Integrating Operations and Finance for Sustainable Development: Theory, Practice, and Opportunities

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Sustainable development demands addressing two core challenges: mobilizing financial resources and aligning stakeholder incentives. This paper honors Professor Christopher S. Tang by surveying the operations-finance interface literature through the lens of "Mobilizing Resources" and "Aligning Incentives" framework. We highlight how his seminal work has advanced our knowledge of mitigating SME financing constraints and crafting operationally-informed financial contracts to internalize externalities. We identify a critical gap: while theoretical models for incentive alignment are well-established, empirical evidence remains limited due to the difficulty of analyzing unstructured data. To bridge this gap, we present Large Language Models (LLMs) as a rigorous methodological toolkit for empirical operations management research. We outline a four-step framework—Problem Definition, Model Selection, Prompt Engineering, and Validation—and illustrate its application via a case study that extracts novel data on supplier finance programs from corporate 10-K filings. We conclude by proposing a unified research agenda for advancing future study at the intersection of operations, finance, and sustainability.

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1. Introduction

Businesses are increasingly integrating sustainable development in core strategies, transcending traditional shareholder value maximization to pursue a broader set of goals (Business Roundtable 2019). To operationalize these expanded objectives, Lee and Tang (2018) propose the "triple bottom line" framework, comprising people (social sustainability), planet (environmental sustainability), and profit (economic sustainability), as an essential guide for achieving the 17 United Nations Sustainable Development Goals (SDGs). As firms strive to integrate these dimensions, they face significant operational and financial hurdles requiring novel and interdisciplinary solutions.

From an operations-finance interface perspective, sustainable development faces two primary challenges: mobilizing sufficient resources and aligning divergent incentives. This "Resource and

Incentive" framework provides a powerful analytical lens for diagnosing problems and structuring solutions at the nexus of operations, finance, and sustainability.

The first challenge, *mobilizing resources*, arises from the substantial capital required for sustainability transition, creating an estimated $4 trillion annual SDG financing gap in developing economies (UNCTAD 2023). This capital scarcity disproportionately affects Small and Medium-sized Enterprises (SMEs), which constitute the vast majority of participants within global supply chains. According to Asian Development Bank (2023), SMEs represent 45% of all trade finance rejections, driving the global trade finance gap to a record $2.5 trillion. Such a financing constraint stems primarily from market frictions, especially information asymmetry. Traditional lenders, like commercial banks, often lack visibility into granular operational data (e.g., production capabilities, order fulfillment history, quality metrics, etc.), hindering accurate credit assessments for opaque SMEs and leading to credit rationing or prohibitive interest rates. Overcoming this friction requires utilizing operations-based information and supply chain relationships to mitigate asymmetry and direct capital to sustainable initiatives.

The second challenge, *aligning incentives*, involves managing externalities inherent in sustainability goals—such as reducing carbon emissions, ensuring product safety, or improving labor conditions—where costs or benefits are not captured in market prices. Consequently, these objectives often exhibit the characteristics of public goods, often lacking private incentives for individual contributions. For instance, a supplier might opt for cheaper, environmentally harmful materials to cut costs, even if it damages the reputation of the entire supply chain and harms the environment. Similarly, a hospital might underinvest in post-discharge care if it is not financially penalized for patient readmissions. Resolving such market failures requires operationally grounded financial contracts and mechanisms. By structuring payments and financing terms to reward desired operational behaviors, firms can internalize these externalities, effectively aligning the goals of disparate stakeholders—including suppliers, buyers, employees, and investors—with sustainability targets.

As a thought leader, Professor Christopher S. Tang has championed a broader vision where operational decisions and financial strategies converge to foster sustainable development. During his tenure as M&SOM's Editor-in-Chief, he advanced the field through two landmark special issues: the 2018 issue on the *Interface of Finance, Operations, and Risk Management (iFORM)* and the 2023 issue on the *Interface of Operations, Finance, and Technology (OpsFinTech)*. His work establishes theoretical and empirical foundations for tackling resource mobilization and incentive alignment. Table 1 summarizes these contributions, organized by the "Resource and Incentive" framework guiding this review.

The paper is organized as follows. Section 2 and 3 review the literature on mobilizing resources and aligning incentives, emphasizing Professor Christopher S. Tang's key contributions. Section 4

Table 1 Summary of Professor Tang's Key Contributions to the Operations-finance Interface

Mobilizing Resources	Aligning Incentives
• Compare two innovative financing schemes: purchase order financing and buyer direct financing (Tang et al. 2018)	• Managing opportunistic supplier product adulteration (Babich and Tang 2012)
• Franchise contracting with debt financing (Babich and Tang 2016)	• Project management contracts with delayed payments (Kwon et al. 2010)
• Dynamic trade finance with information frictions and FinTech (Lee et al. 2023)	• Impact of different payment schemes in healthcare (So and Tang 2000, Andritsos and Tang 2018, Guo et al. 2019, Olsder et al. 2023)
• New business models to finance nanostores at the base of the pyramid (Escamilla et al. 2021)	• Sales mechanisms for weather index insurance and farmer welfare (Zhang et al. 2023)
• EV infrastructure investment under Battery as a Service (BaaS) model (Jiang et al. 2024)	• Market reaction to environmental incidents (Lo et al. 2018)
	• Market performance of Diversity, Equity, and Inclusion (DEI) commitments (Li et al. 2025)

introduces Large Language Models (LLMs) as a novel methodological tool for analyzing unstructured data to address gaps in empirical research. Section 5 concludes with a comprehensive framework for future research.

2. Mobilizing Resources for Sustainable Operations

Meeting sustainable development's financing demands requires moving beyond traditional lending models. The operations-finance interface literature offers diverse solutions leveraging operational relationships and data to mitigate market frictions that constrain capital flow. This section surveys this body of work, beginning with the foundational role of financial frictions and trade credit (§2.1), and then progressing to more complex, structured forms of supply chain finance (§2.2) and their application in specific development contexts (§2.3).

2.1. Theoretical Foundations: Financial Frictions and Trade Credit

At its core, the operations-finance interface analyzes how financial frictions constrain a firm's operational decisions in inventory, production, and capacity. Such frictions include agency costs (Chod and Zhou 2014, Iancu et al. 2017, Ning and Babich 2018, de Véricourt and Gromb 2019, Babich et al. 2021), bankruptcy costs (Xu and Birge 2004, Boyabatlı and Toktay 2011, Li et al. 2013), information asymmetry (Schmidt et al. 2015, Alan and Gaur 2018, Lai and Xiao 2018), imperfect credit market competition (Buzacott and Zhang 2004, Dada and Hu 2008), and bank capital regulation (Zhang et al. 2022). By jointly analyzing a firm's financing and operating decisions, these single-firm operations-finance models demonstrate the value of integrated decision-making and provide a foundation for future research.

In supply chains, the most commonly used form of financing is trade credit, where a supplier allows a buyer to delay payment for goods or services. This payment deferral serves dual roles: short-term financing for buyers and an operational tool influencing ordering behavior and relationship dynamics. Theoretically, trade credit enables sellers to gain competitive advantages by enhancing horizontal benefits in competition (Peura et al. 2017), facilitating risk sharing through inventory financing portfolios (Yang and Birge 2018), and curbing retailer opportunism through transaction ties (Cai et al. 2014, Chod 2017). Comparative analyses further clarify when trade credit outperforms or complements bank loans (Kouvelis and Zhao 2012, 2018). Empirical studies corroborate these insights, demonstrating that trade credit smooths suppliers' cash flows (Osadchiy et al. 2025), improves firm performance under competition (Lee et al. 2018), and provides buyer flexibility through late payments without significantly harming suppliers (Wu et al. 2020). However, these benefits entail strategic and financial trade-offs, including supplier free-riding (Chod et al. 2019) and the need of mitigating default risks through trade credit insurance (Yang et al. 2021).

2.2. Innovations in Supply Chain Finance

Building on the above literature, structured Supply Chain Finance (SCF) solutions have emerged, often involving third-party institutions to infuse liquidity into the supply chain by leveraging the credit strength and operational information of a large, focal firm. Table 2 summarizes key SCF solutions.

Purchase Order Financing and Buyer Direct Financing: A critical financing gap often occurs before a supplier can begin production, and two prominent solutions address this: Purchase Order Financing (POF), where a financial institution lends to a supplier based on a credible purchase order from a reputable buyer, and Buyer Direct Financing (BDF), where the buyer lends directly to its supplier. Tang et al. (2018) provide a rigorous analysis of the trade-offs between these two schemes, accounting for supplier performance risk. They show that BDF offers a "control advantage" through the joint optimization of the sourcing contract and loan terms, and an "information advantage" from the buyer's superior knowledge of supplier capabilities. These make BDF particularly effective in emerging economies with underdeveloped financial markets and severe information asymmetries.

This rationale for BDF persists even when the buyer's opportunity cost of capital is high. Deng et al. (2018) demonstrate buyers may accept financing losses in order to gain operational benefits such as improved inventory support and lower purchasing prices. Thus, BDF remains attractive even when the buyer's capital cost exceeds the bank's risk-free rate. However, BDF is not without its challenges. A practical limitation is the potential for fund misuse by suppliers, a risk amplified

Table 2 Summary of Supply Chain Finance Solutions

Solutions	Definition	Mechanisms to Mitigate Market Frictions	Selected Literature
Buyer direct financing (BDF)	Buyers directly finance suppliers' production.	Buyers have superior knowledge of suppliers' capabilities compared to banks; buyers can determine both sourcing contracts and loan terms.	Tang et al. (2018)
Purchase order financing (POF)	Financial institutions lend to suppliers based on purchase orders issued by reputable buyers.	The committed purchase order from a large buyer may constitute valuable information about the supplier's demand prospects.	Reindorp et al. (2018)
Reverse factoring	Buyer-initiated financing solution to provide suppliers with the option of receiving early payment on approved invoices through a third-party financial institution.	Financing cost primarily depends on large buyers' creditworthiness; buyers can negotiate extended payment terms with suppliers.	Kouvelis and Xu (2021)
Platform/Buyer intermediated financing	Buyers act as intermediaries or underwriters, with a third-party bank lending money to suppliers.	Buyers have better information about the reliability of suppliers than banks; buyers provide guarantee to their suppliers' loan repayment.	Tunca and Zhu (2018)

in developing economies where monitoring is often infeasible or prohibitively costly. In such cases, Reindorp et al. (2018) focus on mitigating information problems under POF using purchase order commitments from large reputable buyers.

Reverse Factoring: After goods have been delivered, suppliers still face cash flow pressures due to extended payment terms imposed by buyers. Reverse factoring addresses this challenge by enabling buyers to facilitate early payment to suppliers through a financial institution, leveraging the buyer's stronger credit for lower financing costs. This mechanism is especially valuable in developing economies, where SMEs typically lack access to affordable credit. Notable examples include the Mexico's NAFIN program (Klapper 2006, De la Torre et al. 2017), Argentina's BICE e-Factoring platform, India's Trade Receivables Discounting System, and China's Receivables Financing Service Platform (International Finance Corporation 2021).

Although often portrayed as mutually beneficial (Seifert and Seifert 2011), reverse factoring involves a critical trade-off: buyers may extend their payment terms in exchange for facilitating this financing. This can increase the supplier's working capital requirements, potentially offsetting the benefits of the reduced financing cost. Consequently, the net value for SME suppliers is not guaranteed and depends heavily on program specifics and market conditions (Van der Vliet et al. 2015, Tanrisever et al. 2015, Lekkakos and Serrano 2016).Specifically, Kouvelis and Xu (2021) model when factoring or reverse factoring is optimal as a function of credit ratings and recourse provisions.

Empirically, suppliers' adoption speeds of reverse factoring vary significantly. Wuttke et al. (2019) find faster adoption among suppliers with limited access to traditional financing. However, their subsequent research confirms that the availability of reverse factoring can unintentionally motivate buyers to further delay payments (Wuttke 2025), highlighting the need for careful program design to alleviate supplier liquidity constraints without encouraging buyer's opportunistic behavior.

Bank and Platform Intermediation: In recent years, banks and platforms have increasingly acted as intermediaries in supply chain finance, harnessing data and technology to structure innovations. Lee et al. (2023) introduce Dynamic Trade Finance (DTF), a bank-intermediated contract where interest rates are dynamically adjusted as orders advance through the trade process. This innovation, enabled by financial technologies such as blockchain that provide real-time visibility, allows banks to manage information frictions and refine risk pricing.

Similarly, platforms such as JD.com and Amazon use their extensive transactional data to finance their third-party sellers (Dong et al. 2019, Gupta and Chen 2020, Yi et al. 2021, Huang et al. 2025). Beyond direct lending, platforms or buyers can also serve as intermediaries by guaranteeing supplier loan repayments, facilitating banks to extend credit with reduced risk (Tunca and Zhu 2018, Zhao and Huchzermeier 2019, Li et al. 2023, Sriraman et al. 2024). Empirical evidence from JD.com indicates that this supplier finance program lowers suppliers' borrowing costs, leading to reduced wholesale prices and improved operational performance for both parties (Tunca and Zhu 2018). Relatedly, Zhang et al. (2024) demonstrate how large sellers can orchestrate financing programs for downstream dealers to mitigate the constraints imposed by bank capital regulations.

2.3. Financing in Specific Sustainable Development Contexts

The principles of operations-finance interface prove particularly salient for sustainable business models in emerging economies, where firms often operate beyond formal financial systems, as well as for capital-intensive green transitions.

Franchising in Emerging Economies: Franchising is a powerful model for promoting entrepreneurship, but franchisees, typically SMEs, often face capital constraints. Babich and Tang (2016) analyze the optimal design of franchise contracts when the entrepreneur needs to seek debt financing. They show that a franchisor who ignores the franchisee's financial constraints may set suboptimal contract terms (e.g., excessive royalty rate), leading to delayed store openings and elevating bankruptcy risks. Their work suggests that franchisors can benefit by facilitating or directly offering financing to their franchisees, a key insight for expanding sustainable business models in developing markets.

Financing Nanostores at the Base of the Pyramid: Nanostores—small independent neighborhood outlets—are a primary grocery channel across developing economies and serve billions of low-income consumers. These micro-enterprises face severe operational and financial challenges, including limited access to formal credit and tight liquidity. Escamilla et al. (2021) propose a 5A framework (Agility, Adaptability, Alignment, Accessibility, Affordability) to analyze innovations in this sector. They highlight how new technologies like mobile payments and novel business models foster financial inclusion. Recent empirical and behavioral studies identify specific mechanisms easing capital constraints. For example, order-based trade credit and increased supplier visit frequency can boost order volumes and improve logistics efficiency, mitigating cash flow pressures for nanostore owners (Escamilla et al. 2024a,b, Villa et al. 2024). This body of work underscores innovative supply chain financing mechanisms in bolstering the base-of-the-pyramid nanostore ecosystem.

Infrastructure Investment for Sustainability: Integrating operations and finance is crucial for capital-intensive green transitions like electric vehicles (EVs). The "Battery as a Service" (BaaS) model exemplifies financial innovation through servitization, lowering the capital barrier of EV ownership for consumers (Jiang et al. 2024). From an operational perspective, the key issue is whether EV manufacturers or battery suppliers should invest in swapping networks. The authors find that this strategic choice significantly impacts EV adoption rates and firm profitability, depending on cost structures and competitive dynamics. Complementing this perspective, Babich et al. (2020) and Yu et al. (2022) analyze the coordination between governments and firms, highlighting how subsidies and policy design impact investment in solar panels and EV charging infrastructure. These studies demonstrate that integrating operational models with financial strategies is essential for scaling sustainable ecosystems.

3. Aligning Incentives for Sustainable Outcomes

Beyond mobilizing capital, the operations-finance interface designs mechanisms to align the self-interest of individual actors with broader sustainability goals. This involves structuring operationally-informed financial contracts and leveraging market forces to incentivize desirable operational behaviors and discourage harmful ones.

3.1. Designing Operationally-Informed Financial Contracts

Financial contracts can be powerful tools for mitigating moral hazard and ensuring that supply chain partners adhere to quality, safety, and timeliness standards. The key is to appropriately link financial payoffs to verifiable operational outcomes.

Product Quality and Safety: Ensuring product safety is a cornerstone of responsible consumption and production (SDG 12). However, suppliers may be tempted to use substandard or adulterated inputs to reduce costs, creating moral hazard problems. When massive product recalls have raised serious concerns about product safety around the world, Babich and Tang (2012) compare two mechanisms to deter such behavior: inspection and deferred payment (a form of trade credit). They show that when inspection is costly or inaccurate, deferring some fraction of the payment until after the product's quality is revealed in the market can internalize opportunism risks. Rui and Lai (2015) further extend this in endogenous quantity decision. Complementing theoretical work, Davis and Hyndman (2017) empirically investigate the efficacy of monetary and relational incentives in managing supplier product quality using behavioral experiments.

Project Timeliness: In large-scale infrastructure and development projects, delays often pose significant economic and social costs. Such delays often stem from misaligned incentives between project managers and their suppliers or contractors (Tang et al. 2009). Kwon et al. (2010) build a tractable model to compare delayed versus no-delayed payment schemes for parallel projects, revealing that a simple delayed regime, where a supplier is paid only when all suppliers have completed their tasks, will not incentivize suppliers to be on time since they anticipate others being late. Subsequent theoretical work follows to design more sophisticated, operationally-informed contracts. Chen and Lee (2017), for instance, propose a coordinating contract that optimizes the fraction and timing of delayed payments, linking them directly to a supplier's adherence to a specific delivery schedule. Dawande et al. (2019) extended the analysis by deriving optimal incentive contracts for more general project structures. Empirically, Meng and Gallagher (2012) confirm in a survey that appropriate incentive mechanisms in construction projects enhance project timeliness.

3.2. Incentive Alignment in Critical Sectors: Healthcare and Agriculture

The principles of incentive alignment are especially critical in sectors with strong externalities, where the actions of providers directly impact public welfare.

Healthcare Operations: The design of healthcare reimbursement systems has profound implications for the quality and cost of care. Professor Christopher S. Tang and his coauthors have conducted extensive research in this domain. So and Tang (2000) examine the impact of outcome-based reimbursement policies on drug usage. Andritsos and Tang (2018) and Guo et al. (2019) compare fee-for-service, pay-for-performance, and bundled payment schemes, analyzing their respective impacts on hospital readmission rates, patient waiting times, and overall social welfare. Olsder et al. (2023) further integrate outcome-based payment and government subsidies to enhance access to costly rare disease treatments. These studies demonstrate that thoughtfully designed contracts align the financial incentives of providers with the societal goal of delivering high-quality, efficient healthcare. Complementing analytical work, empirical research reveals complex provider responses to different payment schemes. For instance, while some pay-for-performance schemes are found to induce gaming like upcoding (Bastani et al. 2019), other penalty-based programs demonstrate mixed success, reducing readmissions but not consistently improving mortality (Qiu et al. 2022).

Agricultural Sustainability: Smallholder farmers in developing countries are highly vulnerable to weather risks, exacerbated by climate change. Traditional indemnity-based crop insurance often fails due to high administrative costs and information asymmetries. Zhang et al. (2023) examine weather index insurance, linking payouts to an objective, verifiable index like rainfall. Analyzing a "sell-through" mechanism where insurance is bundled with seed sales, they find that the seed seller is motivated to subsidize the insurance premium to encourage adoption, as insured farmers are more likely to purchase seeds and plant, ultimately benefiting all stakeholders and enhancing food security.

Shifting to the public sector, Lu et al. (2024) model an optimal government subsidy for index-based yield protection, noting that such policies can inadvertently increase farmers' income variability due to the index's imperfect correlation with actual yield. Empirical research underscores the potential and challenges of these innovations. Field studies reveal low demand for index insurance hampered by high price sensitivity, basis risk, liquidity constraints, limited financial literacy, and a lack of trust (Cole et al. 2013, Karlan et al. 2014). Bundling insurance with complementary products, such as agricultural inputs (Bulte et al. 2020, Boucher et al. 2024) or credit (Mishra et al. 2021), can help boost adoption. This aligns with broader findings in microcredit, which highlight the need for product bundling and incentive alignment to achieve financial inclusion (Banerjee et al. 2015, Crépon et al. 2015).

3.3. The Role of Capital Markets as an External Incentive Mechanism

Beyond inter-firm contracts, capital markets can exert external force, rewarding or penalizing corporate behavior to align incentives on sustainability. Lo et al. (2018) find negative stock reactions to Chinese firms' environmental incidents, mitigated by government ownership or social recognition but worsened by executive political ties. Conversely, Li et al. (2025) show positive stock returns from commitments to Diversity, Equity, and Inclusion (DEI) in U.S. manufacturing, suggesting that investors view such commitments as a positive signal about a firm's culture, risk management, and long-term financial health. Broader research confirms that financial markets interact with operational factors in various ways, such as technology adoption (Klöckner et al. 2022), operational productivity (Jacobs et al. 2016, Agrawal and Osadchiy 2024), global sourcing strategies (Jain and Wu 2023, Hsu and Wu 2024), and risk propagation (Osadchiy et al. 2016, Agca et al. 2022). Together, these studies show that financial markets are increasingly pricing sustainability events, operational risks and opportunities into firm valuations.

A notable gap, however, exists in the empirical literature regarding incentive alignment. While theoretical models proposing specific contractual mechanisms are well-developed, empirical validation of their real-world effectiveness remains limited due to the data nature: specific details regarding incentive structures, contractual terms, and sustainability targets are typically embedded within vast amounts of unstructured text of supply chain contracts, ESG reports, and financial disclosures. Extracting this granular information manually is costly and inefficient, hindering researchers from testing theoretical mechanisms across broad samples.

Artificial Intelligence (AI) and Large Language Models (LLMs) offer a transformative solution by enabling the efficient extraction of information from unstructured data. LLMs can parse complex documents and quantify variables such as climate risks or supply chain complexities. Converting unstructured text into structured data allows researchers to empirically validate incentive alignment theories at a scale. In the following section, we introduce LLMs as a novel methodological tool and provide a practical guide for researchers.

4. Methodological Toolbox: LLMs for Unstructured Text Analysis

Large Language Models (LLMs) have brought numerous opportunities for textual analysis in Operations Management. Researchers are using the LLM tools to analyze texts in financial documents (Niu et al. 2024, Osadchiy et al. 2025, Siano 2025, Breitung and Müller 2025), ESG reports (Rouen et al. 2024), news articles (Yoganarasimhan and Iakovetskaia 2024), and customer reviews (Gao et al. 2025). These texts contain valuable operations-related information, such as the link-level trade credit contracts, and the manager attributions of operations performance, as shown in Appendix Table A1.

Compared to traditional text mining methods, LLMs offer the following advantages (de Kok 2025): (i) **Adaptability:** LLMs use natural language prompts to flexibly address complex tasks, making them adaptable to a broad range of applications. (ii) **Reasoning:** Their reasoning capabilities, based on extensive world knowledge, enable them to address tasks that are difficult or even impossible to solve with existing natural language processing (NLP) techniques. (iii) **Scalability and efficiency:** They process and recall vast amounts of information with superhuman speed and consistency, offering a scalable alternative to manual coding.

In this section, we provide a four-step framework for LLM textual analysis, demonstrated by an empirical application—extracting information on supplier finance programs from 10-K reports.

4.1. A Framework for Using LLMs in Textual Analysis

Our framework contains four steps. Figure 1 includes the steps and specific examples (highlighted in blue) from the case study in Section 4.2, which concretely demonstrate the content and execution of each step. Below, we detail each step for researcher guidance.

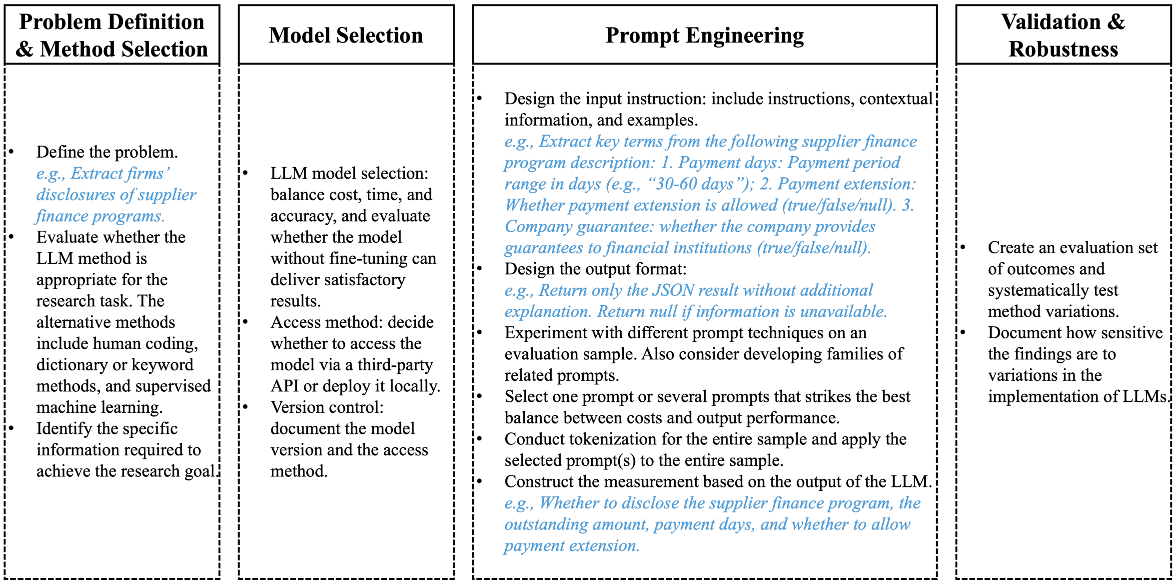

Figure 1 LLM Approach Roadmap

Step 1: Problem Definition and Method Selection.

The first step is to define the problem and evaluate whether LLMs are the appropriate tool. Alternatives like human coding provide a nuanced interpretation of context but lack scalability; dictionary or keyword methods are computationally efficient but struggle with semantic complexity and context; and supervised machine learning requires substantial training data (Carlson and Burbano 2025). LLMs can solve complex semantic tasks at scale without extensive training, albeit with limitations such as textual reproducibility and output reliability. Therefore, method selection must align with specific research tasks.

Once researchers choose to use LLMs, it is essential to identify the specific information required to achieve the research goal, including background, domain knowledge, and relevant examples. We recommend manually analyzing the task on a small set of examples to understand the decision-making process and information requirements, allowing researchers to provide LLMs with sufficient information and obtain more reliable outputs.

Step 2: Model Selection.

The second step is to decide which model to use. With the rapid development of LLMs, researchers must carefully evaluate the following considerations:

(i) Cost-performance balance: Each API call incurs costs based on the number of input and output tokens, and both the time and cost of using an LLM increase with the token count. Rather than defaulting to the highest-performing model, researchers should balance cost, speed, and accuracy. We recommend beginning by evaluating whether the model, without additional fine-tuning, can deliver satisfactory results. If it does not meet the construct validity needs, switch to model fine-tuning. Once the approach is determined, experiment with different model sizes using a smaller sample of the data, and choose the smallest model that provides satisfactory performance. Appendix B provides a detailed overview of LLMs.

(ii) Access method: Decide whether to access the model via a third-party API or deploy it locally. While APIs offer convenience for urgent tasks or access to proprietary models, local deployment is preferable for sensitive data, open-source LLMs, or persistent workloads where investing in dedicated hardware can be more cost-effective.

(iii) Version control: For reproducibility and transparency purposes, researchers need to document the model version and the access method.

Step 3: Prompt Engineering.

The third step is to design and evaluate prompts that provide LLMs with natural-language input to guide their behavior and generate the desired output. The focus is on designing the input instructions and defining the output format. While fine-tuning offers a valuable extension for complex needs (Carlson and Burbano 2025), prompt engineering remains the most accessible method for basic textual analysis. The prompts typically contain input and output parts.

(i) Input design and iteration: Researchers can employ various prompting strategies, as shown in Carlson and Burbano (2025), such as zero-shot, few-shot, role-based, chain of thought (CoT), and tree of thought (ToT). Given that different models may vary in response quality to the same prompting strategies, it is crucial to conduct experiments on evaluation samples. Instead of relying on a single optimal prompt, we recommend developing and documenting families of related prompts to ensure robustness.

(ii) Structured output: Researchers need to ensure readable and parsable output. Instead of unstructured outputs (e.g., "19.7% of accounts receivable was due from Walmart at November 2, 2012..."), researchers should instruct the LLM to return structured ones, such as a JSON object for processing simplicity (e.g., `["year": 2012, "customer": "Walmart", "receivable": "19.7%"]`).

Finally, researchers need to construct the measurement based on the LLM's output. Although the prompt ensures the structured output format, researchers need to transform raw extractions into quantitative variables for empirical analysis, including post-processing (e.g., standardizing units or converting percentages to decimals) and further calculation (e.g., creating a binary dummy variable indicating the disclosure of the program, or calculating a ratio based on extracted numerical values).

Step 4: Validation and Robustness.

The final step is to validate the LLM outputs and robustness. Researchers should create an evaluation set of outcomes generated by human experts and systematically test method variations. When dealing with multiple outcomes, evaluate and report each outcome independently.

Additionally, it is important to document how sensitive the findings are to reasonable variations in the implementation of LLMs. For instance, when using a family of prompts, researchers can test their impact on downstream analysis and produce bounded estimates that account for the methodological uncertainty (Carlson and Burbano 2025).

4.2. Case Study: Extracting Supplier Finance Program Disclosures via LLMs

We apply the above framework to a real-world setting, using the LLM to extract firms' disclosures of supplier finance programs. In 2022, the Financial Accounting Standards Board (FASB) issued an accounting standards update that applies to all entities that use supplier finance programs in connection with the purchase of goods and services. This update requires that a buyer in a supplier finance program disclose the following information in each annual reporting period: (i) The key terms of the program, including payment days, payment term extensions, and guarantees to financial institutions. (ii) The outstanding confirmed amount. (iii) A description of where those obligations are presented in the balance sheet. (iv) Rollforward of those obligations during the annual period. Table A2 in Appendix C shows an example of Ralph Lauren's information disclosure.

We scrape 10-K filings from January 2022 to June 2025 for 5,455 firms, extract relevant paragraphs via keywords, then employ LLMs to identify the reported supplier finance program details, including key terms and outstanding amounts. LLMs are a good fit for this extraction task, as they offer the semantic nuance needed to interpret complex disclosures at scale without the need for extensive labels required by traditional NLP models.

Balancing cost and efficiency, we use the Llama-3.1-70B-Instruct model for the task. We also use the GPT-OSS-120B model to examine whether the extracted results are consistent. Appendix D offers implementation details on the keyword list, model selection, full prompts, and validation.

We identify 257 buyer firms that disclose supplier finance program obligations. Table 3 shows total firm counts, disclosure ratios, and example firms by Fama-French 12 industries. The consumer nondurable industry has the highest ratio of using supplier finance programs, followed by the manufacturing, chemical, consumer durable, and wholesale and retail industries.

We also use LLMs to extract the key terms, including payment days, payment term extensions, and guarantees to financial institutions. There are 115 firms that provide this information, and Figure 2 presents the distribution of average payment days.[1] Most firms have average payment days of fewer than 150 days, but some firms have extremely long payment days. For example, the leading printed circuit board manufacturer, TTM Technologies, has payment days ranging from 160 days to 360 days in 2024. Monro, an automotive services company, has 360 payment days in

[1] Firms usually disclose the range of payment days, such as 60-90 days. In that case, we define the average payment days as 75.

Table 3 Descriptive Statistics of Supplier Finance Program and Payment Term Extensions by Industry

Fama-French12 Industry	Total Number of Firms	Disclosure Ratio	Examples of Disclosing Firms	Extension Rate	Examples of Firms with Extending Terms
Consumer Nondurables	196	19.9%	Ralph Lauren, Mattel	30.8%	PepsiCo, Mondelēz International
Consumer Durables	118	14.4%	Ford Motor, Whirlpool	17.6%	Hubbell
Manufacturing	394	19.0%	Caterpillar, General Electric	18.7%	Boeing, Parker Hannifin
Energy	171	2.3%	Halliburton, Baker Hughes	0.0%	
Chemicals	114	16.7%	Dow Chemical, DuPont	5.3%	Chemours
Business Equipment	866	1.7%	HP, Western Digital	6.7%	Fluence Energy
Telephone & TV Transmission	71	8.5%	Verizon Communications, Warner Bros. Discovery	50.0%	AT&T, Charter Communications
Utilities	191	7.3%	Consumers Energy, CMS Energy	85.7%	Duke Energy, NextEra Energy
Wholesale & Retail Services	374	12.6%	Target, Walmart	8.5%	LKQ, Ingram Micro
Healthcare	1,229	1.1%	Johnson & Johnson, Pfizer	7.7%	Boston Scientific
Other	684	1.0%	3M, FedEx	14.3%	Honeywell

2024. There are 52 firms that report extending payment terms with suppliers through the supplier finance program during the sample period, including Boeing, Mondelēz International, and PepsiCo. For example, Boeing's 10-K report in 2024 states that: "The majority of amounts payable under these programs are due within 30 to 90 days but may extend up to 12 months."

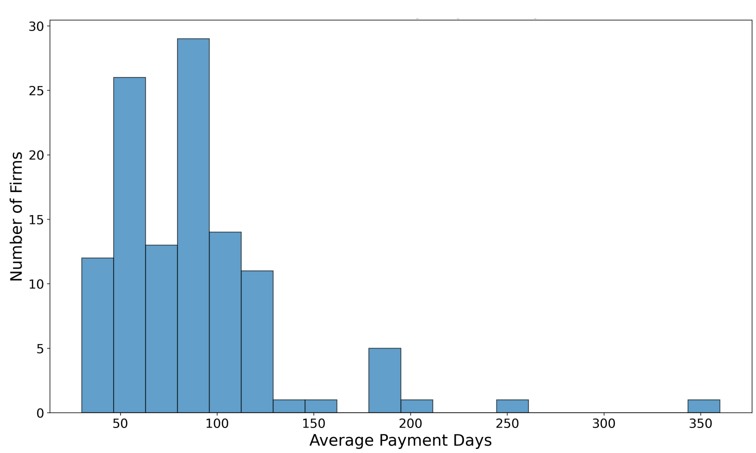

Figure 2 Distribution of Average Payment Days

The last two columns of Table 3 show the proportion of firms with payment term extensions and example firms by industries. The utility industry has the highest proportion of payment term extensions, followed by the telephone and television transmission industries and the consumer non-durable goods industry. Such evidence demonstrates the practice of extending payment terms under supplier finance programs, potentially raising supplier working capital requirements. Building on these initial analyses, future research could leverage the granular data extracted by LLMs to investigate the net supplier impact of these programs. Specifically, researchers may test whether the liquidity benefits provided by SCF are sufficient to offset the costs imposed by extended payment terms, thereby validating theoretical trade-offs regarding the net value of reverse factoring. Furthermore, the significant variation in contract terms across industries warrants further investigation into how operational factors—such as inventory turnover or supply chain power dynamics—shape the strategic design of financial contracts.

5. Future Research Directions: A Unified Framework

Finally, we propose a framework organizing research opportunities at the intersection of operations, finance, and sustainability. Structured by two *Core Challenges* (Mobilizing Resources and Aligning Incentives), two primary *Methodologies* (Theoretical Modeling and Empirical Investigation), and three key *Levers of Change* (Business Innovation, Government & Policy, and Technological Advancement), this $2 \times 2 \times 3$ structure yields 12 distinct but interconnected research domains for advancing this field (Table 4).

The Business Lever: The private sector spurs sustainable operations-finance innovation through novel business models and contracts. Future research should address both optimal contract design and causal evaluation of such innovations. Theoretically, key challenges include structuring contracts to mobilize resources for sustainable models—such as revenue-sharing, Product-as-a-Service (Wang et al. 2023, IFC 2025), and circular-economy leasing arrangements—and designing Sustainability-Linked Supply Chain Finance (SL-SCF) contracts that tie financing terms to supplier sustainability KPIs (PUMA 2016, Walmart 2021). Research could model optimal KPI selection, interest-rate structures, and trade-offs between target ambition and supplier participation. Empirically, studies could examine the causal effects of these innovations on SME growth, resilience, and sustainability outcomes (e.g., emissions).

The Government Lever: Governments shape the sustainable operations-finance landscape through regulation and as investors or catalysts for private capital. Theoretically, research is needed on optimal blended finance models that use public or concessional funds to mitigate risk and crowd in private capital from impact investors, who seek both financial returns and measurable sustainability outcomes (OECD 2018, Global Impact Investing Network 2025). A key question is how

Table 4 A Unified Framework for Future Research

	Mobilizing Resources	Aligning Incentives
Business Innovation	**Theoretical:** Design of financing contracts for new sustainable business models (e.g., circular economy). **Empirical:** Causal impact of SCF programs on SME growth, resilience, and financial inclusion.	**Theoretical:** Optimal contract design for sustainability-linked supply chain finance (SL-SCF). **Empirical:** Operational effectiveness of SL-SCF and other ESG-linked incentives on actual sustainability outcomes (e.g., emissions).
Government & Policy	**Theoretical:** Optimal public-private investment models for large-scale green infrastructure. **Empirical:** Analysis of intended and unintended consequences of financial policies.	**Theoretical:** Modeling the impact of regulations on sustainable innovation and investment. **Empirical:** The real effects of ESG-related regulations on supply chain transparency and reconfiguration.
Technological Advancement	**Theoretical:** Optimal design of platform tokenization and AI-powered credit scoring models. **Empirical:** Impact of AI-powered lending on credit access and default rates for underserved populations.	**Theoretical:** Design of blockchain-enabled systems for transparent and verifiable multi-tier incentive alignment. **Empirical:** Using LLMs to analyze unstructured data (e.g., contracts, ESG reports) for the large-scale validation of contractual incentive theories.

to structure minimal public subsidies to maximize private investment in large-scale sustainable projects (e.g., EV charging networks). Empirically, researchers should analyze both intended and unintended consequences of such policies. For instance, policies accelerating SME payments may lower inventory levels and increase project delays (Chen et al. 2023, Dhingra et al. 2023), underscoring the need for data-driven analysis of policy interactions with complex operational systems.

The Technology Lever: Technologies such as blockchain and AI are powerful catalysts for solving fundamental financial frictions such as information asymmetry (Babich and Hilary 2020), opening a vibrant “OpsFinTech” research frontier as highlighted in the M&SOM special issue on the topic (Iancu and Yang 2023). Theoretically, work can explore next-generation mechanisms for resource mobilization, including platform tokenization to alleviate moral hazard (Chod et al. 2022) and AI-driven lending models that leverage alternative data for credit assessment (Biallas and O’Neill 2020). Theoretical research should also examine how to balance predictive accuracy, fairness, and profitability in algorithmic design. Empirically, studies may assess the real-world impact of AI-powered lending on financial inclusion.

For incentive alignment, blockchain enables sustainability-linked incentives across deep-tier supply chains, which is a frontier in current theoretical research (Shibuya and Babich 2021, Huang et al. 2022, Dong et al. 2023a,b, Hou et al. 2025). Meanwhile, Large Language Models (LLMs) offer a methodological breakthrough in empirical research by extracting structured, operational data from unstructured texts (e.g., ESG reports, contracts, news).

Specifically, on one hand, LLMs can be used to test sustainability-related contractual incentive designs empirically by parsing thousands of sustainability-linked loans, supply chain finance agreements, and ESG reports to extract granular contractual terms and identify which incentive designs are most effective at aligning supplier behavior with sustainability targets. On the other hand, LLMs enable the quantification of informal incentives—such as reputational costs—by analyzing media sentiment, analyst reports, and earnings calls to capture the real-time costs of misalignment. This facilitates rigorous examination of how market-based forces complement formal governance in promoting sustainable outcomes.

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Appendix A: Examples of Operations-Related Texts

Table A1 presents the examples of operations-related texts from data sources such as 10-K reports and transcripts of conference calls.

Table A1 Examples of Operations-Related Texts

Data Source	Example Text	Operational Features	Related Paper
10-K reports	*"There are no significant concentrations of credit risk other than with* ***The Home Depot, Inc. and Lowe's Companies, Inc. who together represented approximately 24% and 20% of our net trade receivables*** *as of December 31, 2009 and 2008, respectively."*	Link-level trade credit	Osadchiy et al. (2025)
Transcripts of conference calls	*"Question: You mentioned supply chain and inventory issues in the material business that was also burdening profitability. Can you specify those issues?* *Answer: …We did see some challenges here. It was actually* ***a supplier of one of our suppliers which missed the delivery schedules.*** *It was actually a plant shutdown which had to be extended, and this was somehow creating a situation where we had quite tight on certain materials…"*	Firms' self-attribution tendencies in the context of operations and supply chain performance	Niu et al. (2024)

Appendix B: LLM Overview and Discussion

Large Language Models (LLMs) are generally distinguished by five characteristics (de Kok 2025):

1. Parameter scale: A model's complexity is defined by its parameter count. While higher parameter counts (e.g., 70B+) correlate with superior reasoning and generalization, they impose higher computational costs and latency than smaller, more efficient variants (e.g., 7B).

2. Post-training specialization: Raw models undergo specific tuning processes to align them with user needs. This includes "instruction tuning" for conversational utility or domain-specific fine-tuning (such as coding or medical tasks). This stage determines whether a model acts as a neutral predictor or a helpful assistant.

3. Context window: This metric defines the maximum number of tokens for the combined input and output. While extended context windows enable processing of large documents, retrieval accuracy is not uniform.

4. Distribution method: Models are categorized as either proprietary or open-source. Proprietary models (e.g., GPT-4, Gemini) are accessed exclusively via API, hiding their internal architecture. Conversely, open-weight models (e.g., Llama 3) allow researchers to download and host the neural network locally, offering greater control over data privacy.

5. Precision and quantization: To mitigate hardware constraints, models may undergo quantization, a compression technique that reduces the precision of weights (e.g., from 16-bit to 4-bit). This significantly reduces memory usage and inference costs, though it comes at the cost of generation quality.

For a complete, up-to-date reference, please visit this website: `https://huggingface.co/models`.

Appendix C: Examples of Disclosed Supplier Finance Program Information

According to the accounting standards issued by the Financial Accounting Standards Board (FASB), all firms using supplier finance programs need to disclose the following information in each annual reporting period: (i) The key terms of the program. (ii) The outstanding confirmed amount. (iii) A description of where those obligations are presented in the balance sheet. (iv) A rollforward of those obligations during the annual period. Table A2 shows Ralph Lauren's disclosed supplier finance program information as an example.

Table A2 **Example of Ralph Lauren's Disclosed Supplier Finance Program Information in 2025 10-K Report**

SCF Features	Example Text
Key terms of the program	*"The Company supports a voluntary supplier finance program which provides certain of its inventory suppliers the opportunity, at their sole discretion, to sell their receivables due from the Company (which are generally due within 90 days) to a participating financial institution in exchange for receipt of a discounted payment amount made earlier than the payment term stipulated between the Company and the supplier. The Company's vendor payment terms and amounts due are not impacted by a supplier's decision to participate in the program. The Company has not pledged any assets and does not provide guarantees under the supplier finance program."*
Outstanding value of obligations and where they are presented in the balance sheet	*"The Company's payment obligations outstanding under its supplier finance program were $181.0 million and $129.2 million as of March 29, 2025 and March 30, 2024, respectively, which were recorded within accounts payable in the consolidated balance sheets."*
Rollforward of the obligations	*"A rollforward of obligations confirmed as valid under the Company's supplier finance program is presented as follows: Fiscal Year Ended: March 29,2025 (millions) Beginning obligations outstanding: 129.2; Invoices confirmed during the year: 935.3; Confirmed invoices paid during the year: (883.5); Ending obligations outstanding: 181.0."*

Appendix D: Implementation Details of the Case Study

Keyword list

We first use keywords to extract relevant paragraphs. To construct the keyword list, we refer to the accounting standards update of Financial Accounting Standards Board (No. 2022-04), which mentions that *"Supplier finance programs, which also may be referred to as reverse factoring, payables finance, or structured payables arrangements"*. The Python code is as follows:

```
pattern = re.compile(
        r'supplier\s*finance|'
        r'supplier\s*financing|'
```

```
        r'supply\s*chain\s*finance|'
        r'supply\s*chain\s*financing|'
        r'scf\s*program|'
        r'reverse\s*factoring|'
        r'payables\s*finance|'
        r'payables\s*financing|'
        r'structured\s*payables|'
        r'accounts\s*payable\s*finance|'
        r'accounts\s*payable\s*financing|'
        r'supplier\s*payment\s*program|'
        r'supply\s*finance\s*arrangement',
        re.IGNORECASE
    )
```

Model selection

The task is to extract information from the given paragraphs, without a complex reasoning process. We first experiment with different models using a small sample of data (i.e., about 10 firms) and evaluate their performance. The performance of information extraction does not vary significantly across models. Considering the balance of cost and efficiency, we choose the open-source Llama-3.1-70B-Instruct model as our main model, and use GPT-OSS-120B to validate the results. Since all the information is public and poses no privacy concerns, we access the model via a third-party API.

Prompt for extracting supplier finance program information

After extracting relevant paragraphs using keywords, we use LLMs to analyze them and extract information on supplier finance programs. For the input design and iteration, since this information extraction task does not involve complex reasoning, we use a few-shot strategy and include detailed instructions and examples. For the output part, we instruct the LLM to return structured data. We iterate the prompts several times, adding instructions such as: (i) details of examples; (ii) constraints like *"Copy the EXACT text from the document WITHOUT summarizing, paraphrasing, or modifying it in any way"*; (iii) instructions on information beyond the direct disclosed requirements, such as company's role in the supplier finance program as suppliers or customers; (iv) structured output format. The final prompt is as follows:

```
You are an AI that extracts information about Supply Chain Finance (SCF) or Supplier
↪  Finance programs from financial report text. Please extract three types of
↪  information:

1. KEY TERMS: Extract the RAW text of the key terms, including program's main features,
↪  payment terms, and how the program works. Copy the EXACT text from the document
↪  WITHOUT summarizing, paraphrasing, or modifying it in any way. Include ALL relevant
↪  sentences that describe the program.

2. OUTSTANDING AMOUNTS: Extract ALL outstanding amounts related to SCF/Supplier Finance
↪  programs at reporting dates:
   - Include all final/ending balances at each year-end
```

```
   - Also include the beginning balance of the earliest year as the ending balance of the
   ↪  previous year
     (For example, if 2023's beginning balance is $992, include "December 31, 2022: $992"
     ↪  as an outstanding amount)
   - Distinguish between the company's role in the SCF program:
     - "Customer Role" - when the company is the customer (buyer) and the amount refers
     ↪  to accounts payable
     - "Supplier Role" - when the company is the supplier (seller) and the amount refers
     ↪  to accounts receivable sold

3. ROLLFORWARD INFORMATION: Extract the beginning balance, confirmations during the year,
↪  payments made, and ending balance for each year mentioned.
   - Include the year in your extraction
   - Extract all years available in the text

IMPORTANT: Follow these format rules EXACTLY:
- For KEY TERMS, copy the exact text from the document without any modifications.
- For Outstanding Amounts, use format: [Date]: [Amount] [Role: Customer/Supplier] [SCF
↪  Related: Yes/No]
- Always put Role information in square brackets exactly like this: [Role: Customer] or
↪  [Role: Supplier]
- Always put SCF Related information in square brackets exactly like this: [SCF Related:
↪  Yes] or [SCF Related: No]

Format your response as follows:
Found: Yes/No

1. Key Terms:
[EXACT raw text about the SCF program copied from the document]

2. Outstanding Amounts:
[Date]: [Amount] [Role: Customer/Supplier] [SCF Related: Yes/No]
[Date]: [Amount] [Role: Customer/Supplier] [SCF Related: Yes/No]

3. Rollforward Information:
Year: [Year]
Beginning Balance: [Amount]
Confirmed during year: [Amount]
Paid during year: [Amount]
Ending Balance: [Amount]

Year: [Year]
Beginning Balance: [Amount]
Confirmed during year: [Amount]
Paid during year: [Amount]
Ending Balance: [Amount]

If no information is found, respond with:
Found: No
Reason: [brief explanation]
```

Prompt for further extracting key terms

After extracting the full text of key terms, we further use the LLM to extract detailed information from them, including payment method, payment days, payment term extensions, supplier discount, and guarantees to financial institutions.

```
Extract key terms from the following supplier finance program description. Return a JSON
↪  with these fields (return null if information is unavailable):

    1. payment_method: How the company pays the financial institution (e.g., according to
    ↪  original supplier terms, regular payments, deferred payments)
    2. payment_days: Payment period range in days (e.g., "30-60 days")
    3. payment_extension: Whether payment term extension is allowed (true/false/null)
    4. supplier_discount: Discount rate or fee for suppliers to receive early payment
    ↪  from financial institution (e.g., "2%", "LIBOR+1%")
    5. company_guarantee: Whether the company provides guarantee to financial institution
    ↪  (true/false/null)
    6. guarantee_details: Details of guarantee if provided

    Return only the JSON result without additional explanation. If a field cannot be
    ↪  determined, set its value to null.
```

Validation and Robustness

The Step 4 of our framework emphasizes the importance of validating LLM outputs and checking the robustness. In this case study, we focus on extracting objective, standardized financial information from 10-K filings. Given the low-inference nature of this task, where the target information is explicitly stated in the documents with minimal semantic ambiguity, we employed a manual check and cross-model verification strategy (comparing Llama-3.1-70B with GPT-OSS-120B) to ensure robustness. While this validation suffices to demonstrate the feasibility of extracting explicit information, we strongly advise researchers to perform rigorous validation (e.g., by creating an evaluation set of outcomes generated by human experts and testing model and prompt variations) for tasks involving subjective interpretation, where semantic nuance is higher.