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Research paper

Managing Financial Dependence Through AI: A Resource Dependence Theory-Based Study in Textile SMEs

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Abstract

This qualitative study explores how finance managers in textile SMEs utilize artificial intelligence (AI) to manage financial resource dependence, framed within the lens of Resource Dependence Theory (RDT), providing preliminary insights in an area where qualitative research remains scarce. Conducted through in-depth interviews with AI-using finance managers from seven textile enterprises based in Istanbul, Türkiye, the research investigates how AI influences access to and reliance on external financial resources such as short-term loans, leasing, and supplier credit. The findings reveal that AI-supported decision-making contributes to strategic financial planning, reduces dependence on short-term credit, and enables proactive resource management. Themes such as data-driven investment timing, AI-based customer risk scoring, and internal cash flow optimization emerged from the analysis. The study also highlights the critical role that managerial competence in leveraging AI plays in transforming traditional financial behavior and dependency structures. By taking into account sector-specific constraints such as foreign exchange input costs and seasonal demand fluctuations, this study extends the theoretical application of RDT in the context of digital finance. While AI may reduce certain types of financial dependency, it may also introduce new forms of technology and data reliance that require deliberate managerial oversight. The research findings suggest that SMEs attempting to reduce their financial exposure with the help of AI are developing a reliance on software companies. This dependency is expected to increase over time, potentially limiting businesses' ability to make critical decisions.

Keywords: *Resource Dependence Theory; Financial Dependence; Artificial Intelligence; Textile; SMEs*

1. Introduction

In sectors like textiles that are highly exposed to market volatility, foreign currency fluctuations, and seasonal demand, small and medium-sized businesses (SMEs) often face significant challenges accessing and managing financial resources. Due to their limited bargaining power and internal capital reserves, SMEs tend to rely heavily on external financial instruments such as short-term bank loans, leasing agreements, and supplier credits. As a result of structural dependency, they are vulnerable to financial shocks, especially during periods of macroeconomic instability. In response to these challenges, an increasing number of SMEs have been integrating digital technologies, in particular artificial intelligence (AI), into their financial decision-making. AI tools enable firms to predict cash flow, create dynamic prices, and segment customers based on risk, which can aid in planning for the future, reducing uncertainty, and improving strategy. The impact of AI adoption, however, on resource dependence management has never been explored extensively in research literature, not even with regard to qualitative, theory-oriented research. It falls into the tradition of Resource Dependence Theory (RDT), according to which organizations lack autonomy and need to formulate strategies to cope with their reliance upon key external resources. By examining how AI is utilized among finance managers working in textile SMEs in coping with financial constraints, this research intends to expand the use of RDT into the digital finance domain. In Istanbul, it utilizes qualitative research relying upon in-depth interviews with finance managers who are active users of AI tools. As well as examining how AI alleviates financial dependency, it also examines how it creates new technological and data-driven dependency. In this way, this research arrives at an in-depth understanding of AI being both an alleviating as well a potentially complicating factor in resource dependence.

2. Purpose and Research Question

The major idea of this paper is to define the usage of AI tools in SMEs operating in the textile industry to cope with the reliance on financial resources. In particular, it focuses on learning about the strategic position of AI in decreasing the reliance on external financials, namely, short-term loans, supplier credits, and lease agreements. Although AI has been marketed extensively as a technology that makes it easier to plan financially and manage risks [1], [2], [3], few studies have been conducted [4], [5] to determine the effects of AI on the dependency relationships of SMEs on external financial actors.

This research aims to fill such a gap by analyzing the advantages and novel types of reliance that occur through the use of AI. The study is based on RDT and narrowed down to finance managers of the SMEs related to textiles in Istanbul who are actively adopting AI in their practices. Focused interviews are undertaken to answer the following research question (RQ):
How do finance managers in textile SMEs use artificial intelligence to manage financial resource dependence, and what new dependencies—if any—emerge from the use of these technologies?
By answering this question, the research will serve to develop a more complex knowledge on the dualistic contribution of AI to the formation of financial strength and strategic independence of SMEs.

3. Related Works and Literature Review

It is necessary to acquire familiarity with several lines of academic thought to comprehend the interplay of financial management, AI, and the dependence of the organization. This section includes the significant works of research on the topic of financial resource dependence in SMEs, AI in the financial decision-making practice, and the RDT theoretical framework.

3.1 Resource Dependence Theory

The work The External Control of Organizations: A Resource Dependence Perspective by Pfeffer and Salancik [6] was instrumental in establishing the RDT as a widely recognized framework in the field [7]. Adopting an open systems perspective argues that no organization is entirely self-sufficient. In order to maintain their production activities, organizations require various inputs, namely resources [8]. The significance of these resources, as well as the means of acquiring them, differ from one to another. According to Pfeffer and Salancik [6], understanding organizational behavior is only possible through an assessment of the relative importance of these resources. The importance of a resource can be assessed by its share in total production. It may also be judged by its criticality, that is, how far an organization can operate without it or its market [7].
Since resources of varying importance are held by different organizations, a dependency relationship inevitably emerges that must be managed. The nature of this relationship depends on the importance and scarcity of the resources, as well as the degree of control other organizations have over them. When a resource is important, scarce, and under the control of another organization, the relationship becomes asymmetric, granting power to the organization that possesses it. The party holding such power can leverage it to influence or constrain the behavior of other organizations or stakeholders [6], [9]. Consequently, the survival and success of organizations depend on their ability to manage these dependency relationships to their advantage. They must also secure stable access to key resources and respond effectively to external pressures and threats.
In this sense, rather than merely adapting to external conditions as in contingency theory, organizations also take deliberate actions to manage their exposure to external resources. Their success hinges on their ability to act effectively in response to environmental demands. These can be mergers, acquisitions, and hiring of the best executives, interlocking directorates, and participation in political events [10]. Nevertheless, rational foresight alone does not determine action; decisions are shaped by external power-dependency dynamics and internal organizational relations. For instance, when the departments have capabilities, skills, or knowledge that eliminate or depreciate uncertainty and reliance on the organization, the departments hold power. In the long run, strong departments can gain sustainability and influence. Top managers shape strategy by prioritizing decisions such as investments, partnerships, or acquisitions. These choices reinforce their power and that of their department [6]. Overall, Resource Dependence Theory explains why organizations act as they do in response to expectations [11] and has been empirically tested, providing managers with validated insights [12].
RDT helps understand how financing limitations implied in the case of SMEs, particularly those in the unstable and dynamically fluctuating industries such as textiles, influence the organizational strategies. With limited internal capital, these firms rely on external financing, leaving them vulnerable to economic downturns and market shifts.
AI and other digital technologies are increasingly embedded in financial decision-making. RDT can help us understand whether these technologies reduce reliance on traditional financial intermediaries and institutions, or instead create new dependence on data suppliers, algorithms, and platform infrastructures. In this way, the theory of RDT is quite applicable when examining organizational adaptation in the digital age.

3.2 Resource Dependence Theory in Practice

RDT has been widely used in organizational research to understand how firms manage their reliance on external actors and resources. In practical terms, RDT helps explain why organizations form alliances, adapt governance structures, and invest in internal capabilities to reduce exposure to environmental uncertainty and external control [6].
One of the most prominent applications of RDT is in the study of corporate governance. Hillman, Withers, and Collins [10] demonstrate that firms often appoint board members with external ties to key stakeholders—such as financial institutions, government agencies, or large customers—in order to secure critical resources and reduce uncertainty. These appointments serve both symbolic and strategic purposes, particularly in industries that are highly regulated or capital-intensive.
Drees and Heugens [13] provide further evidence through a meta-analysis showing that organizations frequently engage in mergers, partnerships, and joint ventures to manage resource dependencies. For example, companies facing technological gaps may collaborate with startups or research institutions to access innovation without fully internalizing the associated costs or risks. Similarly, SMEs often adopt RDT principles in their behavior to overcome such limitations. Due to limited internal resources, SMEs are often more dependent on external financing sources, supply chain actors, or industry networks. To mitigate this vulnerability, SMEs can join cooperatives, cluster initiatives, or regional alliances to increase collective bargaining power and resource access. Teece [14] highlights how developing dynamic capabilities, such as technological adaptability, digital integration, and strategic agility, reduces firms' dependence on external organizations. By building internal capabilities that enhance responsiveness and innovation, organizations can shift from passive dependency to proactive resource management. Although not limited to RDT, this approach aligns with its core principle: organizations attempt to control critical dependencies by reshaping their internal capabilities and external relationships. In their study, Abousaber & Abdalla [15] discuss how AI can help companies automate tasks, make smarter decisions, and enhance digital services, but do not address its role in reducing dependence on external resources. Nishant et al. [16] show that AI has the potential to address sustainability challenges by enabling processes and practices to reduce resource and energy use, but faces challenges in implementation. In Ughulu's [17] study, AI can help businesses automate and scale operations, and reducing reliance on external resources is a key concern for SMEs. Mohammed et al. [18] show that AI

enhances business efficiency and supply chain management, but its role in lowering exposure to external finance is not directly addressed. RDT studies show that while firms reduce dependence on external actors, they often create new ones. In the digital age, financial and supply dependencies shift toward technology and data, requiring constant adaptation.

3.3 Managing Resource Dependence Through Artificial Intelligence in Financial Decisions

Within the framework of RDT, organizations are viewed to be intrinsically dependent on other actors to provide their necessary inputs in terms of capital, information, and infrastructure. Firms generally use options like diversification of resource channels, strategic alliances, internal capability building, or vertical integration to counter these dependencies [6], [19].

In recent years, using AI in an organizational process has become one of the most effective methods of redesigning the identification, measurement, and mitigation of these [20]. AI tools- especially those utilized in predictive analytics, risk assessments, and financial forecasts helps companies to make better decisions in situations of uncertainty. As RDT would view it, this is a technological capability as a form of strategic buffer that helps in decreasing overdependence on external financial institutions and intermediaries. For example, AI-based cash flow models allow companies to predict liquidity shortages, reducing the need for short-term borrowing. Similarly, dynamic pricing algorithms and segmenting customers tools improve revenue predictability, with organizations being able to negotiate better credit terms or less reliance on supplier financing [21].

AI is like a replacement for institutional help in the financial sector, especially among the SMEs that have less access to capital markets. AI tools can also allow finance managers to model financing situations, determine the most cost-effective way to finance an operation, and evaluate lender behavioral dynamics. Such insights not only limit the risk of opportunistic behavior by the financial partners but also minimize the risk of the underutilization of the internal resources. AI, however, can only have such effects as reducing the traditional dependence in finance, but it introduces a dependency on data providers, transparency of algorithms, and technology vendors. In the AI age, dependency management must focus on two areas: reducing exposure to critical resource vulnerabilities and addressing risks associated with technological adoption [22], [23].

4. Methodology

In this study, a qualitative research design was used to explore how AI is used by SMEs in the textile industry to address financial resource dependency following a framework based on RDT. The research had a theory-driven and exploratory character, which made the qualitative method the most suitable one to identify the contextual specifics of managerial decision-making processes [24].

The study was conducted in Istanbul, the largest textile and financial hub in Türkiye, where the SMEs in the textile industry face a highly competitive environment and are very cash-strapped. The main entity of focus was SMEs because it is disproportionately affected by the issue of resource dependency, especially in emerging economies. In Türkiye, SMEs often face structural financial pressures that constrain long-term strategic planning, R&D investment, international expansion, and sustainable growth. These predicaments render the SMEs the perfect environment to study the adoption of AI with the aim of minimizing financial vulnerability.

A single sector (textiles) was deliberately selected to control for industry-specific variables and to avoid discrepancies that might arise from cross-sector differences in digital maturity or capital intensity. Data were collected through semi-structured, in-depth interviews with financial managers in seven SMEs. While the sample size of this study was limited, the qualitative research approach provided in-depth data. Small samples are often preferred in qualitative research to generate detailed insights that larger samples might miss [25,26]. Based on the research question (RQ) and interview questions (IQ), the sources covered financial resources, including internal versus external finance [25], formal versus informal financing preferences, and challenges related to bank guarantees [26,27]. The sources also addressed the effects of resource scarcity and concentration, alliance and joint venture strategies [28,10,29], and the impact of resource uncertainty and financial resource diversification [30,31,32].

The initial interviewee was chosen using a purposive sampling method, and the rest were chosen by snowball, making a total of n = 7 interviews. After the seventh interview, theoretical saturation was reached because no new codes or themes emerged, and further data collection was unnecessary. The rationale of this methodology lies in adherence to the norms of qualitative research, as further increases of the sample at the level of saturation could have introduced a factor of non-analytical complexity [33]. The interviewed financial managers were assured that their companies' names would not be disclosed. This anonymity was made presumable so as to make the subjects answer the interview questions with more clarity and openness.

All interviewees were assumed to have decision-making authority and practical experience with artificial intelligence tools in financial operations. Importantly, the participating companies were not only users of AI technology but also integrated AI into their strategic resource management processes. This made sure that the acquired insights had a basis in practical experience and were applicable in the theoretical scope of the study.

As per the research design, interview questions had been formulated with reference to the central research question (RQ) and had been modeled in a manner to obtain detailed and reflective feedback in line with the theoretical context. Each question was coded for a specific aspect of the research purpose, thus providing a systematic mapping between empirical data and conceptual constructs. During the interviews, finance managers provided in-depth and contextualized responses to each of these coded questions.

After transcription, the interview data were subjected to thematic content analysis. Responses were examined question-by-question and coded individually. The resulting codes were grouped into higher-level categories: financial fragility, AI-assisted forecasting, decision-making autonomy, and strategic planning. This coding allowed comparisons across participants while preserving the richness of individual responses.

Finally, all seven cases were analyzed comparatively. Code matrices were created to identify recurring themes and common patterns across firms. This cross-case synthesis produced an overarching thematic structure, which is presented in the results section and further interpreted in the discussion. The process ensured analytical depth and theoretical consistency, providing robust insights into how SMEs use AI to manage external financial dependencies.

5. Findings

Under this heading, the answers given to the interview questions were analyzed by categorizing and coding them. The tables include data from all seven businesses. Before the tables, there are sample statements presented as direct quotations from the responses of three businesses. In this context, the first interview question (IQ1) aims to reveal which financial resources businesses are most dependent on, and sample responses from selected businesses are presented.

Interview Question 1 (IQ1): What are the types of financial resources on which businesses are most dependent?

Business A: "We are particularly dependent on short-term bank loans. We buy raw materials like yarn and cotton in foreign currency, but we sell our products in Turkish Lira. The exchange rate risk is very high. We can't import on credit; suppliers demand cash or short-term payment. In such cases, we take out a revolving loan from the bank. Furthermore, we use factoring because we offer 120-day installments to chain stores. Leasing only comes into play for investment; for example, we leased an automatic fabric cutting machine this year."

Business C: "Energy, water, and chemical costs are very high for companies in the painting business. Therefore, we use foreign currency-based working capital loans to manage production expenses... Electricity and steam costs are indexed to euros. Furthermore, prepayment is often required for chemical procurement, making us dependent on cash flow. Leasing isn't very common in our country, but we did lease a reactive dye automation system last year because the price was €180,000."

Business G: "Organic production companies often start with equity capital but are forced to turn to other sources for growth. In the last two years, we've primarily used green transformation loans and TÜBİTAK (The Scientific and Technological Research Council of Turkey)-supported grants… We steer clear of traditional loans because interest rates are high. We also have a production financing model based on a partnership with a Swedish buyer, which includes a down payment. This provides pre-production financing."

The responses to the first question reveal the varying dependence of businesses on financial resources. Particularly, short-term bank loans, foreign currency-based loans, leasing, and grants are prominent financing tools. In order to systematically compare these findings, the responses were coded and summarized in Table 1. It summarizes the responses of seven businesses by coding them, highlighting their dependence on financial resources. As seen in the sample statements, it is noteworthy that Businesses A and C tend to rely heavily on credit financing, while Business G utilizes grants and green loans. Other businesses adopt diverse financial strategies. Specifically, Business B relies on revolving credit and forward-dated yarn procurement, Business D prioritizes spot credit and equity, Business E uses foreign currency loans and export rediscount credits, and Business F supplements short-term bank loans with checks and promissory notes. This diversity shows that financing preferences of enterprises differ depending on their operating conditions and strategic priorities.

Table1: The Codes of IQ1- Financial Resource Instruments

Business Code	Codes
Business A	Short-term bank loans, factoring, and leasing.
Business B	Revolving credit, forward yarn supply
Business C	Foreign currency-based business loans, prepaid chemical supply, and leasing
Business D	Spot credit, equity priority, distance from credit
Business E	Foreign exchange loans, export rediscount credits, and leasing investment
Business F	Checks, promissory notes, and short-term bank loans
Business G	Green loan, grant, prepaid partnership financing

The second interview question examined how businesses' use of artificial intelligence shapes their access to financial resources and their relationships with these resources. Sample answers were also presented.

IQ2: How does the use of artificial intelligence affect businesses' access to financial resources and their relationship with these resources?

Business B: "We used to approach banks with estimated Excel spreadsheets, but frankly, they weren't very convincing. Now, we present the banks with three-scenario cash flow statements generated by the AI system. For example, the graphs clearly show how much of a deficit we'll be in if the exchange rate hits 33 TL, 35 TL, or 36 TL. This way, we support our loan requests with much more robust data. Bank representatives now find us more institutional and predictable."

Business D: "Thanks to AI, our supply chain analyses have become clearer. We now know which raw materials we'll need in which periods. This gives us a significant advantage in pre-financing planning… Our AI system warned us that capacity would exceed 80% in the next two months. With this information, we were able to go to the bank and say, 'We'll need more cash during this period.' It doesn't provide direct loans, but it allows us to take early action. This positively impacts our relationships."

Business F: "In the past, we generally negotiated leasing agreements with the guidance of sales representatives. Now, with AI, we create realistic payment plans based on the amortization period and productivity of the device. This has allowed us to negotiate more favorable rates... The analytical support from AI has given us greater bargaining power."

The responses reveal how businesses develop various forms of dependencies and leverage in accessing and interacting with financial resources through AI, with cash flow forecasting, supply chain forecasting, and payment planning being particularly prominent. Table 2 illustrates the transformative effects of AI on sample firms' access to financial resources and their relationships with these resources. For example, Business B provides more compelling information to banks with three-scenario cash flow statements. While Business D gains an advantage in pre-financing planning enabled by supply chain analysis, Business F creates depreciation and efficiency-based leasing plans. These applications reveal the decision-support role of artificial intelligence and its function in increasing the bargaining power of businesses. Other businesses in the table also use AI in various ways. Some optimize credit planning by estimating energy costs, plan credit use through raw material forecasts, and leverage green loan applications using carbon footprint data. These findings indicate that AI enhances both data-driven decision-making and strategic credit management in financial relationships.

Table2: The Codes of IQ2- AI Impact on Financial Resource Relations

Business Code	Codes
Business A	Data-backed credit reports in communication with banks
Business B	Accelerating credit processes with scenario analysis
Business C	Credit planning with energy-cost estimation
Business D	Planned loan usage with raw material forecast
Business E	AI's contribution to leasing timing
Business F	AI provides bargaining power in depreciation-based leasing planning
Business G	Applying for a green loan with your carbon footprint

The impact of artificial intelligence on short-term and long-term financial instrument selection decisions was asked of the interviewees through IQ3.

IQ3: How does AI factor into decisions about choosing short-term or long-term financial resources?

Business D: “Because our production schedule is so variable, we generally use short-term resources… Our AI system only offered us a long-term loan recommendation, but management declined because the system's forecasting isn't fully reliable. Therefore, we still manage labor and fabric financing with 3-month spot loans. In short, the AI couldn't influence the decision, but it did at least provide an analysis.”
Business E: “AI now clearly tells us: short-term loans are unsustainable. Especially considering currency fluctuations and investments with long amortization periods, long-term leasing and investment loans have become much more logical… This year, for the first time, we invested in carbon reduction as part of the 'green agreement' and used a 48-month lease. Our AI system calculated the investment's payback period, and based on this analysis, the bank relaxed its collateral requirements."
Business G: "For the last two years, we've been focusing on long-term development loans and leasing options because our AI system can calculate the return on investment. For example, for our last machine purchase, the system predicted a 28-month return, so we opted for a 36-month lease… Furthermore, the AI analyzed our carbon emission values, showing we were also eligible for a green loan. This enabled us to establish a more sustainable structure with long-term financing."
These responses illustrate how AI is impacting the selection process for financial resources based on their maturity and shaping businesses' strategies for choosing short- or long-term financial resources. Sample interview data highlight that the shift from short-term spot loans to long-term leasing and investment loans has a significant impact on risk management and sustainability objectives.

Table 3: The Codes of IQ3- AI Role in Short- vs. Long-Term Financing

Business Code	Codes
Business A	Shifting from short-term to long-term use in borrowing using AI
Business B	First 1-year loan with cost-benefit analysis over 6 months offered by AI
Business C	24-month loan decision based on energy analysis
Business D	Short-term resource retention despite AI recommendation
Business E	Long-term leasing, green investment loan preference
Business F	Early loan application after order forecast, but still committed to short-term
Business G	Long-term leasing and development loan preferences based on AI data

Business D cannot afford to abandon short-term loans and uses AI analytics only as a reference. Business E, on the other hand, prefers long-term leasing and green investment loans, while Business G ensures sustainability with long-term financing based on AI data. This demonstrates the decision-support and guidance role of AI. Some other businesses in Table 3 plan transitions from short-term to long-term with cost-benefit analyses; make credit decisions based on energy analysis; and apply for loans early using order forecasts. Other businesses, however, still rely on short-term resources. These findings show that artificial intelligence provides both analytical insights in financial decision processes and supports long-term sustainable financing strategies.
The fourth interview question explored how AI reduces reliance on external financial resources by optimizing internal resource use through inventory management and cost control. The use of AI in businesses directly contributes to improvements in inventory turnover, reducing energy costs, reducing credit usage, and improving cash flow.
IQ4: What role does artificial intelligence play in encouraging businesses to use internal resources and reduce their dependence on external resources?
Business A: "We used to hold more inventory than necessary because we were manually planning sales and supply. The AI application analyzed our inventory turnover and showed that we held 90 days' worth of inventory on some products. Now, we've reduced that inventory to 30 days. The difference is that we have cash on hand. We used to meet this cash need with bank loans, but now, thanks to the system's predictions, we can use our internal resources efficiently… So our credit usage decreased by approximately 20% in the last quarter."
Business C: "We switched to a night shift system based on AI's suggestion because energy costs were too high during the day. The system showed that night shifts would consume 15% less energy. This switch reduced our electricity costs, allowing us to pay suppliers earlier. We previously applied for revolving credit for those payments. Now, we're using this cost advantage as an internal resource. By optimizing spending, AI indirectly reduces the need for credit."
Business F: "The AI system didn't make a significant contribution when it was first installed, but after inventory analysis, we began to better understand when to buy which fabric... We used to buy excess yarn and keep it in stock for two months. Now, we've reduced that period to three weeks. It didn't eliminate our direct credit needs, but it did eliminate the need for short-term bank loans for two months. It's a small gain for now, but if it continues this way, the system could be even more effective in generating internal resources."

Table 4: The Codes of IQ4- AI Role in Internal Resource Utilization and Dependency Reduction

Business Code	Codes
Business A	Reducing the need for credit through stock optimization
Business B	Keeping cash in with inventory planning
Business C	Internal payment to suppliers with reduced energy costs
Business D	Reducing overtime costs through shift plan optimization
Business E	Creation of internal resources by reducing the waste rate
Business F	Preventing overstocking and reducing credit usage with AI
Business G	Reducing the need for financing by controlling the waste rate and energy consumption

In the examples, Business A reduced its inventory turnover from 90 days to 30 days, reducing its credit usage. Business C can make early payments to suppliers as a result of energy optimization. Furthermore, Business F temporarily eliminates the need for short-term bank loans through inventory analysis. These applications demonstrate the contributions of AI to internal resource creation in various fields and illustrate how management strategies can be implemented in practice. Similarly, other businesses in Table 4 also reduce financial dependency by using artificial intelligence. Some activate their internal resources through stock optimization and overstocking prevention, while others control shift planning and energy consumption. The findings reveal that AI increases the financial flexibility of businesses both by directly reducing costs and indirectly reducing the need for credit and external financing.
The next part of the interview explored how artificial intelligence transforms traditional financial behavior in organizations, and the fifth interview question was created in this context. The responses demonstrate how AI is transforming risk management and investment-collection practices in financial decision-making. Table 5 summarizes the observed implementations of this transformation across the firms.
IQ5: Has AI led to the development of new practices that differ from traditional forms of financial behavior?

Business B: "We used to work extensively with checks and promissory notes. Now, AI analyzes customer payment performance and generates a risk score. For example, last month, two out of four checks were marked 'high risk.' We planned our goods shipments accordingly. While this may seem like a simple analysis, it saved us from significant losses… Furthermore, the leasing decision was made based on AI reports. We leased the automated quality control system based on this report, resulting in a 15-month amortization period."
Business D: "Our transition to new AI-based behaviors has been very limited. We take it into account when the system indicates a "delay risk" for some customers, but the industry still has a bill-and-check culture. The system's predictions are sometimes accurate, and sometimes they're wrong. Therefore, AI only provides us with "preliminary information. But even this sometimes protects us from significant risks. For example, when the system determined a customer's payment risk was high, we postponed the shipment of goods, and their payment was indeed delayed."
Business E: "We no longer make decisions outside of AI. Previously, we shaped our investment decisions with predictive data; now, we receive an AI system analysis for every investment. For example, before purchasing the automatic winding line last year, the simulation generated by the system calculated an 18% efficiency increase. We presented this report to the leasing company and were able to extend the installment plan to 60 months… We also use customer-based collection algorithms; we assign a risk score based on past payment performance and work with installment plans accordingly. We used to pay with checks and promissory notes; now, even collection has an algorithm."

Table 5: The Codes of IQ5- AI-Driven Innovations in Financial Practices

Business Code	Codes
Business A	Reducing check-bill usage with AI alerts
Business B	Pre-collection risk analysis, leasing decision based on AI
Business C	Chemical stock management optimized with AI, early payment implementation
Business D	Limited AI-based shipping decision methods
Business E	Client risk scoring, automatic investment reporting, and algorithmic collection
Business F	Only stock estimation, traditional system is dominant
Business G	Seasonal production planning and financial calendar synchronized with AI

Business B reduces the use of checks and promissory notes through risk scoring based on customer payment performance. Business D manages payments by considering limited AI-based shipping decisions. Business E bases its investment and collection processes entirely on AI analytics. These applications demonstrate how AI is shaping new forms of behavior compared to traditional financial practices. Businesses using AI to manage chemical inventory, early payments, seasonal production planning, and financial calendar synchronization have developed financial behaviors that differ from traditional practices. Some businesses use AI merely as a support tool, while others transform their financial behavior by moving away from traditional methods.
The next section of the interviews investigates how finance managers' skills in utilizing artificial intelligence generate differences in businesses' access to financial capital and reliance on external funding.
IQ6: How does the ability of financial managers to use artificial intelligence affect their dependence on and access to financial resources?
Business B: "Our managers are very experienced with AI outputs… We've been actively using them since 2023. Before every loan application, we generate scenario-based cash flows from the system and submit them to the bank. When the bank sees these files, they consider us a 'prepared company.' This allows us to access financing more easily. Mastering AI data definitely creates a financial advantage."
Business F: "Frankly, our managers are struggling to use AI. It's been eight months since the system was installed, but we're still relying on external support to produce output... The reports are ready, but they don't know how to interpret them. Therefore, they use the AI system only as a visual representation, and decisions are still made the old-fashioned way. When we meet with banks, we go with traditional balance sheets and projected cash flows, not AI data. The system exists, but it's not usable."
Business G: "Our finance managers are also very knowledgeable about data analysis. Most of them learned to use the AI platform themselves and even manually update the parameters of some system outputs. This skill has given us a significant advantage in green loan and grant programs… For example, we benefited from a zero-interest loan by fully entering carbon footprint data. If he had a traditional manager, we would have missed many of these applications. His mastery of AI has been very effective in reducing our dependence on external resources."
Managers' AI skills create differences in businesses' access to financial resources, with some using AI analytics to enhance cash flow scenarios and facilitate credit access. Others use the system only slightly and rely on traditional reporting methods. These differences indicate that managers' AI competencies influence both the quality of financial decisions and the strategies for accessing financial resources. Table 6 presents the coded responses of the seven firms, highlighting how finance managers' AI proficiency shapes both their reliance on and access to financial resources.

Table 6: The Codes of IQ6- Managerial AI Competence

Business Code	Codes
Business A	Moderate usage, classified AI use in investment decisions
Business B	An AI-savvy manager actively uses data in communication with the bank
Business C	Indirect use of technical expertise, transfer of analysis to the manager
Business D	Management is cautious, has limited trust in AI, and low usage in decision-making processes
Business E	High-level technical skills, direct production of investment-carbon analyses
Business F	Insufficient use, need for external support, classical approach dominant
Business G	Highly skilled grant, green loan, and data-driven application management

Firms have improved their investment decisions through managers' AI know-how, analytical skills, and interpretation of system outputs. Similarly, they have also improved their financial performance in areas such as evaluating carbon and green financing opportunities and bank communication. These findings demonstrate the importance of managers' AI skills in minimizing reliance on external capital. They also highlight how such skills improve access to financial resources.

The final interview question explored how AI analytics can reduce or manage financial managers' reliance on external financial resources in their strategic decision-making processes. The diverse strategic approaches, particularly in areas such as raw material procurement, inventory management, and financial calendar planning, were illustrated.
IQ7: How do AI-supported decisions of financial managers shape strategic measures taken to reduce or manage external resource dependency?
Business A: "Our AI system predicts which quarter of the year raw material prices will be lower. This allows us to make bulk purchases… Our manager used this data to bring yarn purchases three months earlier, giving us a significant financial advantage. Thanks to this strategic decision, we no longer need revolving credit. While we used to make this decision based on intuition, we now make it based on data. In other words, we reduce dependency by predicting resource needs."
Business C: "We're also trying to leverage AI strategically. Based on this, we implemented a new inventory management policy last month. Instead of overbuying, we now only purchase the quantities suggested by AI. This has reduced both inventory costs and the need for short-term credit… While we used to apply for leasing or loans strategically, we now make more cautious and timely decisions with AI insights."
Business E: "With AI analysis, we foresaw that our production capacity would be overloaded during certain periods. Anticipating that this situation could increase the need for external financing, we took early precautions... We timed leasing agreements to coincide with periods where we would experience capacity reductions. Furthermore, our manager synchronized the production calendar with the financing calendar. AI guides this process, and our manager makes strategic decisions based on this data."

Table 7: The Codes of IQ7- AI-Supported Strategic Decisions

Business Code	Codes
Business A	Bulk purchasing based on raw material price analysis, preventing the need for credit
Business B	Financing planning based on order density
Business C	Reducing credit demand through optimization in chemical purchasing and stock management
Business D	Early loan application based on order flow forecast
Business E	Synchronization of the leasing and financing calendar with the production cycle
Business F	Solution without resorting to short-term financial resources with inventory cycle management
Business G	Strategic timing and data-based decisions in grant and funding applications

Table 7 reveals how financial managers' AI-enabled decisions shaped strategic measures taken to reduce or manage external resource dependency. Business A advanced raw material purchases and eliminated revolving credit based on AI forecasts, while Business C reduced short-term credit by following AI recommendations in inventory management. Business E synchronized its leasing and financing schedule with the production cycle using production capacity forecasts. Together, these decisions demonstrate how strategic implementation reduced reliance. Other businesses have implemented AI-enabled measures such as order density forecasting, chemical purchasing optimization, and inventory cycle management.

6. Discussion

Recent studies increasingly view AI as a tool that eliminates traditional financial dependency models. It also creates new technological and data dependencies that require active management controls [15,16,17,18]. According to RDT, AI-based technologies may serve as strategic buffers, helping firms reduce exposure to financial institutions through cash flow forecasting, dynamic pricing, and customer segmentation. However, they also create new dependencies on data providers, algorithm transparency, and technology suppliers. This dual role highlights the need to conceptualize AI-induced dependencies in two dimensions: mitigating conventional resource vulnerabilities and managing risks linked to technological adoption. On this basis, the discussion of textile SMEs examines the experience and reactions of financial managers to these dynamics. These findings are organized around seven interpretive questions that examine the impact of AI on the conventional financial reliance of firms.
Interview Question 1 (IQ1) investigated the financial resources that SMEs in the textiles sector are most reliant upon. The examination indicated an intensive use of short-term instruments, including bank loans, supplier credit, and leasing. Codes like "intensive use of short-term bank loans" and "credits for raw-material purchases based on foreign exchange" describe firms' reliance on external funds. This strategy helps maintain liquidity in contexts of exchange-rate volatility and import-oriented cost structures. "Seasonal reliance on suppliers' credits" indicates that firms experience seasonal financial constraints due to fluctuating industry demand. These trends validate that financial reliance cannot always be explained circumstantially, but tends to be ingrained in the firm's operating paradigm.
These findings align with recent research highlighting the importance of short-term financial instruments and liquidity management for SMEs. Buyun [36] reveals that exchange rate volatility negatively affects access to bank loans, with banks becoming more risk-averse during unstable periods. Condronegoro and Hasibuan [37] indicate that liquidity limits hedging activities in textile firms, while firm size and financial difficulties increase the likelihood of hedging against exchange rate fluctuations. Khan and Siddiqui [38] show that financial leverage and supply chain financing positively influence textile firm performance, with liquidity playing a significant and central role in this process.
IQ2 was centered around how AI influences firms' access to funds and their dealings with financial institutions. The code "improved access to credit through AI-driven scenario analysis" indicates that predictive analytics help firms provide dynamic, prospective cash flow reports, boosting their bank credibility. "Planned credit use with AI-backed supply forecasts" indicates how AI converts the use of credit from reactive into strategic, enabling firms to forecast requirements and bargain with greater strength. Moreover, "AI-enabled amortization-based leasing negotiation" indicates the increasing prominence of AI in designing and timing financing arrangements better.
The results align with evidence in the literature on the transformation of access to finance for SMEs by AI. For example, Ihuoma et al. [39] show that AI-based cash flow forecasting and dynamic pricing models can enhance the efficiency and profitability of SMEs' decision-making processes. Similarly, Abdul-Azeez et al. [40] demonstrate that banks are increasingly using AI and data analytics to develop more realistic risk assessment and credit scoring systems, which can help integrate SMEs previously excluded from the financial system. Omokhoa et al. [41] highlight the importance of credit scoring applications based on alternative data and machine learning in promoting

financial inclusion by streamlining debt repayment processes. Taken together with field findings, these studies show that AI not only facilitates credit access but also reshapes financial relationships.

IQ3 investigated the impact of AI on financing horizon preferences. More companies began to prefer longer-term financing because of "AI-based leasing timing and credit maturity planning," implying an end to short-termism. The code "preference for long-term development loans and leasing with AI data" illustrates how AI assists companies in coordinating loan terms with payback periods for capital investments. These changes illustrate how AI instruments facilitate financial planning sustainability, enabling companies to coordinate liabilities with production cycles.

Contemporary research partially supports this trend. Ihuoma et al. [39] show that AI-based cash flow forecasts and real-time data improve financial planning and support strategic loan maturities. Zamil [42] finds that AI enhances forecast accuracy, decision speed, and overall financial performance, but does not address shifts from short- to long-term financing. This study adds a new perspective by examining AI's impact on financing maturity preferences. Alirezaie et al. [43] note that transparent AI-based forecasts facilitate access to long-term financing. This study's findings further reveal a transformation in firms' strategic maturity choices. Overall, AI increases accuracy and speed and reshapes companies' financing horizons.

IQ4 explored behavioral transformations in financial practices induced by AI. Codes such as "shift from conventional credit tools to algorithm-based ones" and "replacement of human decision-making with AI simulations" indicate a broader cultural transition in financial management. No longer do companies depend upon interpersonal connections or intuitive judgment but use AI models to simulate cash flows, appraise risks, and time payments. This represents a professionalization of financial behavior with technology.

Current studies show that AI adoption in SMEs is fundamentally transforming financial decision-making from intuition-based to data-driven approaches [39,44]. AI-driven tools, including machine learning and predictive analytics, enhance accuracy, speed, and efficiency in financial processes by automating routine tasks such as invoicing and expense tracking. These systems enable real-time data integration for improved cash flow forecasting and dynamic pricing models that respond to market conditions. While adoption faces barriers such as implementation costs, limited technical expertise, and data privacy concerns, AI fosters a cultural shift toward data-driven decision-making, professionalizing financial practices within SMEs [42,45].

IQ5 gauged the impact of AI on the timing and mode of credit utilization. The code "Installment simulations with AI support for big investments" discloses that companies utilize AI in predicting payment abilities while structuring loans optimally. "Payment timing with AI support based upon receivables" indicates that payment periods could be aligned with inflows more accurately, lowering liquidity risk. The strategies point to where AI increases financial operations' precision while lessening uncertainty about the use of credits.

The study's findings reveal that AI tools play a significant role in optimizing credit utilization in SMEs. Similarly, Ihuoma et al. [39] highlight that AI applications enhance financial decision-making and cash flow forecasting, while Schönberger [46] emphasizes that AI speeds up decisions by optimizing business processes. Kok Wah [47] shows that FinTech and AI solutions improve transparency, raise loan approval rates, and enhance financial inclusion in SME financing. From this perspective, AI enables more data-driven and effective implementation of financial strategies such as loan timing, installment planning, and structuring [41,40,43].

IQ6 concentrated on managerial proficiency in AI use. The code "data-backed communication with financial institutions" shows that AI-proficient managers improve firms' access to financial resources. Similarly, "incorporation of AI into financial decisions" indicates that cross-functional teams better leverage AI outputs. These results validate that adopting AI alone isn't adequate—managerial competency plays an important role as an enabler.

Supported by recent literature, these results demonstrate the importance of managerial competence in AI adoption. For instance, Mammadov et al. [48] show that SMEs led by managers with university degrees or high-level professional training achieve higher adoption rates. Ihuoma et al. [39] highlight that AI tools improve financial management by automating bookkeeping, using predictive analytics, and providing real-time cash flow forecasts, thereby enhancing decision-making accuracy and efficiency. This is particularly relevant for financial risk analysis and investment management in SMEs [49]. Collectively, these studies indicate that managerial competence is a key determinant for SMEs to leverage AI effectively in financial operations.

IQ7 asked if AI brings new dependence. Indicators like "dependency on AI skills," "reliance on software suppliers," and "insufficiency in capacity to interpret AI output" suggest new vulnerabilities. While AI reduces dependence on conventional financial intermediaries, it generates dependency on technical, cognitive, and infrastructural dimensions. This transition reveals a paradox: digital tools designed to reduce external dependency also create new internal constraints that require active governance. These insights contribute to Resource Dependence Theory by highlighting that digitalization reshapes the nature of dependence rather than its extent. AI reconfigures the sources as well as the type of financial dependence. Textile SMEs need to embrace AI instruments, but create within themselves the in-house capabilities as well as strategic insight with which to deal with the new reliance that they engender. In this context, the literature suggests various strategies for managing new dependencies with AI applications. Strategies such as internal corporate training, supplier diversification, and process optimization can effectively reduce the dependencies SMEs encounter during AI integration. Contemporary research supports these observations. For instance, Peretz-Andersson et al. [50] show that manufacturing SMEs manage these dependencies by managing AI resources through structured portfolios and coordinating processes with learning/guidance capabilities. A systematic review of 106 studies by Schwaeke [49] identified eight critical factors influencing the success of AI applications. Oldemeyer et al. [51] highlight lack of knowledge, high costs, and inadequate infrastructure as the most common barriers, emphasizing SMEs' dependence on external funding and advisory support. Failure to effectively manage these factors can lead to AI projects becoming dependent on other resources and conditions. Indeed, Schönberger [46] found that privacy concerns and the need for specialized skills increase dependencies in AI applications among SMEs in Germany. In this context, textile SMEs must build internal competencies and strategic foresight to manage new dependencies arising from AI adoption.

However, even with the small sample size of the research, the results provide some hints into how AI-generated dependencies should manifest in the textile industry in various ways. Even with the small research sample, the results provide insights into how AI-generated dependencies manifest in the textile industry. In the literature, high-quality data access–based dependencies dominate the financial sector, whereas software provider and data governance–based dependencies are decisive in the manufacturing sector [52,53]. Likewise, inadequate governance in other sectors of the state, like health and education, results in the development of dependencies of various kinds [54]. These results can be conceptually linked to data from the textile sector; examples from other sectors and this case study suggest that conceptual inferences can be drawn based on the literature. In this respect, the methodological support is offered by the methods of analytical generalization and conceptual inference proposed by Safari [55] and Broderick et al. [56]. Moreover, Fernandez-Vidal et al. [57], Zhu [58], and Yang et al. [59] present the conceptual underpinning of the significance of cross-sector comparative analyses. Future studies may connect the findings on the textile industry to other industries and discuss dependency and governance more holistically.

Recent surveys show that the adoption rates of AI in the healthcare and finance industries are high. In the manufacturing industry, a large proportion of efficiency and error-detection improvements have been achieved so far [60,61,62]. Yet, the cost, data security, shortage of human resources, and regulations are also common constraints in industries [63]. The presented study provides a small but real contribution to the literature. It shows the approaches companies design to overcome the dependencies they experience, based on interviews in the textile industry.

The examples of dependency across different sectors in the literature offer clues that can be conceptually linked to the findings of the textile study. In this context, the analytical generalization and conceptual inference methods used by Safari [55] and Broderick et al. [56] in the healthcare sector provide methodological guidance. They support drawing conceptual inferences by relating the findings from this single-case study to the literature. Therefore, while the findings cannot be directly generalized to all sectors and regions, they are important for raising awareness and initiating discussions for research in other sectors and regions.

7. Conclusion and Future Work

This study examined how AI shapes financial resource dependence in textile SMEs in Istanbul, Türkiye, through the lens of Resource Dependence Theory (RDT). Findings highlight AI's dual role: reducing traditional financial dependencies while creating new technology- and data-related dependencies, which underscores the need for effective management, targeted training, and cross-functional coordination. Interviews with finance managers revealed improvements in strategic financial planning, credit timing, cash flow simulation, and raw material forecasting, alongside emerging reliance on technical staff, software platforms, and high-quality data. Future research should explore AI governance and dependency dynamics across sectors and economic or cultural contexts, using comparative or longitudinal designs. Quantitative studies could validate these insights by measuring AI adoption, financial performance outcomes, and dependency structures in larger SME samples. Overall, these findings extend RDT's theoretical scope and provide actionable guidance for SMEs to leverage AI as a tool for financial empowerment rather than a source of constraint.

References

[1] Hidayat, M. R. Y., Defitri, S. Y., & Hilman, H. (2024). The Impact of Artificial Intelligence (AI) on Financial Management. Management Studies and Business Journal (PRODUCTIVITY), 1(1), 123–129. https://doi.org/10.62207/s298rx18

[2] Najem, R., Bahnasse, A., Fakhouri Amr, M., & Talea, M. (2025). Advanced AI and big data techniques in E-finance: a comprehensive survey. Discover Artificial Intelligence, 5(1), 102. https://doi.org/10.1007/s44163-025-00365-y

[3] Vuković, D. B., Dekpo-Adza, S., & Matović, S. (2025). AI integration in financial services: a systematic review of trends and regulatory challenges. Humanities and Social Sciences Communications, 12(1), 1-29. https://doi.org/10.1057/s41599-025-04850-8

[4] Abwa, W., Shah, B., Louis, B., & Apenteng, B. (2024). Examining the Association Between the Market Factors and Hospital Characteristics and AI Use in Hospitals, Using the Resource Dependency Theory.

[5] Antony, J., Sony, M., Garza-Reyes, J. A., McDermott, O., Tortorella, G., Jayaraman, R., ... & Maalouf, M. (2023). Industry 4.0 benefits, challenges and critical success factors: a comparative analysis through the lens of resource dependence theory across continents and economies. Journal of Manufacturing Technology Management, 34(7), 1073-1097. https://doi.org/10.1108/JMTM%E2%80%9110%E2%80%912022%E2%80%910371

[6] Pfeffer, J. and Salancik, G. R., The External Control of Organizations: A Resource Dependence Perspective (1978). University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship, Available at SSRN: https://ssrn.com/abstract=1496213

[7] Nienhüser, W. (2008). Resource dependence theory—How well does it explain behavior of organizations? Management Revue, 19(1–2), 9–32. https://doi.org/10.5771/0935-9915-2008-1-2-9

[8] Buchanan, L. (1992). Vertical trade relationships: the role of dependence and symmetry in attaining organizational goals. Journal of Marketing Research, 29(1), 65-75. https://doi.org/10.1177/002224379202900106

[9] Davis, G. F., & Powell, W. W. (1992). Organization-environment relations. Handbook of industrial and organizational psychology, 3, 315-375.

[10] Hillman, A. J., Withers, M. C., & Collins, B. J. (2009). Resource dependence theory: A review. Journal of management, 35(6), 1404-1427. https://doi.org/10.1177/0149206309343469

[11] Davis, G. F., & Adam Cobb, J. (2010). Chapter 2 Resource dependence theory: Past and future. Stanford's organization theory renaissance, 1970–2000, 21-42. https://doi.org/10.1108/S0733%E2%80%91558X(2010)0000028006

[12] Finkelstein, S. (1997). Interindustry merger patterns and resource dependence: A replication and extension of Pfeffer (1972). Strategic Management Journal, 18(10), 787-810. https://doi.org/10.1002/(SICI)1097-0266(199711)18:10%3c787::AID-SMJ913%3e3.0.CO;2-R

[13] Drees, J. M., & Heugens, P. P. (2013). Synthesizing and extending resource dependence theory: A meta-analysis. Journal of Management, 39(6), 1666–1698. https://doi.org/10.1177/0149206312471391

[14] Teece, D. J. (2018). Business models and dynamic capabilities. Long Range Planning, 51(1), 40–49. https://doi.org/10.1016/j.lrp.2017.06.007

[15] Abousaber, I., & Abdalla, H. F. (2023). Review of using technologies of artificial intelligence in companies. International Journal of Communication Networks and Information Security, 15(1), 101-108.

[16] Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International journal of information management, 53, 102104.

[17] Ughulu, P. D. (2022). The role of Artificial intelligence (AI) in Starting, automating and scaling businesses for Entrepreneurs. ScienceOpen Preprints. https://doi.org/10.51505/ijebmr.2025.9119

[18] Mohammed, I. A., Sofia, R., Radhakrishnan, G. V., Jha, S., & Al Said, N. (2024). The Role of Artificial Intelligence in Enhancing Business Efficiency and Supply Chain Management. DOI: 10.52783/jisem. v10i10s.1413

[19] Kotter, J. P. (1979). Managing external dependence. Academy of management Review, 4(1), 87-92. https://doi.org/10.5465/amr.1979.4289188

[20] Ahangar, M. N., Farhat, Z. A., & Sivanathan, A. (2025). AI trustworthiness in manufacturing: challenges, toolkits, and the path to Industry 5.0. Sensors, 25(14), 4357. https://doi.org/10.3390/s25144357

[21] Fahrezi, M. (2024). A Systematic Literature Review: The Use of Artificial Intelligence and Machine Learning in Financial Risk Management and Predictive Analytics. International Journal of Research and Applied Technology (INJURATECH), 4(2), 60-72.

[22] Akande, J. O. (2024). Usıng artificial intelligence (aı) and deep learning technıques in financial risk management. International Journal of Social and Educational Innovation (IJSEIro), 11(22), 233-246. https://doi.org/10.5281/zenodo.14721978

[23] Ahmed, S., Alshater, M. M., El Ammari, A., & Hammami, H. (2022). Artificial intelligence and machine learning in finance: A bibliometric review. Research in International Business and Finance, 61, 101646. https://doi.org/10.1016/j.ribaf.2022.101646

[24] Stake, R. E. (1995), The Art of Case Study Research, Sage Publications, USA.

[25] Creswell, J. W. (2013). Qualitative inquiry and research design: Choosing among five approaches (3rd ed.). SAGE Publications.

[26] Yin, R. K. (2018). Case study research and applications: Design and methods (6th ed.). SAGE Publications.

[27] Kachlami, H., & Yazdanfar, D. (2016). Determinants of SME growth: The influence of financing pattern. An empirical study based on Swedish data. Management research review, 39(9), 966-986. https://doi.org/10.1108/MRR-04-2015-0093

[28] Eniola, A. A., & Entebang, H. (2015). Small and medium business management-financial sources and difficulties. International Letters of Social and Humanistic Sciences, 58, 49-57. doi: 10.18052/www.scipress.com/ILSHS.58.49

[29] Ključnikov, A. (2023). The role of executive characteristics in their evaluation of financial conditions of European SMEs. DOI: 10.15240/tul/001/2023-2-005
[30] Chen, X. (2019). Antecedents of Technological Diversification: A Resource Dependence Logic. Journal of Open Innovation: Technology, Market, and Complexity, 5(4), 80. https://doi.org/10.3390/joitmc5040080
[31] Arroyabe, M. F., Arranz, C. F., De Arroyabe, I. F., & de Arroyabe, J. C. F. (2024). Analyzing AI adoption in European SMEs: A study of digital capabilities, innovation, and external environment. Technology in Society, 79, 102733. https://doi.org/10.1016/j.techsoc.2024.102733
[32] Hessels, J., & Terjesen, S. (2010). Resource dependency and institutional theory perspectives on direct and indirect export choices. Small business economics, 34(2), 203-220. DOI 10.1007/s11187-008-9156-4
[33] Balzano, M., Marzi, G., & Turzo, T. (2025). SMEs and institutional theory: major inroads and opportunities ahead. Management Decision, 63(13), 1-27. https://www.emerald.com/insight/0025-1747.htm
[34] Mubeen, S. K., Vafaei-Zadeh, A., Amran, A., & Ruiqi, C. (2025). Adoption of Internet of Things (IoT) among manufacturing SMEs in developing countries: a TOE framework perspective. International Journal of Communication Networks and Distributed Systems, 31(4), 428-456. https://doi.org/10.1504/IJCNDS.2025.147310
[35] Yin, R. K. (2003), Applications of Case Study Research (2nd ed.), Sage, Thousand Oaks, CA.
[36] Buyun, B. (2024). Does Exchange Rate Volatility Affect the Bank Lending Channel? Journal of Economic Policy Researches / İktisat Politikası Araştırmaları Dergisi, 11(1), 51–61. DOI :10.26650/JEPR1343548
[37] Condronegoro, A. & Hasibuan, H. T. (2023). Leverage, Firm Size, Likuiditas, Financial Distress, dan Aktivitas Hedging Dengan Instrumen Derivatif. E-Jurnal Akuntansi, 33 (8), 2102-2116. https://doi.org/10.24843/EJA.2023.V33.I08.P10
[38] Khan, B.F., & Siddiqui, D.A. (2023). The Effect of Financial Leverage, Supply Chain Finance and Liquidity on Firm Performance in Pakistan: A Comparative Analysis of Cement, Textile, Pharmaceutical and Sugar Sectors. Social Science Research Network (SSRN)Electronic Journal. http://dx.doi.org/10.2139/ssrn.4432266
[39] Ihuoma, N., Okeke, N.I., Bakare, O.A., & Achumie, G.O. (2024). Artificial Intelligence in SME financial decision-making: Tools for enhancing efficiency and profitability. Open Access Research Journal of Multidisciplinary Studies, 08(01), 150–163. https://doi.org/10.53022/oarjms.2024.8.1.0056
[40] Abdul-Azeez, O., Ogadimma, A., & Idemudia, C. (2024). Promoting financial inclusion for SMEs: Leveraging AI and data analytics in the banking sector. International Journal of Multidisciplinary Research Updates, 08(01), 001–014. https://doi.org/10.53430/ijmru.2024.8.1.0037
[41] Omokhoa, H.E., Odionu, C.S., Azubuike, C., & Sule, A.K. (2024). AI-Powered Fintech innovations for credit scoring, debt recovery, and financial access in Microfinance and SMEs. Gulf Journal of Advance Business Research, 2 (6), 411-422. https://doi.org/10.51594/gjabr.v2i6.55
[42] Zamil, M.H. (2025). AI-Driven Business Analytics for Financial Forecasting: A Systematic Review of Decision Support Models in SMEs. Review of Applied Science and Technology, 4(02), 86-117. https://doi.org/10.63125/gjrpv442
[43] Alirezaie, M., Hoffman, W., Zabihi, P., Rahnama, H. & Pentland, A. (2024). Decentralized Data and Artificial Intelligence Orchestration for Transparent and Efficient Small and Medium-Sized Enterprises Trade Financing. Journal of Risk and Financial Management, 17, 38. https://doi.org/10.3390/jrfm17010038
[44] Tawil, A.H., Mohamed, M.A., Schmoor, X., Vlachos, K., & Haidar, D. (2023). Trends and Challenges Towards an Effective Data-Driven Decision Making in UK SMEs: Case Studies and Lessons Learnt from the Analysis of 85 SMEs. ArXiv, abs/2305.15454. DOI:10.48550/arXiv.2305.15454
[45] Rawashdeh, A., Bakhit, M., Abaalkhail, L. (2023). Determinants of artificial intelligence adoption in SMEs: The mediating role of accounting automation. International Journal of Data and Network Science, 7, 25–34. DOI: 10.5267/j.ijdns.2022.12.010
[46] Schönberger, M. (2023). Artificial intelligence for small and medium-sized enterprises: Identifying key applications and challenges. Journal of Business Management, 21, 89-112. DOI: 10.32025/JBM23004
[47] Kok Wah, J.N. (2025). Revolutionizing SME Financing: AI and Fintech for Transparency, Efficiency and Inclusion. Journal of Southwest Jiaotong University, 60 (2), https://doi.org/10.35741/issn.0258-2724.60.2.6
[48] Mammadov, H., Ruiz-Gándara, A., González-Abril, L., & Romero, I. 2024. Adoption of Artificial Intelligence in Small and Medium-Sized Enterprises in Spain: The Role of Competences and Skills. Amfiteatru Economic, 26(67), 848-866. DOI: https://doi.org/10.24818/EA/2024/67/848
[49] Schwaeke, J., Peters, A., Kanbach, D.K., Kraus, S., & Jones, P. (2024). The new normal: The status quo of AI adoption in SMEs. Journal of Small Business Management, 63, 1297-1331. DOI:10.1080/00472778.2024.2379999
[50] Peretz-Andersson, E., Tabares, S., Mikalef, P., & Parida, V. (2024). Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach. International Journal of Information Management, 77, 102781. https://doi.org/10.1016/j.ijinfomgt.2024.102781
[51] Oldemeyer, L., Jede, A., & Teuteberg, F. (2025). Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges. Management Review Quarterly, 75(2), 1185-1227. https://doi.org/10.1007/s11301-024-00405-4
[52] Jacobides, M.G., Brusoni, S., & Candelon, F. (2021) The Evolutionary Dynamics of the Artificial Intelligence Ecosystem. Strategy Science, 6(4):412-435. https://doi.org/https://doi.org/10.3929/ethz-b-000512872
[53] Hoffreumon, C., Forman, C., & Van Zeebroeck, N. (2024). Make or buy your artificial intelligence? Complementarities in technology sourcing. Journal of Economics & Management Strategy, 33(2), 452-479.
[54] Sharma, G.D., Yadav, A., & Chopra, R. (2020). Artificial intelligence and effective governance: A review, critique and research agenda. https://doi.org/10.1016/j.sftr.2019.100004
[55] Safari, K., McKenna, L., & Davis, J. (2023). Promoting generalisation in qualitative nursing research using the multiple case narrative approach: A methodological overview. Journal of Research in Nursing, 28(5), 367–381. https://doi.org/10.1177/17449871231194177
[56] Broderick, K., Vaidyanathan, A., Ponticiello, M. et al. (2024). Generalizing from qualitative data: a case example using critical realist thematic analysis and mechanism mapping to evaluate a community health worker-led screening program in India. Implementation Science, 19 (1), 1-13. https://doi.org/10.1186/s13012-024-01407-2
[57] Fernandez-Vidal, J., Gonzalez, R., Gasco, J. & Llopis, J. (2022). Digitalization and corporate transformation: The case of European oil & gas firms, Technological Forecasting and Social Change, vol. 174, 121293, https://doi.org/10.1016/j.techfore.2021.121293
[58] Zhu, S. (2025). Enhancing Competitive Advantage through AI and Digital Technology: A Case Study of Jiangling Motors Group. Asia Pacific Economic and Management Review, 2 (1). https://doi.org/10.62177/apemr.v2i1.150
[59] Yang, X, Cao, D, Chen, J, Xiao, Z & Daowd, A 2020, 'AI and IoT based collaborative business ecosystem: A case in Chinese fish farming industry', International Journal of Technology Management, 82 (2) ,151-171. https://dx.doi.org/10.1504/IJTM.2020.107856
[60] Reddy, P.K., Gotur, R., & Bhat, V. (2025). Generative AI Adoption in Enterprise: A Comprehensive Case Study Analysis of Implementation Strategies and Outcomes Across Diverse Sectors. 2025 6th International Conference on Recent Advances in Information Technology (RAIT), 1-6. https://doi.org/10.1109/RAIT65068.2025.11089431
[61] Weng, Y., Wu, J., Kelly, T., & Johnson, W. (2024). Comprehensive Overview of Artificial Intelligence Applications in Modern Industries. ArXiv, abs/2409.13059. https://doi.org/10.48550/arXiv.2409.13059
[62] Apu, K.U. (2025). AI-Driven Data Analytics and Automation: A Systematic Literature Review of Industry Applications. Strategic Data Management and Innovation. https://doi.org/10.71292/sdmi.v2i01.9
[63] López-García, J., & Manrique Rojas, E. (2024). Barriers to AI adoption and their influence on technological advancement in the manufacturing and finance and insurance industries. IEEE Conference Proceedings. DOI: 10.1109/COLCOM62950.2024.10720309