

Artificial Intelligence Adoption and Supply Chain Finance: Evidence from China's A-Share Listed Firms

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Abstract. In recent years companies have used artificial intelligence (AI) to raise efficiency, to support decisions and to process data. This paper uses Chinese A-share listed companies to test whether firm-level AI adoption helps supply chain finance to grow. The AI index comes from text analysis of annual reports, and a panel over 2011 to 2023 is estimated; AI adoption is positively related to supply chain finance, and its coefficient stays stable after the model controls firm size, leverage, profitability and market value. The data come from the CSMAR database and annual reports; the sample drops financial and special treatment (ST) firms, keeps firm-years with more than 300 employees, and adds firm and year fixed effects to absorb unobserved firm features and macro shocks. The subsample results show that the positive relation is mainly in medium and large firms; there AI raises financing demand, information transparency and credit access, and this supports supply chain finance. Formal coefficient-difference tests show that this relation is significantly weaker in relatively small firms, and medium-sized and large firms show no statistical difference.

Keywords: artificial intelligence adoption, supply chain finance, firm size heterogeneity, corporate financing

1. Introduction

The latest progress in the field of artificial intelligence (AI) is reshaping the way enterprises organize production, process information and make strategic decisions. The increasingly important position of artificial intelligence is also reflected in the rapid adoption of it by enterprises. According to the Stanford Artificial Intelligence Index Report, in 2023, 55% of the surveyed organizations applied artificial intelligence in at least one business unit or functional area, compared with only 20% in 2017 [1]. In the financial field, artificial intelligence and data-driven technologies are increasingly used to support credit assessment and loan decision-making. Take China's MYbank as an example. The platform uses machine learning technology and transaction data to evaluate the credit status of micro and small enterprises. The number of enterprises covered by its services has expanded from about 21 million in 2019 to 40 million in June 2021 [2]. Its economic importance is not limited to the automation of a single task, because artificial intelligence can also improve the ability of enterprises to process massive amounts of information, generate forecasts, coordinate operations and develop new products and services. The existing corporate evidence is increasingly supporting these broader economic effects. Czarnitzki et.al found that there is a positive correlation

between the adoption of artificial intelligence and enterprise productivity [3]. At the same time, enterprises investing in artificial intelligence showed stronger growth in sales, employment and market value, most of which was related to product innovation [4]. These findings show that the application of artificial intelligence may not only improve the production capacity of enterprises, but also expand their operational scale, increase financing demand, and enhance their ability to access external financial resources.

Supply chain finance (SCF) provides an important research scenario for examining these financial impacts. Supply chain finance refers to the financing arrangement that coordinates the flow of funds with the real logistics and information flow of the supply chain, aiming to optimize the allocation of working capital between buyers, suppliers and financial service providers [5, 6]. Different from conventional lending, SCF arrangements mainly rely on information generated through commercial transactions, such as orders, accounts receivable, accounts payable, inventory, and payment records. As a result, both firms' working-capital demand and the quality of information available to financing providers are important to the development of SCF activities.

Firms' capital pressure can influence SCF adoption [7], and trade-process digitalization, operational capabilities, and financial strength can also affect firms' ability to participate in SCF arrangements [8, 9]. These characteristics provide two main channels through which AI adoption may be associated with SCF activity. On the demand side, AI can improve forecasting, inventory management, production planning, order processing, and coordination with suppliers and customers. These improvements may increase operational efficiency, but they may also support business expansion. As firms process more transactions, purchase more inputs, hold larger inventories, their short-term working-capital requirements may increase. Therefore, AI-related growth can strengthen firms' demand for financing connected to supply-chain transactions. On the supply side, AI-related capabilities can improve firms' ability to collect, organize, and process operational and transaction information. Better information quality can reduce information asymmetry between firms and financial institutions and make firms' business easier to evaluate.

In an empirical study using panel data from Chinese listed companies, Chai et al. [10] show that AI application promotes the progress of supply chain finance, while operational efficiency, innovation capability, and commercial credit serve as main transmission channels. Their findings provide important evidence that AI may influence firms' financing activities. However, several issues remain open for further investigation. Firstly, existing studies commonly measure firm-level SCF using balance-sheet financing indicators. For example, Chai et al. use the ratio of short-term borrowings and notes payable to total assets as a proxy for SCF [10]. Such measures capture the financial magnitude of short-term financing, but they provide a different perspective from firms' disclosed engagement with SCF-related activities in their business operations. Hence, a text-based measure constructed from annual reports will provide complementary evidence by capturing the extent to which firms report SCF-related activities and terminology.

Second, less work has asked whether the link between AI adoption and SCF changes with firm size. This point matters; firms are not alike in transaction scale, digital infrastructure, information-processing capacity, credit conditions, and ties with financial institutions. Past studies also show that the economic gains from AI do not spread evenly over firms. Babina et al. [4] find that the commercial gains from AI-related investment appear mainly in the larger firms. These gaps give a reason to test whether firm size affects the way AI capability is turned into SCF activity.

Based on the above, this paper studies the relation between firm-level AI adoption and supply chain finance in China's A-share listed companies from 2011 to 2023. The estimates rest on firm-year panel data taken from the CSMAR database and from annual reports of the listed companies.

The sample leaves out financial companies and special treatment (ST) companies, and it also drops firm-years with fewer than 300 employees, so that very small businesses will not affect the results. AI adoption is measured by how often AI-related words appear in the annual report; SCF activity is measured by the disclosure frequency of supply-chain-finance words. The AI indicator then enters in logarithm; total assets, employee numbers, leverage, profitability and the price-to-book ratio are controlled in the model.

To examine whether higher AI adoption leads to more SCF activity, this study estimates a baseline panel regression model. The specification includes firm fixed effects to control for time-invariant differences across firms and year fixed effects to account for common macroeconomic shocks and policy changes. The baseline relationship is estimated both without and with firm-level control variables in order to assess whether the AI adoption level and SCF relationship remains statistically significant after observable firm characteristics are taken into account.

A firm-size heterogeneity analysis is conducted later in this study. Firm-year observations are divided into three groups according to terciles of total asset size: small, medium-sized, and large firms. Then, the baseline regression is estimated separately for each group to compare the magnitude of the AI coefficient across different firm-size categories. Additionally, an interaction model is further used to test whether these differences are statistically significant. Pairwise coefficient-difference tests are conducted between medium-sized and small firms, large and small firms, and medium-sized and large firms.

Results show consistent evidence of a positive relationship between AI adoption and SCF activity: as the involvement of AI level increases, the supply chain finance activities increase. Heterogeneity analysis further reveals the obvious differences between different enterprise scale groups. The adoption of artificial intelligence and SCF activities are significantly related mainly in medium-sized and large enterprises, but there is no significant difference between medium-sized and large enterprises.

This research has contributed to the emerging research field of artificial intelligence and supply chain finance from two main aspects. It provides complementary enterprise-level evidence by using text-based supply chain financial activity indicators based on corporate annual reports. In addition, this paper puts the heterogeneity of enterprise scale at the core of the study and applies the formal coefficient-difference test. The results show that in relatively small listed companies, the positive correlation between the adoption of artificial intelligence and supply chain finance is weak. These findings demonstrate that the financial implications of AI adoption depend not only on technological adoption itself but also on firms' organizational and financial conditions.

The subsequent parts of this article are structured as follows: Section 2 outlines the empirical framework, detailing model specifications, data collection, and variable construction. Section 3 presents the hypotheses and the regression results, including the baseline analysis and firm-size heterogeneity tests. Section 4 discusses the findings from both the demand-side and supply-side perspectives and addresses the limitations of the study. Finally, Section 5 concludes the paper and summarizes the main findings and implications.

2. Methodology

2.1. Model and data description

This study uses a firm-year panel regression model to examine the relationship between firm-level AI adoption and supply chain finance activities. Firm fixed effects are included to control for time-

invariant differences across firms. Year fixed effects are included to control for macroeconomic shocks and policy changes that affect all firms in the same year.

To examine the effect of artificial intelligence (AI) adoption on firms' supply chain finance activities, the following econometric specification is employed:

$$Sc_{it} = \beta_0 + \beta_1 AI_{it} + \beta_j Control_{jit} + \delta_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where Sc_{it} denotes the supply chain finance activities of firm i in year t ; AI_{it} measures firm i 's investment of artificial intelligence reflected on their financial reports; $Control_{jit}$ represents a set of j control variables; δ_i and λ_t represent firm and year fixed effects, respectively; and ε_{it} represents the error term.

This analysis selects data from Chinese A-share listed firms from 2011 to 2023, and the data is finalized by merging different datasets and removing observations with missing values. The data stem from CSMAR database and financial statements from listed companies, further merge data sets and proceed reduction to observations with missing key variables. To improve data quality for precise analysis, the investigation has managed excluding ST and Financial industry firms from listed A-share companies. To reduce the influence of abnormal small firms, this study only keeps firm-year observations with more than 300 employees.

2.2. Variable definitions

2.2.1. Independent variable

Levels of firms' adoption of artificial intelligence are derived from examining AI related terminologies included in natural language processing of annual reports and disclosures. The resulting index is transformed to attain the intensity of AI application in firms' inputs through natural log calculations.

The key independent variable is firm-level AI adoption. This variable is measured by the frequency of AI-related terms in firms' annual reports, which is transformed using the natural logarithm to reduce skewness of data to avoid unfairness of data. The higher value of the AI adoption level will indicate the higher level of AI adoption or AI-related attention within the firm.

2.2.2. Dependent variable

Similarly, the dependent variable is supply chain finance activities. The dependent variable is measured using information extracted from firms' annual reports and financial statements, which examines frequencies of terminologies related to supply chain finance activities involved in reports and statements. Results are indicated as total frequencies of supply chain finance activities mentioned in listed A-share firms' annual reports and financial statements. A higher value of the dependent variable means that the firm reports more activities or discussions related to supply chain finance.

2.2.3. Control variables

This study controls several firm-level characteristics to minimize omitted variable bias and ensure the reliability of the empirical analysis. The following firm-level control variables are: employment size ($\ln_emp$), which is measured by the natural logarithm of the number of employees being greater than 300 people every year to avoid abnormal fluctuations in sizes of smaller companies; total assets

(ln_assets), is transformed using the natural logarithm to reduce skewness and improve comparability across firms of different sizes; leverage ratios (ratio of total liabilities and total assets; LeverageTLTA) are winsorized within the 0–1 range, as values outside this interval are economically implausible; Profitability is measured by return on assets (ROA), and which is restricted to the interval $[-1, 1]$ and then winsorized to minimize the influence of outliers; price-to-book (PB) ratios only within the range of 0 to 10, as excessively high values often reflect data errors or extreme cases. Relying on the simplified formulation of Tobin's q introduced by Chung and Pruitt [11], the market price-to-book ratio replaces Tobin's q in our regressions. These trimming criteria limit the distortion of outliers, raise observation consistency, and ensure more reliable model estimates.

3. Regression analysis

Equation (1) tests the relation between firm-level AI adoption and supply chain finance. The null hypothesis is that AI adoption has no significant relation with SCF; the alternative is that the relation is significant. The research hypotheses are therefore as follows:

$$H_0 : \beta_1 = 0$$

$$H_A : \beta_1 \neq 0$$

When the estimated coefficient β_1 is statistically significant with a p-value below 0.05 or 0.01, the test rejects the null hypothesis.

3.1. Baseline regression

Table 1 presents the baseline regression results for Equation (1) with firm-level control variables. The coefficient of AI adoption (ln_AITotal) is 0.0832 and significant at the 1% level; thus, it rejects the null hypothesis of no relationship between AI adoption and SCF, and this shows that enterprises with higher AI adoption report more supply chain finance activities after controlling for asset size, employment, leverage, profitability, and valuation. Therefore, observable firm characteristics do not fully explain the positive association between AI and SCF, and this result provides clear support for a positive relationship between firm-level AI adoption and SCF activities.

Table 1. Baseline regression with control variables

VARIABLES	(1) SCF_level
ln_AITotal	0.0832*** (0.00932)
ln_assets	0.156*** (0.0204)
ln_emp	-0.0323* (0.0188)

Table 1. (continued)

LeverageTLTA	-0.0809 (0.0955)
ROA	-1.292*** (0.286)
PB	-0.0130 (0.00930)
Constant	-4.001*** (0.376)
Observations	3,601
R-squared	0.097

Standard errors in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In addition, the control variables also say something about firm operations. Total assets ($\ln_assets$) get a coefficient of 0.156 at the 1% level; thus, firms with more assets take part in supply chain finance more. Large firms have many daily transactions and a wider partner network, and they therefore have more room for supply chain financing tools. Also, more capital raises creditworthiness, and this helps a firm join supply chain financing programs with third-party financiers [8]. The positive asset coefficient fits the common view that a larger operating scale makes SCF participation easier.

On the other hand, employee headcount ($\ln_emp$) has a negative coefficient of -0.0323 at the 10% level. This estimate should be read together with total asset scale. When assets are held constant, a larger workforce points to labor-intensive production, and staff numbers alone do not create SCF demand; SCF adoption depends mainly on supply networks, IT capability and financial stability [8, 9].

The other control variables give some further background. Financial leverage (LeverageTLTA) has a negative but insignificant coefficient; no uniform relation between the debt ratio and SCF is found in the whole sample. The price-to-book ratio (PB) is also negative and insignificant, and market multiples alone do not explain SCF differences. Return on assets (ROA), by contrast, has a coefficient of -1.292 at the 1% level, and this supports the view that profitable firms hold enough internal cash and need less working-capital support. Wang et al. [7] report that firms short of cash are more willing to use SCF for operating liquidity, and funding pressure works as a driver of SCF adoption.

Estimation outcomes for a restricted version of Equation (1) without firm-level covariates appear in Table 2. In this specification, the coefficient of AI adoption level ($\ln_AITotal$) is 0.114 and is statistically significant at the 1% level. After the control variables are introduced in Table 1, the coefficient decreases from 0.114 to 0.0832 but remains statistically significant at the 1% level. This

suggests that firm characteristics explain part of the relationship, but AI adoption still has an independent positive association with supply chain finance activities.

Table 2. Baseline regression with control variables

VARIABLES	(1) SCF_level
ln_AITotal	0.114*** (0.00756)
Constant	-1.387*** (0.124)
Observations	3,601
R-squared	0.060

Standard errors are reported in parentheses. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

This baseline regression provides consistent evidence of a positive association between AI adoption and SCF activity. Table 1, showing the baseline regression with control variables, has an R-squared of 0.097. Compared with R-squared value of 0.060 in Table 2, the baseline regression without control variables, Table 1 explains more SCF activities than the regression without control variables. Although a substantial proportion of firm-level variation remains unexplained, the increase in explanatory power after introducing firm characteristics indicates that these variables account for part of the variation in SCF activity.

Table 3 exhibits the estimates for firms in the smallest asset-size group. The coefficient on AI adoption is 0.0361 and is positive and statistically significant, showing a positive relationship between AI adoption and SCF activity also performs among relatively small firms. However, the magnitude of the coefficient is considerably smaller than corresponding estimates for medium- and large-sized firms. The reason causing this difference is that small firms possibly have weaker data infrastructure and weaker credit support; therefore, small-sized businesses face greater difficulty in converting AI adoption into supply chain finance activities. These limitations may constrain the extent to which improvements in digital capabilities translate into greater access to or use of SCF. Hence, the positive but relatively small coefficient provides preliminary evidence that the financial implications associated with AI adoption may depend on firms' complementary organizational and financial resources.

Table 3. AI impacts on small sized businesses

VARIABLES	(1) SCF_level
ln_AITotal	0.0361*** (0.0117)
ln_emp	0.102*** (0.0271)
ln_assets	0.0835* (0.0459)

Table 3. (continued)

LeverageTLTA	0.124 (0.114)
ROA	-0.725** (0.315)
PB	-0.00277 (0.0105)
Constant	-2.832*** (0.895)
Observations	1,201
R-squared	0.064

Values in parentheses are standard errors. One, two, and three asterisks show statistical significance at the 10%, 5%, and 1% levels, respectively.

In terms of the control variables, having a positive and statistically significant coefficient of employment suggests firms with larger workforces may have greater operational scale and therefore stronger working-capital needs within small-sized businesses. Total assets are also positively associated with SCF activity, although the relationship is only weakly significant. Leverage and price-to-book ratios are not statistically significant, meaning that both leverage and PB do not have a clear relationship with SCF activities among small firms. ROA has a coefficient of -0.725 and is significant at the 5% level, indicating that when ROA increases, SCF activities decrease, which means more profitable firms tend to have lower SCF activity.

For medium-sized firms, Table 4 shows the coefficient of AI adoption is 0.104 and is significant at the 1% level. This coefficient is higher than the coefficient of AI adoption among small-sized businesses at 0.0361, implying that AI adoption has a higher potential to perform more significant impacts in supply chain finance activities among medium-sized firms.

Table 4. AI impacts on medium sized businesses

VARIABLES	(1) SCF_level
ln_AITotal	0.104*** (0.0154)
ln_emp	-0.0696** (0.0316)
ln_assets	0.175** (0.0840)
LeverageTLTA	0.0632 (0.155)
ROA	-1.749*** (0.473)

Table 4. (continued)

PB	0.00172 (0.0150)
Constant	-4.582** (1.834)
Observations	1,200
R-squared	0.058

Standard errors appear in parentheses. One, two, and three asterisks represent significance at the 10%, 5%, and 1% levels, respectively.

The control variable estimates broadly reinforce this interpretation of greater impacts in SCF activities. Total assets have a positive coefficient of 0.175 and are statistically significant at the 5% level, indicating that greater asset scale within the medium-sized group is associated with higher level of SCF activities. The negative coefficient of employment may suggest that, after controlling for assets, more labor-intensive medium-sized firms are less likely to have higher supply chain finance activities. Leverage has a positive coefficient of 0.0632, but this estimate is statistically insignificant, indicating that there is insufficient evidence of a relationship between leverage and SCF activity among medium-sized businesses. The PB ratio is 0.00172, suggesting that firm valuation does not have a clear relationship with supply chain finance activities among medium-sized firms. Therefore, the price-to-book ratio does not appear to be an important factor in explaining supply chain finance activities in this group. ROA has a coefficient of -1.749 , and it is statistically significant at the 1% level, which indicates that more profitable medium-sized firms tend to have lower levels of supply chain finance activities. One possible explanation is that firms with higher profitability may have stronger internal cash flows. These firms may not need as much external financing support. As a result, their demand for supply chain finance may be lower.

Taken together, the medium-sized-firm results reveal a considerably stronger AI–SCF association than that observed among small firms. However, comparing coefficients from separate regressions alone is not sufficient to establish whether this difference is statistically meaningful. The formal coefficient-difference tests reported below therefore provide an important additional step.

Table 5 illustrates a similar but stronger pattern of large-sized firms' impacts on SCF activities from AI adoption, compared to small- and medium-sized firms. The coefficient on AI adoption is 0.111 and is statistically significant at the 1% level. This is the largest point estimate among the three size groups and indicates a strong positive association between AI adoption and reported SCF activity among large firms, demonstrating the relationship between AI adoption and supply chain finance activities may be more pronounced among large firms.

Table 5. AI impacts on large sized businesses

VARIABLES	(1) SCF_level
ln_AITotal	0.111*** (0.0199)
ln_emp	-0.121*** (0.0384)

Table 5. (continued)

ln_assets	0.183*** (0.0541)
LeverageTLTA	-0.858*** (0.237)
ROA	-2.184*** (0.718)
PB	-0.0391* (0.0236)
Constant	-3.809*** (1.129)
Observations	1,200
R-squared	0.053

Standard errors are reported in parentheses. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

One explanation is that large firms possess more developed conditions for integrating AI into their financial and supply-chain operations. Large-sized firms' massive transaction volumes can generate richer operational data, while established information systems may allow such data to be collected and processed more effectively. Large firms may also have more stable relationships with banks and other financial institutions and may occupy core positions within their supply chains. These structural strengths help channel AI-related efficiency gains in information management directly into SCF practices. However, deciding whether medium and large firms diverge meaningfully calls for statistical difference tests rather than inspecting raw numerical gaps alone.

A few steady patterns are again shown by the control variables. Total assets have a positive coefficient of 0.183 at the 1% level, and firm scale is again linked to SCF volume. Leverage has a negative coefficient of -0.858 at the 1% level, so heavily indebted large firms report less SCF activity. A high debt load leaves less balance-sheet room against total assets, and such firms can take on less new credit. Larger interest and principal payments also raise default risk when lenders review a request for more financing. Levered firms therefore meet more friction if they try to widen their SCF programs. This result agrees with Caniato et al. [8], who treat the financial stability of the anchor firm as a necessary condition for SCF uptake. Profitability (ROA) has a significant coefficient of -2.184 ; profitable large firms thus use SCF less. A firm with strong profits builds its own liquidity and relies less on third-party working-capital finance. Employee numbers are negatively related to SCF once asset scale is fixed, so a bigger workforce does not mean more SCF activity at the same firm size. Lastly, the PB ratio has a small negative relation with SCF at the 10% level, and market-valuation conclusions stay tentative.

3.2. Comparison analysis

Empirical estimates from the interaction-term specification are reported in Table 6, where the moderating role of firm scale in connecting AI adoption to supply chain finance is directly evaluated. Across all three size brackets examined, the estimated marginal association between AI

adoption and SCF remains positive. For small firms, the estimated marginal association is 0.0361 and is statistically significant at the 5% level ($p = 0.028$). The corresponding estimates increase to 0.1042 for medium-sized firms and 0.1114 for large firms, both of which are statistically significant at the 1% level. Thus, higher AI adoption is associated with greater SCF activity among small, medium-sized, and large firms. Importantly, however, differences in the magnitude of these estimates must be formally tested before concluding that the relationship varies by firm size.

Table 6. Coefficient difference tests by firm size

Comparison	F-statistic	p-value	Result
Medium-sized firms vs. Small firms	8.75	0.0031	Significantly different
Large firms vs. Small firms	10.85	0.0010	Significantly different
Medium-sized firms vs. Large firms	0.10	0.7517	Not significantly different

Notes. This table reports coefficient-difference tests based on a pooled interaction specification between AI adoption and firm-size groups. Small firms serve as the reference group in the comparisons with medium-sized and large firms. Marginal effects from the interaction specification may have different standard errors from the separately estimated subgroup regressions reported in Tables 3–5.

The coefficient-difference test comparing medium-sized and small firms yields an F-statistic of 8.75 and a p-value of .003. Therefore, the null hypothesis that the AI coefficients are equal across the two groups is rejected at the 1% significance level. Given that the estimated marginal association is larger for medium-sized firms (0.1042) than for small firms (0.0361), the result provides formal evidence that the positive AI–SCF association is significantly stronger among medium-sized firms.

A similar pattern emerges when large firms are compared with small firms. The coefficient-difference test produces an F-statistic of 10.85 and a p-value of .001, allowing the null hypothesis of equal AI coefficients to be rejected. Given that the estimated marginal association reaches 0.1114 for large enterprises versus 0.0361 for smaller counterparts, the positive association between AI adoption and SCF is found to be more pronounced in large firms than in small firms.

However, no clear gap is found between medium-sized firms and large firms. The F-statistic is 0.10 and the p-value is .752, so the test fails to reject the null hypothesis, and equal AI coefficients in the two groups remain possible. Large firms do have a slightly higher estimated marginal association (0.1114) than medium-sized firms (0.1042), but this gap in the numbers lacks statistical significance. Therefore, there is no empirical support for the claim that large firms gain more SCF benefit from AI adoption than medium-sized firms do.

Clear firm-scale disparities in the link connecting AI adoption with SCF activity are confirmed by the coefficient-difference tests. While positive point estimates are observed across all three size categories, smaller enterprises exhibit a weaker relationship compared to their medium-sized and larger peers. At the same time, the difference between medium-sized and large firms is not statistically significant. Therefore, the heterogeneity pattern should not be interpreted as a continuous increase in the AI–SCF relationship with firm size. Rather, the evidence suggests a distinction between small firms and the two larger firm-size groups. These results provide the basis for the following discussion of why medium-sized and large firms may be better positioned than small firms to translate AI-related capabilities into SCF activity.

4. Discussion

The above results reveal two main patterns. Firstly, firm-level AI adoption is positively associated with reported supply chain finance (SCF) activity, and this relationship remains statistically significant after controlling for observable firm characteristics. Secondly, the strength of this relationship varies across firm-size groups. Although the estimated association is positive for small, medium-sized, and large businesses, it is significantly weaker among relatively small firms than among medium-sized and large firms. Supply chain finance is the outcome of both firms' demand for working-capital financing and financing providers' willingness to supply funds. Because AI may affect both sides of this financing relationship, examining demand-side and supply-side channels provides a more complete economic interpretation of the positive AI adoption level and SCF association. The following paragraphs will discuss the impacts of AI adoption on SCF of both the supply side and the demand side. Moreover, the following paragraphs will evaluate the limitations of this investigation.

From the demand side, AI adoption may affect firms' need for SCF through two opposing forces. On the one hand, firms may operate more efficiently through improvements in forecasting, inventory management, production planning, and supply-chain coordination. For a given level of output, better forecasting and inventory control could reduce unnecessary inventory holdings and shorten operating cycles, potentially lowering the amount of working capital required. On the other hand, AI-related improvements in productivity and operational efficiency may also support business expansion. Firms that process more orders, serve more customers, or expand their relationships with suppliers may require additional funds for procurement, production, logistics, inventory, and accounts receivable. This is because firms that invest in AI experience stronger growth in sales and employment, which indicates that AI-related capabilities may be accompanied by an increase in the scale of business activity [4]. Therefore, the positive AI and SCF association resulting from the above analysis may reflect a situation in which the additional financing needs generated by business expansion outweigh the working-capital savings created by greater operational efficiency. At the same time, business expansion may increase firms' short-term financing needs. Wang et al. identify capital pressure as an important driver of supply chain finance (SCF) adoption among Chinese firms, suggesting that firms facing greater working-capital needs have stronger incentives to use SCF [7]. Therefore, if AI-related improvements lead firms to expand transaction volumes, the resulting increase in procurement, inventory, and receivables may strengthen their demand for SCF.

Since medium-sized and large firms generally operate at a greater transaction scale and are likely to maintain broader relationships with suppliers and customers, improvements in forecasting, production coordination, or order processing may translate into larger changes in procurement volumes, sales, receivables, and other components of working capital. Relatively smaller firms, in comparison, could possibly operate through narrower transaction networks, limiting the extent to which AI-related improvements generate additional financing demand. Results from this study align with Babina et al.'s finding emphasizing the importance of firm size that the economic gains associated with AI investment are concentrated among larger firms [4].

Supply-side evidence indicates that AI adoption can foster SCF activity by enhancing the quality and practical usability of corporate operational information. SCF is strongly supported by commercial transaction data, such as purchase orders, payment records, inventory status, accounts receivable, and buyer-supplier relations. If this information is incomplete or hard to verify, financial institutions face higher uncertainty when evaluating operational status and credit risk. In firms with stronger AI-related capabilities, operational records can be collected and organized more efficiently,

making business activities clearer to financing providers. Song et al. [9] show that operational capabilities and supply-chain network information reduce information asymmetry with financial institutions and improve access to working-capital funds; therefore, information quality and operational signals are essential for external financing.

The AI index measures AI-related activity at the firm level, and operating records are collected and handled better with AI tools, so the data reach financial providers in a more structured form. Information asymmetry about operating conditions then falls, and lenders can judge repayment capacity, the soundness of the underlying trade, and financing needs more exactly. Supply chain financing channels are opened more easily once financial institutions get richer operational information. This information mechanism also helps explain the firm-size differences in our baseline regressions. Large and medium-sized firms usually have a long operating record, mature digital systems, stable balance sheets and bank ties; AI-generated information is therefore easier to verify and to use in loan approval. Small firms, by contrast, often keep fragmented transaction records and have weaker credit standing, and their gains in digital information do not turn into real credit lines. Caniato et al. [8] stress trade digitalization and the financial strength of the lead firm in SCF adoption, and Song et al. [9] find that operational capability and supply-chain information together decide working-capital access. Overall, the weaker AI–SCF relation in small firms comes from their limited ability to turn better information into credit access. At the same time, the absence of a significant difference between medium-sized and large firms suggests that the mechanism needs a threshold of information quality and credit capacity, and it does not keep growing with firm size.

Capital pressure is treated as a main driver of supply chain finance adoption [7]. A firm with higher profits has more internal funds and needs less outside working-capital support; a firm with weaker internal financing carries heavier capital pressure. The negative relation between profitability and SCF is therefore further evidence for the demand-side view. Internal capital needs remain unobserved here, however, so the ROA result should be read as suggestive support, not as direct proof of this channel.

These results can also be placed in the new literature on AI applications in supply chain finance. Chai et al. [10] report that AI adoption expands SCF among Chinese listed firms, and they name gains in operating efficiency, firm innovation and access to commercial credit as the main channels. That main conclusion is supported by our estimates. However, our analysis by firm size adds new evidence; small listed firms gain less, and medium-sized and large firms remain indistinguishable. The financing benefit from AI does not grow steadily with firm size, and it seems to require a basic level of organizational and financial capacity.

This study has several limitations. First, the proxies for AI adoption and for SCF intensity both come from annual report disclosures, so the measurement is partly subjective. Part of the estimated co-movement may reflect reporting habits and not a real change in operations. Firms that file long narrative reports, or that want to show technological awareness, may mention AI-related and SCF-related words together more often. Firm fixed effects absorb disclosure styles that stay constant over time, and year fixed effects pick up macro-level shifts in the reporting environment. Time-varying differences in reporting behavior, however, are still left uncontrolled. Later work may test whether the same patterns hold when direct measures of realized supply chain credit are used.

Second, empirical associations rather than strict causal relationships are observed in this paper. Although the regression models control for observable firm variables and include firm and year fixed effects, reverse causality and omitted variables cannot be completely excluded. Firms with more complex supply-chain operations or greater existing engagement in SCF may themselves have stronger incentives to adopt AI-related technologies. In addition, broader changes in managerial

quality or digital transformation may simultaneously affect both AI adoption and SCF activity. Thus, the interpretation of the estimated coefficient of a relationship between AI adoption and SCF activity leans towards explaining a robust relationship between AI adoption and SCF activity due to existence of unobservable variables and factors.

Lastly, the firm-size classifications are relative to the sample of Chinese A-share listed firms. Firms in the lowest asset-size tercile are classified as relatively small within this sample, but they should not be interpreted as equivalent to small enterprises under official definitions of small and medium-sized enterprises. Therefore, the heterogeneity results primarily indicate that relatively smaller listed firms exhibit a weaker AI and SCF association than medium-sized and large listed firms, and the findings should be generalized to the broader population of small and micro enterprises with caution.

Overall, the findings provide evidence of a positive relationship between firm-level AI adoption and reported SCF activity. On the demand side, AI-related improvements in operations may support business expansion and increase working-capital requirements, although efficiency gains may simultaneously reduce some financing needs. From the supply perspective, stronger information-processing ability can enhance the quality and transparency of operational records, helping reduce information friction with financial institutions. Heterogeneity tests further show that this relationship is much weaker in relatively small firms; in contrast, medium-sized and large enterprises exhibit a stronger positive association between AI adoption and SCF activity.

5. Conclusion

In this paper, the relationship between firm-level artificial intelligence adoption and supply chain finance is examined among Chinese A-share listed companies from 2011 to 2023. Based on the firm-year panel data and the text indicators in the company's annual report, the empirical results confirm that there is a stable positive correlation between the adoption of artificial intelligence and supply chain finance. After controlling the size of the enterprise, the number of employees, the leverage ratio, profitability and market valuation, as well as the fixed effect of the enterprise and the year, this correlation is still statistically significant. These findings suggest that enterprises with a higher degree of adoption or attention to artificial intelligence tend to be more actively involved in supply chain finance activities. In addition, heterogeneity analysis further shows that this relationship differs in business groups of different sizes. Although the adoption level of artificial intelligence in small, medium and large enterprises is positively related to financial activities in the supply chain, the estimated intensity of this relationship is more significant in large enterprises.

These findings contribute to the emerging literature on AI and supply chain finance in two respects. First, this study provides supplemental evidence by measuring both AI adoption and SCF activity through textual information disclosed in annual reports rather than relying exclusively on balance-sheet financing indicators. Second, it highlights firm-size heterogeneity and shows that the relationship between AI adoption and SCF is particularly weaker among relatively small listed firms. Nevertheless, limitations of the exploration and findings should be included in consideration. Because both key variables are constructed from annual-report disclosures, the estimated relationship may partly reflect differences in firms' reporting behavior. In addition, the relatively small firms examined in this study are small only within the sample of A-share listed companies and should not be treated as equivalent to small and micro enterprises more broadly. Future research could address these limitations by using direct measures of AI investment and realized SCF financing, applying stronger causal identification strategies, and extending the analysis to non-listed and smaller enterprises. Empirical evidence indicates that higher AI adoption corresponds to greater

supply chain finance engagement, but the intensity of this relationship depends on firms' organizational and financial foundations.

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