang's calculation formula, the expected probability of the validity of the empirical study is calculated.

**Third**, the validity of current empirical research in accounting is not ideal. Many empirical research results are actually the opposite of what their respective literature claims. There are at least two main reasons for this. The first reason is that the relationship between the model setup and the data is logically disconnected. The second reason is that researchers focus solely on the t-test significance of parameters, while intentionally or unintentionally ignoring the statistical explanatory power of the model itself. This second reason is actually the direct driving force behind various operational practices in modern empirical research, such as data omission, data cleaning, sample size expansion, and the addition or removal of variables, among many other expediciencies. Yet these practices are often regarded as successful experiences and widely disseminated, seemingly gradually evolving into a mainstream model of empirical research, forming an academic ecological phenomenon that can tentatively be called the 'illusion of empirical research'.

**Fourth**, AI technology is constrained by its structural limitations and cannot surpass the current modeling concepts and methods of traditional research, resulting in AI technology not fundamentally resolving many of the academic issues faced by current empirical accounting research.



**Fifth** is the research conclusion of this paper, which, through variance analysis and the calculation of information entropy, corroborates the scientificity and rationality of the conclusions obtained in this paper from another perspective.

**Six**, the specialized application of AI technology in engineering is commendable, and the realization of certain functions can even be impressive or 'surprising!' However, in theoretical research, the risk of declining academic quality is difficult to suppress or effectively avoid. Nevertheless, the conclusions of this study can still be applied to the academic evaluation of empirical research.

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