MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, Jan-June 2026, Pages: 125-140

Research on the Impact of Enterprise Intelligence on Commercial Credit Acquisition: Mechanism, Heterogeneity and Empirical Test

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Abstract:
This study explores the impact of enterprise intelligence on trade credit acquisition, as well as its boundary conditions and underlying mechanisms. This study takes Chinese A-share listed companies from 2010 to 2023 (excluding the financial, real estate, software and information technology service industries) as the research sample, measures trade credit acquisition by the proportion of accounts payable plus notes payable to total assets, and characterizes enterprise intelligence from three dimensions: Overall intelligence (AI), intelligence intensity (AIint, the natural logarithm of the frequency of AI-related keywords plus 1), and intelligence type (AItype, the natural logarithm of the category of AI-related keywords plus 1).
The empirical results show that: (1) Enterprise intelligence significantly promotes the acquisition of trade credit - compared with non-intelligent enterprises, the trade credit obtained by intelligent enterprises (relative to total assets) increases by 0.9 percentage points; There are also significant positive effects on intelligence intensity and type, with coefficients of 0.0054 and 0.0058 respectively (both significant at the 1% level). (2) Asset specificity has a positive moderating effect: Higher asset specificity enhances the positive impact of enterprise intelligence on trade credit acquisition (the interaction term coefficient AI×ASI is 0.0423, which is significant at 1%). (3) Heterogeneity analysis indicates that the promoting effect is more prominent in high-tech enterprises, executive teams with high financial backgrounds, and enterprises in the growth/maturity stage. (4) Mechanism tests have confirmed that enterprise intelligence promotes the acquisition of trade credit through three paths: optimizing business quality (increasing patent applications and R&D investment), enhancing production efficiency (improving total factor productivity), and reducing high-risk events (lowering the risk of bankruptcy).

Keywords: Enterprise Intelligence; Commercial Credit Acquisition; Asset Specificity; Empirical Test

1. Introduction

How to effectively reduce financing costs has always been an important issue in the field of enterprise financial management. Previous studies have focused on the financial market, and based on the debt, equity or hybrid securities issued by companies, classic achievements such as the financing order theory have been formed (e.g. Myers,1984). In the product market, when enterprises choose the credit sales or pre-purchase contract model for transactions between them, the span of the time points for the transfer of goods and services and the receipt and payment of funds provides the credit purchasing or pre-receiving enterprises with nearly zero-cost rights to use funds, that is, commercial credit financing [3]. Due to the existence of the time value of money, the commercial credit obtained by enterprises naturally reduces the average cost of capital usage and has an invisible advantage over financing from financial institutions.

In recent years, the development of the financial market has made equity financing or debt financing entrusted to financial institutions a hot topic, but academic discussions related to commercial credit are relatively scarce. Compared with the former, commercial credit acquisition has higher enterprise autonomy and independence: on the one hand, financial institutions' financing is independent of the enterprise's production process and pays more attention to the data of business results, while commercial credit acquisition is formed in the production and circulation links of the enterprise's products or services, which is a monetary lending credit relationship based on transactions and is more strongly influenced by the enterprise's business status [1]; On the other hand, the acquisition of commercial credit is an independent act of both credit subjects. Under the premise of legality and compliance, there is no need for third-party rating or approval. The development situation of enterprises has a more direct impact on credit contracts [5].

In conclusion, an enterprise's ability to obtain commercial credit is closely related to its own characteristics. In recent years, technological development has brought about significant changes to enterprises. As a general-purpose technology, artificial intelligence has had the most extensive and profound impact. With the rapid development of artificial intelligence, enterprises are constantly strengthening their adoption of its technology, and the degree of assistance and substitution of AI for human capital is continuously increasing [8]. Research in the field of enterprise management shows that internally, enterprise intelligence can reduce production costs and enhance the technical level of innovative work. Externally, by relying on demand forecasting models, potential customer mining algorithms and dynamic market opportunity capture, the sales conversion efficiency can be significantly optimized [11]. After multiple cycles of development, the impact of intelligence on business operation models has been confirmed by many parties.

From the perspective of enterprise technological participation, the proportion of A-share listed companies in China applying artificial intelligence technology has been continuously increasing. The proportion of traditional enterprises' intelligent development has risen from 5.59% in 2010 to 43.74% in 2023. This may lead to two completely different economic consequences: On the one hand, the change in the value creation model has led enterprises into an era of collaborative management and AI, and intelligent development has become a common trend and an inevitable question [6]; On the other hand, as a disruptive technological revolution, the impact direction of artificial intelligence on the financial situation of enterprises is still unclear, and enterprises face high pressure and risks when exploring the application of AI [10]. Will enterprise intelligence enhance support for the upstream and downstream of the supply chain or prompt them to avoid risks? Will artificial intelligence bring trust growth or decline to enterprises? The academic community has not yet made a systematic response to the relevant issues.

Based on this, this chapter takes Chinese A-share listed companies that are not in the financial, real estate, or software and information technology service sectors from 2010 to 2023 as research samples to examine the impact of enterprise intelligence on the acquisition of commercial credit, analyze the moderating effects of asset specificity and information transparency, and explore heterogeneity from the perspectives of enterprise characteristics, the financial background of senior executives, and the enterprise life cycle. Examine the mechanism of action of "optimizing business quality, enhancing production efficiency, and reducing high-risk risks", and finally make a summary.

2. Literature Review

2.1 The Definition and development of artificial intelligence

Human exploration of artificial intelligence can be traced back to the 1950s. Alan Turing, the father of computer science, proposed the concept of machine intelligence and published "Computational Machines and Intelligence" in the magazine Thought in 1950. Outline important branch concepts in the field of artificial intelligence such as Turing tests, machine learning, genetic algorithms, and reinforcement learning. The definition of "artificial intelligence" is generally believed to have originated from an artificial intelligence symposium held in the United States in 1956. After eight weeks of discussion, ten experts from fields such as mathematics, computer science, cognitive psychology, economics, and philosophy defined artificial intelligence, advocating the creation of machines capable of thinking like humans through symbolic reasoning and symbolic representation. At the meeting, the "Logician" program demonstrated by Newell and Simon used machines to prove some of the principles in Chapter Two of "Principles of Mathematics", showing that machines can perform similar reasoning tasks. In both theoretical development and economic practice, with the rapid iteration of related technologies and the continuous emergence of applications, the definition of artificial intelligence has been constantly evolving and changing, giving rise to numerous viewpoints and debates.

As early as 1961, computer scientist Minsky proposed that artificial intelligence is the science that enables machines to perform tasks that originally required human intelligence. In academic research outside the field of computer science, different scholars have given different definitions from their own perspectives. [2] They believe that artificial intelligence is the development and creation of "thinking machines" that can imitate, learn and replace human intelligence. Cerka et al. proposed that artificial intelligence is different from traditional computer algorithmic intelligence and can be defined based on the factors of a thinking human and rational behavior, that is, a system that thinks and acts rationally like a human. Zhang and Wang pointed out that artificial intelligence is different from conventional computer technology that performs computing or control tasks according to pre-determined programs. It has the characteristics of self-learning, self-organization, self-adaptation and self-action of biological intelligence. [12] It can be seen from this that the emergence and development of artificial intelligence are centered on the discipline of computer science, and its technology originated from here and has been continuously iterated.

Corresponding to the definition and development of artificial intelligence, under the joint influence of basic resources, technology and environment, the development of artificial intelligence has gone through three core stages: the 1950s - 1970s, the 1980s - 1990s and the present from 2000. The first generation of artificial intelligence was in the rule-driven stage, with the goal of enabling machines to think like humans and establish "reasoning models based on knowledge and experience". Expert systems that input corresponding knowledge into computers were the main representatives of this period. However, due to their inability to learn independently from experience and their difficulty in handling complex problems, their applications were limited. The second-generation artificial intelligence has entered a new stage with the development of knowledge representation and reasoning technologies, beginning to solve problems by leveraging a large number of knowledge bases established based on rules and facts. It can handle more complex issues, but still mainly relies on manually input knowledge and data. [4] The development of the third-generation artificial intelligence benefits from the popularization of the Internet and the emergence of big data, breaking through the previous framework and simultaneously applying the four elements of knowledge, data, algorithms and computing power. The rise of deep learning enables artificial intelligence systems to automatically learn features and patterns from large amounts of data, significantly enhancing their ability to handle complex tasks and generalization capabilities, promoting the transformation of artificial intelligence from a computer professional technology to a general technology, and facilitating the continuous emergence of its applications in various industries.

2.2 Definition and Evolution of Enterprise Intelligence

The definition of enterprise intelligence originated from the definition of artificial intelligence. As a general technology with the attributes of new infrastructure, artificial intelligence has differentiated application prospects and a wide range of applications in different industries. Therefore, outside the field of computer science, both academic research and economic practice of "artificial intelligence" are based on the application layer, that is, the integration of artificial intelligence technology with organizational strategies or specific business operations, rather than the innovation or development of artificial intelligence technology itself. In the field of enterprise management, enterprise intelligence can be broadly understood as the adoption of AI technology by enterprise entities at all levels [13].

The definition of enterprise intelligence changes along with the evolution of the definition of artificial intelligence, the application level of artificial intelligence technology, and the characteristics of the integration of artificial intelligence with industries. The variability of its connotation is greater than that of artificial intelligence itself. Excluding the transformation of artificial intelligence technology within the computer field, the different generalizations and classifications of artificial intelligence at the application level, as well as the different application forms among industries, all reflect different understandings of its connotation. From the perspective of detailed technologies, the technical applications of artificial intelligence include computer vision, deep learning, machine reasoning, machine learning and natural language processing, etc. [9] From the perspective of specific application scenarios, Yablonsky proposed that the level of enterprise intelligent systems can be divided into three stages: auxiliary intelligence (assisting the daily work of humans and organizations), enhanced intelligence (providing complementary capabilities), and autonomous intelligence (independently solving problems). From the perspective of application implementation forms, common manifestations of artificial intelligence include chatbots, intelligent assistants, intelligent recommendations, service robots, decision support, and automation, etc. [14]

An important feature of research in the field of enterprise intelligence is its high degree of relevance to The Times, which stems from the unpredictable impact of disruptive technological breakthroughs on various

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
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business decisions of enterprises. Therefore, this article explores the economic consequences of enterprise intelligence from the perspective of working capital management.

2.3 Research Review Based on Literature Analysis

The introduction of artificial intelligence has broken the conventional model where natural persons dominate decision-making in traditional enterprises. At present, a large number of literatures have conducted in-depth research on the impact of enterprise intelligence in areas such as enterprise strategy, operation and organizational structure, and the relevant research content is becoming increasingly rich and diverse. However, in the research on the relationship between enterprise intelligence and commercial credit, that is, the research on enterprise intelligence in the field of financial management, the exploration of existing literature is very limited. Overall, under the premise of meeting ethical norms, the positive effects of artificial intelligence on enterprise management and operation have been initially recognized. Given that the impact process of artificial intelligence on business decision-making is complex and non-linear, a thorough analysis of the specific role and boundaries of enterprise intelligence on commercial credit not only holds academic innovation potential but also has practical significance for business operation practices.

Existing research reveals that the impact of artificial intelligence on enterprise management is mainly reflected in two aspects: First, it assists in product production and management decision-making based on a larger knowledge base and information network, thereby enhancing operational efficiency; Second, in certain fields, it can replace natural persons and provide more redundant time and decision-making space for human decision-making. However, it is still unclear whether enterprise intelligence will have an impact on business credit decisions. In the process of transforming from "manual" to "intelligent", this paper attempts to explore, under the current situation of intelligent development of enterprises, how commercial credit decisions will be affected, as well as their mechanism of action and boundary conditions.

3. Theoretical analysis and hypothesis proposal

The buyer's market theory explains the acquisition of commercial credit by enterprises from the perspective of transaction advantage, pointing out that the essence of the widespread existence of commercial credit stems from the strong position and excellent credit qualifications of buyers - suppliers tend to provide credit support to such customers to promote sales [20]. This theory holds that a company's ability to obtain commercial credit is directly related to its own characteristics (such as bargaining power and historical performance records), rather than relying solely on the active supply from the seller. Early studies have shown that larger enterprises are more likely to obtain credit funds in transactions because suppliers tend to provide liquidity to enterprises with higher market positions and better reputations [18]. Therefore, when the buyer has strong bargaining power and high credit quality, the possibility of obtaining credit benefits such as delayed payment increases significantly.

Further research has found that factors such as the financial quality of enterprises, internal governance, and external image can also affect the acquisition of business credit: Chen et al. discovered that the quality of accounting information is significantly positively correlated with the acquisition of business credit; Revise and verify the negative effect of enterprise financial fraud on the amount of commercial credit financing. Overall, in the commercial credit model, the key factors influencing an enterprise's liquidity acquisition level are its transaction position and the ability to control capital risks, which reflects the spillover effect of an enterprise's operational capacity and credit quality in the supply chain.

From the perspective of business quality, the positive impact of enterprise intelligence on the quality of products or services has been widely recognized. In the process of production and operation, enterprise intelligence relies on small-batch customized flexible production, which can dynamically adapt to the dual constraints of cost control and market dynamic demands: it not only reduces unit production costs by eliminating scale diseconomic losses, but also builds an agile response advantage through production flexibility, strengthening the ability of differentiated operation [14]; At the same time, technological innovation is promoted by accelerating knowledge creation and technology spillover, enhancing learning and absorption capabilities, and increasing investment in research and development and talent, thereby improving market competitiveness [22]. In addition, enterprise intelligence has a positive impact on the quality of production services and the level of innovation: it not only helps to enhance the consistency of business processes to improve the quality of production services and reduce error rates, but also promotes the technical level of innovative work, stimulates overall innovation capabilities, and thereby strengthens brand building and ensures the level of sustainable development [13].

In conclusion, the higher the level of intelligence of an enterprise, the stronger its auxiliary ability for production processes and business decisions, and the more conducive it is to enhancing the market competitiveness of its products. At the same time, the stronger the self-supervision ability of the business process is, the more attention and supervision the market will pay to the enterprise, and the more conducive it is to enhancing the trust of the enterprise. The differences in the application level of artificial intelligence can lead to different economic consequences, which have been verified by the mathematical derivation of economic models and significantly supported by empirical research data [21]. Therefore, this paper explores the differences in the impact of different levels of enterprise intelligence on the acquisition of commercial credit and puts forward the following hypotheses:

Hypothesis 1: Enterprise intelligence has a positive impact on the acquisition of commercial credit.

Hypothesis 1-1: The intensity of enterprise intelligence has a positive impact on the acquisition of commercial credit.

Hypothesis 1-2: The types of enterprise intelligence have a positive impact on the acquisition of commercial credit.

The level of asset specificity is an important indicator for measuring the resource infrastructure of an enterprise, reflecting the proportion of resources allocated by the enterprise to meet specific purposes or transactions, and demonstrating the depth of investment in specific fields and the professional level of specific technologies [19]. The higher the level of specificity of an enterprise's assets, the stronger its original value and difficulty in imitation, and the higher the possibility that artificial intelligence technology will be integrated and applied to specific business links. This is more conducive to empowering enterprises with intelligence to establish competitive advantages and thereby improving the level of commercial credit acquisition. Conversely, the lower the level of asset specificity, the more severe the homogenization of enterprises, and the limited competitive advantage of differentiation reflected after the integrated application of artificial intelligence technology. It can be seen that the impact of enterprise intelligence on the acquisition of commercial credit may have contingency characteristics due to the influence of basic conditions. The following hypotheses are proposed:

Hypothesis 2: The level of asset specificity has a positive moderating effect on the relationship between enterprise intelligence and the acquisition of commercial credit.

Hypothesis 2-1: The level of asset specificity has a positive moderating effect on the relationship between the intensity of enterprise intelligence and the acquisition of commercial credit.

Hypothesis 2-2: The level of asset specificity has a positive moderating effect on the relationship between the types of enterprise intelligence and the acquisition of commercial credit.

4. Data analysis

4.1 Sample and Data Sources

This chapter selects Chinese A-share listed companies from 2010 to 2023 as the initial research samples. To ensure data quality, the following preprocessing is carried out: ① Exclude samples with abnormal operations (stock codes marked as ST and *ST); ② Excluding the samples of the financial industry, real estate industry, and information transmission, software and information technology services industry (I63, I64, I65) - The accounting standards details of the financial industry and real estate industry are significantly different from those of traditional listed companies, and there are many extreme and abnormal values in their financial indicators. The text disclosure or R&D projects of information industry companies may involve more research on basic artificial intelligence technologies. Interfere with the research context; ③ Exclude samples of cross-listing of A, B and H shares, as different market regulatory rules may affect corporate decisions; ④ Eliminate financial anomaly samples with missing key variable values and asset-liability ratios greater than 1 or less than 0. After the above screening, a total of 22,903 company-annual observations from 3,784 companies were finally obtained.

The sample screening process and industry distribution are shown in the table below:

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ISSN: 1053-7899
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Sort	Samlpings
The sample screening process of Panel A	Initial total sample: 49,493; Subtract the samples of ST and *ST: 1582; Subtract the specific industry sample: 6192; Subtract the cross-listing sample: 2020; Subtract the sample with abnormal data: 16,794; Final sample: 22903
Industry distribution of Panel B samples	Agriculture, Forestry, animal husbandry and fishery: 331; Mining Industry: 406 Manufacturing industry: 18339 Electricity, heat, gas and water production and supply industry: 477; Construction industry: 583 Wholesale and retail trade: 864 Transportation, warehousing and postal services: 321; Accommodation and catering industry: 56 Leasing and Business Services: 296 Scientific research and technical services industry: 365 Water conservancy, environment and public facilities Management industry: 395; Resident services, repair and other service industries: 10; Education: 20 Health and Social Work: 68 Culture, sports and entertainment industry: 260 Comprehensive: 112

Table 1 Sample screening process and industry distribution

The data sources of this article are as follows: The "Management Analysis and Discussion" (MD&A) of the annual reports of listed companies for enterprise intelligent text analysis and the initial texts of artificial intelligence-related development projects are sourced from the CSMAR database. The initial data of patents related to artificial intelligence were manually collected through the sub-website of the National Intellectual Property Administration. The remaining data mainly come from the CSMAR database. To mitigate the impact of potential outliers, all continuous variables at the micro level are truncated at the 1% and 99% levels.

4.2 Variable parsing

(1) Explained variable: Commercial Credit Acquisition (TC_fin

Considering that accounts payable is the core manifestation of commercial credit acquisition, the proportion of an enterprise's accounts payable (the sum of accounts payable and notes payable) to total assets is selected to measure the level of commercial credit acquisition. The larger this value is, the more commercial credit funds the enterprise has obtained. Conversely, the less.

(2) Explanatory variables

Enterprise intelligence (AI) : Currently, direct data on enterprise intelligence is relatively scarce, and the existing research characterization methods have limitations (for instance, the installation density of industrial robots only reflects applications in the industrial field). The artificial intelligence structured feature word library constructed in this paper extracts and matches some data words of the MD&A in the annual reports of listed companies using Python. At the same time, referring to Dong Zhiqing et al. (2023), match the names of valid patents and development projects of listed companies with the characteristic words of artificial intelligence to form an annual report disclosure and behavioral indicator system. If any system of an enterprise contains a feature word related to "artificial intelligence", AI is assigned a value of 1; otherwise, it is assigned 0.

Enterprise Intelligence Intensity (AIint) : Based on the total number of times the keyword "artificial intelligence" appears in the MD&A section of the annual report, patent or development project names, add 1 and take the natural logarithm for measurement. The more artificial intelligence feature words there are in the original text, the higher the intensity of the enterprise's intelligence.

Enterprise intelligence type (AItype) : Based on the number of categories where the keyword "artificial intelligence" appears in the MD&A section of the annual report, patent or development project names, add 1

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and take the natural logarithm to measure, reflecting the number of categories of artificial intelligence technologies applied by enterprises.

(3) Adjust the variables

Asset Specificity (ASI) : Based on the details of fixed assets in the notes to the enterprise's financial statements, excluding houses, buildings, land and leased assets, the fixed asset items of tools, equipment and machinery are screened out. The total net amount at the end of the year is obtained by adding them up by "enterprise - year", and the asset specificity is measured by its proportion of fixed assets.

Information Transparency (CO) : Quantify the "transparency of listed companies" data disclosed by the exchange (assign values of 4, 3, 2, and 1 to A, B, C, and D respectively), and the larger the value, the higher the information transparency.

(4) Control variables

Select the company Size (Size, natural logarithm of total operating revenue), asset-liability ratio (Lev, total liabilities/total assets), company Age (Age, sample year - establishment year), return on total assets (ROA, net profit/total assets), and Growth rate of total assets (Growth) (Year-end total assets - total assets at the end of the previous year)/Total assets at the end of the previous year), cash flow from operating activities (CFO, net cash flow from operating activities/total assets), enterprise inventory (Invent, net inventory/total assets), enterprise digitalization (Digital) Annual report MD&A, patent or development expenditure with big data, cloud computing, blockchain feature words is 1, otherwise it is 0), book-to-market ratio (BM, share price per share/book value per share), customer concentration (CusHHI, the sum of the squares of the sales proportion of the top five customers), supplier concentration (SupHHI) The sum of the squares of the supply volume proportions of the top five suppliers and the nature of property rights (SOE, 1 for state-owned enterprises and 0 otherwise) are used as control variables at the company's characteristic and operational levels.T he scale of joining the Board of directors (Board, number of board members), the shareholding ratio of the board of directors (Dshare, shareholding ratio of board members), the proportion of independent directors (Inddir, number of independent directors/total number of board members), and the concentration of equity (Top10, The sum of the shareholding ratios of the top ten shareholders and the quality of auditing (Big4, 1 for the four major audits, otherwise 0) are used as control variables for corporate governance.

4.3 Empirical Model Design

The following model is constructed to test the positive impact of enterprise intelligence on commercial credit acquisition, and it is expected that the regression coefficients of AI, AIint, and AItype will be positive:

$$TC\_fin_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \alpha_2 Controls_{i,t} + \sum IndFE + \sum YearFE + \varepsilon_1$$

$$TC\_fin_{i,t} = \beta_0 + \beta_1 AIint_{i,t} + \beta_2 Controls_{i,t} + \sum IndFE + \sum YearFE + \varepsilon_2$$

$$TC\_fin_{i,t} = \gamma_0 + \gamma_1 AItype_{i,t} + \gamma_2 Controls_{i,t} + \sum IndFE + \sum YearFE + \varepsilon_3$$

Next, by constructing a model, an empirical test will be conducted on Hypothesis 2 and its sub-hypotheses, that is, to test the moderating effect of asset specificity (ASI). Hypothesis 2 proposes that the level of asset specificity enhances the positive impact of enterprise intelligence on commercial credit acquisition. Therefore, the expected regression coefficients of AI×ASI, AIint×ASI, and AItype×ASI are positive:

$$TC\_fin_{i,t} = \delta_0 + \delta_1 AI_{i,t} + \delta_2 ASI_{i,t} + \delta_3 AI \times ASI_{i,t} + \delta_4 Controls_{i,t} + \Sigma IndustryFE + \Sigma YearFE + \varepsilon_4$$

$$TC\_fin_{i,t} = \epsilon_0 + \epsilon_1 AIint_{i,t} + \epsilon_2 ASI_{i,t} + \epsilon_3 AIint \times ASI_{i,t} + \epsilon_4 Controls_{i,t} + \Sigma IndustryFE + \Sigma YearFE + \varepsilon_5$$

$$TC\_fin_{i,t} = \theta_0 + \theta_1 AItype_{i,t} + \theta_2 ASI_{i,t} + \theta_3 AItype \times ASI_{i,t} + \theta_4 Controls_{i,t} + \Sigma IndustryFE + \Sigma YearFE + \varepsilon_6$$

4.3 Descriptive Statistics

To avoid the interference of outliers, Winsorize is applied to all continuous variables at the 1% level. The statistical results show that the average value of the proxy variable TC_fin for the explained variable commercial credit acquisition is 0.131, indicating that the average commercial credit acquisition obtained by

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ISSN: 1053-7899
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the sample enterprises can account for approximately 13.1% of the total assets of the company. Meanwhile, the maximum and minimum values of this variable are 0 and 0.767 respectively, indicating that there is a significant gap in the level of commercial credit acquisition among different companies. The underlying reasons need to be explained. As for the explanatory variable AI, the proxy variable of enterprise intelligence, its average value is approximately 0.258, indicating that among all the listed company samples, about 25.8% of the samples have already applied artificial intelligence technology. Meanwhile, when exploring the intensity of enterprise intelligence of enterprises, the mean and standard deviation of the proxy variable AIint are 0.362 and 0.650 respectively, which indicates that there are significant differences in the application intensity among different enterprises. Furthermore, according to the statistics of the proxy variable AItype for the types of enterprise intelligence, it can be known that the number of artificial intelligence technology types involved by the sample companies is relatively large, and there are still significant differences among different samples. From the above data, it can be found that there are significant differences among different enterprises in terms of the degree of enterprise intelligence, application intensity and types. This chapter intends to explore through an empirical model what economic consequences this difference will bring about in the acquisition of commercial credit. The moderating variables involved in the empirical model of this chapter are asset specificity (ASI) and information transparency (CO), respectively. The measurement methods for the two are respectively the proportion of fixed assets to total assets and the exchange transparency rating level. As can be seen in Table 3.3, the mean value of ASI is 0.102, which is close to the statistical information of this variable obtained in most studies. Meanwhile, the average value of CO is 3.027, indicating that in terms of transparency, most enterprises are at a good or excellent level, but there is still a certain proportion of listed companies with average transparency. In terms of control variables, the mean of Size is 21.970 and the standard deviation is 1.107, indicating that the distribution of enterprise scale is relatively concentrated. The average and median of the debt-to-asset ratio (Lev) are concentrated around 38%, with the maximum value reaching as high as 0.998, reflecting the significant differentiation characteristics of the capital structure of listed enterprises in China. The mean of Growth is 0.220 and the standard deviation is 0.522, indicating that there are significant differences in the growth rates of enterprises and there may be extreme values. The average value of Digital is 0.416, with a median of 0. Considering the long sample time, it is speculated that this data situation is due to the lower degree of digitalization of the early samples. The mean values of CusHHI and SupHHI were 6.267 and 5.535 respectively, and the standard deviations were 11.050 and 8.771 respectively, indicating a significant difference in the concentration of customers and suppliers. The average value of SOE is 0.227, indicating a relatively low proportion of state-owned enterprises in the sample, which is close to the values disclosed by relevant studies in recent years. The mean value of the Board is 8.256 and the standard deviation is 1.549, indicating that the board sizes of enterprises are relatively similar. The mean value of Dshare is 0.169 and the standard deviation is 0.201, indicating that there are significant differences in the shareholding situation of the board of directors of enterprises. The average value of the equity concentration ratio (top 10) is 0.584, which is close to the median of 0.595 and the data from existing studies. This also indicates the relatively high equity concentration ratio of A-share listed companies in China. The Big4 data statistics show that the average proportion of listed companies choosing the Big Four accounting firms for auditing has dropped below 3.2%, which is relatively low. Overall, the data distribution is relatively symmetrical, but the standard deviations of some variables such as Growth, CusHHI and SupHHI are relatively large, and there may be extreme values.

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Variable	N	Mean	SD	Min	p50	Max
TC_fin	22903	0.131	0.097	0.000	0.107	0.767
AI	22903	0.258	0.438	0.000	0.000	1.000
AIint	22903	0.362	0.650	0.000	0.000	4.977
AItype	22903	0.357	0.635	0.000	0.000	3.135
ASI	22798	0.102	0.102	0.000	0.070	0.776
CO	21259	3.027	0.605	1.000	3.000	4.000
Size	22903	21.970	1.107	18.220	21.820	27.070
Lev	22903	0.391	0.200	0.015	0.379	0.998
Age	22903	2.918	0.337	0.693	2.944	4.043
ROA	22903	0.034	0.080	-2.834	0.038	0.644
Growth	22903	0.220	0.522	-0.896	0.097	37.030
CFO	22903	0.047	0.073	-0.647	0.046	0.839
Invent	22903	0.127	0.095	0.000	0.108	0.931
Digital	22903	0.416	0.493	0.000	0.000	1.000
BM	22903	0.607	0.233	0.037	0.610	1.460
CusHHI	22903	6.267	11.050	0.000	2.174	100.000
SupHHI	22903	5.535	8.771	0.000	2.434	100.000
SOE	22903	0.227	0.419	0.000	0.000	1.000
Board	22903	8.256	1.549	3.000	9.000	18.000
Dshare	22903	0.169	0.201	0.000	0.064	0.801
Inddir	22903	0.377	0.054	0.167	0.364	0.714
Top10	22903	0.584	0.148	0.130	0.595	0.951
Big4	22903	0.032	0.176	0.000	0.000	1.000

Table 2 Descriptive analysis of variables

4.5 Empirical analysis and verification

Based on the research hypotheses, this chapter examines the impact of enterprise intelligence on the acquisition of commercial credit. Specifically, if there is a significant positive correlation between intelligence (AI), intelligence intensity (AIint), and intelligence type (AItype) and the level of enterprise commercial credit acquisition (TC_fin), it indicates that the positive effect of enterprise intelligence in commercial credit financing has been preliminarily verified statistically. In the main test, the article measures the level of commercial credit acquisition of enterprises based on the common credit sales - credit purchase model in enterprises and taking accounts payable as the basis. To enhance the robustness of the empirical results, in the following text, the commercial credit generated by the relatively less frequently used prepayment - prepayment model will also be included, and this variable will be remeasured. The relevant results are presented in the robustness test. The impact of enterprise intelligence, the intensity and types of enterprise intelligence on the acquisition of commercial credit was successively demonstrated. The results showed that the regression coefficients of AI, AIint and AItype were 0.0090, 0.0054 and 0.0058 respectively, and all were significant at the 1% level. The preliminary results indicate that enterprise intelligence and its various dimensions have a positive impact on the acquisition of commercial credit. Therefore, Hypothesis 1 and its sub-hypotheses have been preliminarily verified.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, Jan-June 2026, Pages: 125-140

VARIABLES	TC_fin	TC_fin	TC_fin
	(1)	(2)	(3)
AI	0.0090***		
	(6.75)		
AIint		0.0054***	
		(6.08)	
AItype			0.0058***
			(6.24)
Size	-0.0071***	-0.0071***	-0.0071***
	(-10.31)	(-10.35)	(-10.36)
Lev	0.2779***	0.2781***	0.2780***
	(69.63)	(69.66)	(69.66)
Age	-0.0062***	-0.0061***	-0.0061***
	(-3.65)	(-3.61)	(-3.60)
ROA	0.0903***	0.0906***	0.0906***
	(6.33)	(6.34)	(6.34)
Growth	-0.0023	-0.0023	-0.0023
	(-1.63)	(-1.64)	(-1.64)
CFO	0.0358***	0.0357***	0.0357***
	(3.89)	(3.89)	(3.89)
Invent	0.0273***	0.0272***	0.0272***
	(3.84)	(3.82)	(3.83)
Digital	0.0086***	0.0089***	0.0087***
	(7.67)	(7.81)	(7.71)
BM	0.0210***	0.0211***	0.0212***
	(7.64)	(7.66)	(7.68)
CusHHI	0.0005***	0.0005***	0.0005***
	(9.44)	(9.42)	(9.40)
SupHHI	-0.0009***	-0.0009***	-0.0009***
	(-13.48)	(-13.51)	(-13.52)
SOE	0.0061***	0.0060***	0.0060***
	(4.12)	(4.05)	(4.06)
Board	-0.0007*	-0.0007*	-0.0007*
	(-1.71)	(-1.69)	(-1.69)
Dshare	0.0025	0.0025	0.0025
	(0.90)	(0.88)	(0.88)
Inddir	-0.0524***	-0.0523***	-0.0523***
	(-4.65)	(-4.63)	(-4.64)
Top10	0.0394***	0.0395***	0.0395***
	(10.35)	(10.40)	(10.40)
Big4	-0.0202***	-0.0202***	-0.0202***
	(-6.96)	(-6.98)	(-6.98)
Constant	0.0941***	0.0944***	0.0945***
	(5.71)	(5.72)	(5.73)
Industry	YES	YES	YES
Year	YES	YES	YES
Observations	22,903	22,903	22,903
R-squared	0.439	0.439	0.439

Table 3 The Impact of enterprise intelligence on commercial credit acquisition

Furthermore, the boundary conditions of the above-mentioned influence effects were examined. Assets with high specificity have high heterogeneity and high value in specific uses or environments, which builds entry barriers for other competitors. Therefore, in the process of exploring the economic consequences of enterprise intelligence, the impact of its asset specificity cannot be ignored. Based on this, the moderating effect of asset specificity on the relationship between enterprise intelligence and commercial credit acquisition is demonstrated. The results show that the cross-multiplication terms of AI, AIint and AItype with ASI are 0.0423, 0.0400 and 0.0391 respectively, and all are statistically significant at the 1% level. This result indicates that with the enhancement of asset specificity, the positive impact of enterprise intelligence and its various dimensions on the acquisition of commercial credit has been further strengthened. Hypothesis 2 and its sub-hypotheses have been preliminarily verified.

VARIABLES	TC_fin	TC_fin	TC_fin
	(1)	(2)	(3)
AI	0.0050***		
	(2.95)		
ASI	-0.0748***	-0.0780***	-0.0776***
	(-11.96)	(-12.56)	(-12.49)
AI×ASI	0.0423***		
	(3.45)		
AIint		0.0019*	
		(1.74)	
AIint×ASI		0.0400***	
		(4.69)	
AItype			0.0023**
			(1.97)
AItype×ASI			0.0391***
			(4.50)
Size	-0.0068***	-0.0068***	-0.0068***
	(-9.95)	(-10.02)	(-10.03)
Lev	0.2837***	0.2838***	0.2838***
	(69.74)	(69.78)	(69.77)
Age	-0.0075***	-0.0074***	-0.0074***
	(-4.46)	(-4.42)	(-4.42)
ROA	0.0889***	0.0894***	0.0893***
	(6.20)	(6.22)	(6.22)
Growth	-0.0054***	-0.0054***	-0.0054***
	(-4.86)	(-4.88)	(-4.89)
CFO	0.0477***	0.0474***	0.0474***
	(5.12)	(5.08)	(5.08)
Invent	0.0170**	0.0169**	0.0169**
	(2.35)	(2.33)	(2.34)
Digital	0.0073***	0.0075***	0.0074***
	(6.47)	(6.60)	(6.51)
BM	0.0245***	0.0247***	0.0247***
	(8.84)	(8.90)	(8.92)
CusHHI	0.0006***	0.0005***	0.0005***
	(9.96)	(9.93)	(9.92)
SupHHI	-0.0008***	-0.0008***	-0.0008***
	(-12.50)	(-12.53)	(-12.53)
SOE	0.0068***	0.0067***	0.0067***
	(4.60)	(4.59)	(4.59)
Board	-0.0006	-0.0006	-0.0006
	(-1.41)	(-1.42)	(-1.42)
Dshare	0.0011	0.0011	0.0011
	(0.39)	(0.38)	(0.38)
Inddir	-0.0514***	-0.0513***	-0.0513***
	(-4.59)	(-4.57)	(-4.57)
Top10	0.0400***	0.0401***	0.0401***
	(10.61)	(10.65)	(10.65)
Big4	-0.0202***	-0.0200***	-0.0200***
	(-7.19)	(-7.14)	(-7.15)
Constant	0.0979***	0.0990***	0.0991***
	(5.96)	(6.02)	(6.02)
Industry	YES	YES	YES
Year	YES	YES	YES
Observations	22,798	22,798	22,798
R-squared	0.444	0.444	0.444

Table 4 The moderating effect of asset specificity on the relationship between enterprise intelligence and commercial credit acquisition

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ISSN: 1053-7899
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When studying the promoting effect of enterprise intelligence on the acquisition of commercial credit, endogeneity problems may arise due to sample selection bias. For instance, enterprises that choose to undergo intelligent transformation may inherently possess certain traits, such as a more forward-looking management team and a better resource base. These traits may simultaneously influence the enterprise's level of intelligence and its ability to obtain business credit. Although the empirical model corresponding to the benchmark regression already includes control variables in multiple dimensions such as enterprise characteristics, enterprise operation, corporate governance, and supply chain cooperation relationships, due to the difficulty in covering all information in variable measurement, the endogeneity problem resulting from this may affect the test results. Therefore, an endogeneity test was conducted in this section.

VARIABLES	**TC_fin (Entropy Balancing)**	**TC_fin (Entropy Balancing)**	**TC_fin (Entropy Balancing)**	**TC_fin (PSM)**	**TC_fin (PSM)**	**TC_fin (PSM)**
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.0087***			0.0095***		
	(6.26)			(5.57)		
AIint/high_AIint		0.0051***			0.0073***	
		(5.53)			(4.64)	
AItype/high_AItype			0.0055***			0.0073***
			(5.69)			(4.60)
Size	-0.0040***	-0.0041***	-0.0041***	-0.0046***	-0.0046***	-0.0046***
	(-4.57)	(-4.68)	(-4.68)	(-4.34)	(-4.35)	(-4.35)
Lev	0.2940***	0.2943***	0.2943***	0.3027***	0.3028***	0.3028***
	(55.41)	(55.43)	(55.43)	(47.47)	(47.47)	(47.47)
Age	-0.0049**	-0.0048**	-0.0048**	-0.0036	-0.0038	-0.0038
	(-2.19)	(-2.15)	(-2.14)	(-1.38)	(-1.44)	(-1.45)
ROA	0.0678***	0.0683***	0.0682***	0.1032***	0.1038***	0.1037***
	(3.66)	(3.67)	(3.67)	(5.00)	(5.02)	(5.02)
Growth	-0.0010	-0.0011	-0.0011	-0.0013	-0.0013	-0.0013
	(-0.78)	(-0.78)	(-0.79)	(-0.72)	(-0.72)	(-0.72)
CFO	0.0714***	0.0718***	0.0717***	0.0660***	0.0657***	0.0657***
	(5.67)	(5.70)	(5.69)	(4.50)	(4.48)	(4.48)
Invent	0.0679***	0.0680***	0.0680***	0.0587***	0.0591***	0.0591***
	(7.10)	(7.12)	(7.11)	(4.88)	(4.90)	(4.89)
Digital	0.0052***	0.0045***	0.0046***	0.0047***	0.0047***	0.0047***
	(3.84)	(3.34)	(3.35)	(2.76)	(2.71)	(2.71)
BM	0.0136***	0.0140***	0.0140***	0.0158***	0.0155***	0.0155***
	(3.85)	(3.93)	(3.95)	(3.71)	(3.64)	(3.64)
CusHHI	0.0006***	0.0006***	0.0006***	0.0008***	0.0008***	0.0008***
	(8.13)	(8.04)	(8.04)	(9.41)	(9.36)	(9.36)
SupHHI	-0.0009***	-0.0009***	-0.0009***	-0.0010***	-0.0010***	-0.0010***
	(-10.01)	(-10.01)	(-10.03)	(-8.41)	(-8.40)	(-8.40)
SOE	0.0102***	0.0101***	0.0101***	0.0105***	0.0107***	0.0107***
	(4.83)	(4.80)	(4.80)	(4.14)	(4.19)	(4.19)
Board	-0.0010*	-0.0010*	-0.0010*	-0.0019***	-0.0019***	-0.0019***
	(-1.89)	(-1.81)	(-1.83)	(-2.92)	(-2.89)	(-2.89)
Dshare	0.0087**	0.0084**	0.0084**	0.0073*	0.0072	0.0072
	(2.32)	(2.23)	(2.24)	(1.67)	(1.64)	(1.64)
Inddir	-0.0641***	-0.0637***	-0.0639***	-0.0915***	-0.0913***	-0.0913***
	(-4.50)	(-4.47)	(-4.48)	(-5.33)	(-5.31)	(-5.31)
Top10	0.0390***	0.0396***	0.0394***	0.0312***	0.0316***	0.0316***
	(7.67)	(7.79)	(7.77)	(5.20)	(5.27)	(5.27)
Big4	-0.0248***	-0.0250***	-0.0250***	-0.0218***	-0.0219***	-0.0219***
	(-6.75)	(-6.79)	(-6.79)	(-5.01)	(-5.02)	(-5.03)
Constant	0.0149	0.0165	0.0166	0.0306	0.0309	0.0308
	(0.71)	(0.78)	(0.79)	(1.15)	(1.16)	(1.16)
Industry	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Observations	22,903	22,903	22,903	9,793	9,793	9,793
R-squared	0.451	0.451	0.451	0.451	0.451	0.451

Table 5 Endogeneity test

It is found that enterprise intelligence can significantly enhance the level of commercial credit acquisition. Next, heterogeneity analysis will be conducted respectively from the perspectives of enterprise characteristics, executive background, and enterprise life cycle to discuss the applicable boundaries of the impact of enterprise intelligence on the level of commercial credit acquisition, in order to obtain more abundant research conclusions. (1) Grouping enterprise characteristics Many studies have shown that traditional enterprises and high-tech enterprises have significant differences in industry environment, market competition, operation mode, etc. Compared with traditional enterprises, high-tech enterprises emphasize dynamic capabilities and flexible development, and pay more attention to organizational change and market potential. The research samples of this chapter are classified into two groups: high-tech enterprises and traditional enterprises. The samples of the two groups are respectively substituted into the original model to participate in the regression. In the sample of high-tech enterprises, the impact of enterprise intelligence on the acquisition of commercial credit still exists significantly at the 1% level, but in traditional enterprises, the above-mentioned influence relationship is only close to significant. This indicates that the influence of enterprise intelligence requires the support of the internal environment of the enterprise, further verifying the logical inference made earlier. The F-statistic of the grouped Chow test was 24.35, indicating that there was a significant statistical difference in the regression results between the two groups. (2) Group research on the financial background of senior executives shows that those with a financial background are more familiar with the financial situation of the enterprise and can communicate better with stakeholders, thereby reducing the level of information asymmetry between the two. Meanwhile, some literature also points out that senior executives with a financial background are more concerned about improving the quality of internal control and operational efficiency within the organization. Therefore, the higher the proportion of senior executives with a financial background in a company, the more conducive it may be to focusing on the management ability of working capital and ensuring the information transmission ability of the supply chain during the process of intelligent development of the enterprise, thereby improving the level of commercial credit acquisition of the enterprise. Based on whether the proportion of executives with financial backgrounds in the team exceeded one fifth, the sample companies were divided into the high financial background group and the low financial background group, and regression was conducted using the data of the two groups of samples respectively. In the high financial background group, the impact effect of enterprise intelligence on commercial credit acquisition remains significantly positive at the 1% level, but it is only nearly significant in the low financial background group. Moreover, the F-statistic of the Chow test is 24.09, indicating that the difference in coefficients between the two groups is statistically significant. (3) Grouping the enterprise life cycle: Under the analytical framework of the enterprise life cycle, the risks of enterprise intelligence show significant phased differences. Firstly, enterprises in the growth stage have broken through the bottleneck of market verification, possess strong resource absorption capacity and technology digestion efficiency, and can form differentiated competitive advantages through intelligent reconstruction of the value chain. Mature enterprises are under pressure from diminishing marginal benefits. Through process reengineering and data asset accumulation, intelligence can break through the trap of diseconomies of scale and achieve a second growth curve. However, during the introduction period, enterprises are constrained by resources and have uncertain demands. Intelligent investment may lead to technological mismatch and cost rigidity. Enterprises in the decline stage are subject to a severe path dependence lock-in effect. The intelligent transformation requires breaking through the constraints of organizational inertia and asset specificity, coupled with the pressure of market demand contraction. Therefore, enterprises are prone to fall into the "transformation paradox" predicament. Therefore, enterprises are classified into the introduction stage, the growth stage, the mature stage and the decline stage. Furthermore, the samples in the growth stage and the mature stage were grouped into one group, and the samples in the introduction stage and the decline stage were grouped into another group. The two groups of samples were respectively substituted into the original model to participate in the regression. The results show that the positive impact of enterprise intelligence on commercial credit acquisition remains significant in the growth and maturity stages, but its influence in the introduction and decline stages has not passed the test. Meanwhile, the F-statistic of the Chow test is 27.09, indicating that the difference between the two groups of coefficients is statistically significant.

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ISSN: 1053-7899
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VARIABLES	TC_fin (High-tech Enterprise)	TC_fin (Non-high-tech Enterprise)	TC_fin (High Financial Background Executives)	TC_fin (Low Financial Background Executives)	TC_fin (Growth/Maturity Stage)	TC_fin (Introduction/Decline Stage)
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.0111***	0.0049	0.0127***	0.0047	0.0118***	0.0031
	(6.67)	(1.62)	(6.57)	(1.53)	(7.44)	(1.29)
Size	-0.0075***	-0.0075***	-0.0077***	-0.0048***	-0.0076***	-0.0057***
	(-8.25)	(-6.24)	(-7.98)	(-3.04)	(-9.95)	(-3.95)
Lev	0.3008***	0.2330***	0.2708***	0.2729***	0.2837***	0.2697***
	(59.94)	(31.43)	(49.21)	(30.49)	(60.30)	(39.21)
Age	-0.0011	-0.0193***	-0.0075***	-0.0178***	-0.0086***	-0.0004
	(-0.53)	(-5.75)	(-3.24)	(-4.80)	(-4.37)	(-0.14)
ROA	0.1446***	0.0454**	0.0734***	0.0901***	0.1291***	0.0684***
	(11.75)	(2.12)	(3.99)	(4.27)	(10.25)	(3.41)
Growth	-0.0040***	-0.0011	-0.0001	-0.0117***	-0.0021	-0.0028
	(-3.40)	(-0.51)	(-0.11)	(-5.74)	(-1.31)	(-1.38)
CFO	0.0441***	0.0021	0.0371***	0.0253	0.0059	0.0384**
	(3.93)	(0.14)	(2.99)	(1.30)	(0.48)	(2.42)
Invent	0.0635***	-0.0061	0.0380***	-0.0094	0.0701***	-0.0267**
	(6.13)	(-0.57)	(3.92)	(-0.59)	(7.29)	(-2.54)
Digital	0.0056***	0.0098***	0.0092***	0.0054**	0.0084***	0.0090***
	(3.83)	(4.67)	(5.95)	(2.12)	(6.35)	(4.18)
BM	0.0343***	-0.0017	0.0159***	0.0171***	0.0229***	0.0193***
	(9.38)	(-0.36)	(4.01)	(2.60)	(7.20)	(3.74)
CusHHI	0.0009***	0.0001	0.0004***	0.0007***	0.0005***	0.0007***
	(11.59)	(1.21)	(5.52)	(4.94)	(7.36)	(6.23)
SupHHI	-0.0012***	-0.0009***	-0.0010***	-0.0011***	-0.0007***	-0.0011***
	(-13.47)	(-8.29)	(-11.26)	(-8.31)	(-8.80)	(-10.45)
SOE	0.0136***	-0.0041	0.0068***	0.0005	0.0067***	0.0050*
	(6.89)	(-1.60)	(3.58)	(0.13)	(3.84)	(1.82)
Board	-0.0019***	0.0005	-0.0010*	0.0003	-0.0008*	-0.0008
	(-3.36)	(0.59)	(-1.66)	(0.36)	(-1.72)	(-0.92)
Dshare	-0.0018	0.0151***	0.0085**	0.0005	0.0014	0.0031
	(-0.50)	(2.74)	(2.18)	(0.09)	(0.45)	(0.58)
Inddir	-0.0568***	-0.0651***	-0.0586***	-0.0356	-0.0567***	-0.0493**
	(-3.78)	(-3.19)	(-3.77)	(-1.38)	(-4.38)	(-2.22)
Top10	0.0361***	0.0557***	0.0431***	0.0537***	0.0327***	0.0545***
	(7.29)	(8.08)	(8.40)	(5.97)	(7.56)	(7.29)
Big4	-0.0174***	-0.0217***	-0.0162***	-0.0259***	-0.0209***	-0.0170**
	(-4.72)	(-4.02)	(-3.86)	(-3.63)	(-6.60)	(-2.54)
Constant	0.1354***	0.1618***	0.1033***	0.0953***	0.1123***	0.0509
	(6.34)	(5.66)	(4.46)	(2.58)	(6.08)	(1.49)
Industry	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Observations	12,826	6,882	12,163	4,353	15,879	6,978
R-squared	0.443	0.468	0.434	0.437	0.449	0.434
Chow Test	24.35 [0.000]	-	24.09 [0.000]	-	27.09 [0.000]	-

Table 5 Heterogeneity Analysis of the Impact of Enterprise Intelligence on Commercial Credit Acquisition

4. Conclusion

The acquisition of commercial credit is an important component of a company's commercial credit and also a significant source of financing for enterprises. This paper takes the A-share listed companies in China from 2010 to 2023, which have been screened according to standards, as the research sample to investigate the impact of enterprise intelligence on the acquisition of commercial credit. The research results reveal that: Firstly, compared with samples that have not applied artificial intelligence, intelligent enterprises can achieve a higher level of business credit, and this effect is more prominent in high-tech enterprises, enterprises with executives having financial backgrounds, and enterprises in the growth and maturity stages. Secondly, as the intensity and variety of enterprise intelligence increase, the amount of commercial credit obtained by enterprises also grows. Finally, an important boundary condition that affects the acquisition of commercial credit through enterprise intelligence is the specificity of assets. The higher the asset specificity of an enterprise is, the stronger the positive role of artificial intelligence in obtaining business credit will be. Mechanism tests have found that the intelligence of enterprises enhances their commercial credit acquisition level through optimizing business quality, improving production efficiency and reducing high-risk risks. The research conclusions of this paper not only enrich the study of the influencing factors of commercial credit acquisition, but also expand the exploration of economic consequences in the field of enterprise intelligence.

References

[1] Alasubramanian, N., Ye, Y., & Xu, M. (2022). Substituting human decision-making with machine learning: Implications for organizational learning. *Academy of Management Review*, 47(3), 448-465.
[2] Barker, V. L., & Mueller, G. C. (2002). CEO characteristics and firm R&D spending. *Management Science*, 48(6), 782-801.
[3] Bastos, R., & Pindado, J. (2007). An agency model to explain trade credit policy and empirical evidence. *Applied Economics*, 39(20), 2631-2642.
[4] Bouheas, S., Mateut, S., & Mizen, P. (2009). Corporate trade credit and inventories: New evidence of a trade-off from accounts payable and receivable. *Journal of Banking & Finance*, 33(2), 300-307.
[5] Cao, S., Jiang, W., Yang, B., et al. (2023). How to talk when a machine is listening: Corporate disclosure in the age of AI. *The Review of Financial Studies*, 36(9), 3603-3642.
[6] Dass, N., Kale, J. R., & Nanda, V. (2015). Trade credit, relationship-specific investment, and product market power. *Review of Finance*, 19(5), 1867-1923.
[7] Devos, E., & Li, H. (2021). Vertical integration to mitigate internal capital market inefficiencies. *Journal of Corporate Finance*, 69, 101994.
[8] Dickinson, V. (2011). Cash flow patterns as a proxy for firm life cycle. *The Accounting Review*, 86(6), 1969-1994.
[9] Dreyfus, H. L. (2012). A history of first step fallacies. *Minds and Machines*, 22(2), 87-99.
[10] Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254-280.
[11] Fisman, R., & Love, I. (2003). Trade credit, financial intermediary development, and industry growth. *The Journal of Finance*, 58(1), 353-374.
[12] Garcia-Appendini, E., & Montoriol-Garriga, J. (2013). Firms as liquidity providers: Evidence from the 2007–2008 financial crisis. *Journal of Financial Economics*, 109(1), 272-291.
[13] Goldfarb, A., Taska, B., & Teodoridis, F. (2023). Could machine learning be a general purpose technology? A comparison of emerging technologies using data from online job postings. *Research Policy*, 52(1), 104653.
[14] Gordini, N. (2014). A genetic algorithm approach for SMEs bankruptcy prediction: Empirical evidence from Italy. *Expert Systems with Applications*, 41(14), 6433-6445.
[15] Gregory, R. W., Henfridsson, O., Kagamer, E., et al. (2021). The role of artificial intelligence and data network effects for creating user value. *Academy of Management Review*, 46(3), 534-551.
[16] Jia, N., Luo, X. M., Fang, Z., et al. (2024). When and how artificial intelligence augments employee creativity. *Academy of Management Journal*, 67(1), 5-32.
[17] Kong, D., Pan, Y., Tian, G. G., et al. (2020). CEOs' hometown connections and access to trade credit: Evidence from China. *Journal of Corporate Finance*, 62, 101574.
[18] Li, W. L., Xu, X. X., & Long, Z. N. (2020). Confucian culture and trade credit: Evidence from Chinese listed companies. *Research in International Business and Finance*, 53, 101232.
[19] Liu, Q., Lu, R. S., Lu, Y., et al. (2021). Import competition and firm innovation: Evidence from China. *Journal of Development Economics*, 151, 102650.
[20] Longoni, C., & Cian, L. (2020). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. *Journal of Marketing*, 86(1), 91-108.
[21] Molina, C. A., & Preve, L. A. (2009). Trade receivables policy of distressed firms and its effect on the costs of financial distress. *Financial Management*, 38(3), 663-686.
[22] Murfin, J., & Njoroge, K. (2015). The implicit costs of trade credit borrowing by large firms. *Review of Financial Studies*, 28(1), 112-145.

Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions

The manuscript has a single author who was solely responsible for the research design, data collection and analysis, and the drafting and revision of the manuscript.

Conflict of Interest Statement

The author declares no conflicts of interest.

Ethical Statement

This study adhered to all relevant ethical standards for academic research. Where applicable, any research involving humans or animals was conducted in accordance with ethical guidelines.