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A Study of Supply Chain Operations and Master Data Localization with Proposed AI Implementation at Atlas Copco

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Abstract **- Manufacturers of industrial equipment depend on sourcing decisions that shape lead times, inventory and delivery reliability, and those decisions in turn depend on the quality of procurement master data. The literature on supply chain performance, data quality, total cost of ownership and supply risk stresses reliable records, balanced supplier measures and careful comparison of global and local sourcing, while work on procurement digitisation and artificial intelligence gives context for more automated support. This descriptive, applied study draws on a one-year placement in the sourcing function of Atlas Copco (India) Pvt. Ltd., Pune, from November 2025 to November 2026. Its objectives were to understand sourcing, procurement and warehouse operations; to gain exposure to SAP-based procurement and apply data validation and cleansing; to examine supplier performance through lead time and delivery-date adherence in an Excel-based Sourcing Dashboard; to contribute to a Master Data Localization project; and to outline a conceptual, human-supervised AI-enabled Sourcing Assistant. Evidence comes from observation, participation, progress notes and mentor updates; supplier identities, commercial terms and performance figures are withheld under confidentiality.**

Five qualitative findings emerged. Data validation had to precede reliable analysis; lead time and delivery adherence were practical indicators of supplier reliability; sourcing decisions were visibly linked to warehouse safety stock; localization proved to be a staged, criteria-based process and not a single decision; and routine purchase-order tracking created recurring manual work, which motivated the Sourcing Assistant concept. The assistant was not built, piloted or tested, and no savings or localization outcomes are claimed. The study concludes that reliable master data is the groundwork for supplier monitoring, localization and any later digital support. It suggests recurring data validation, consistent localization criteria, a narrowly scoped and governed pilot of the assistant on low-risk queries, and human decision authority throughout.

Keywords - Supply Chain Management, Master Data Localization, Supplier Performance Analytics, Procurement Optimization, Artificial Intelligence in Sourcing

I. INTRODUCTION

Industrial equipment manufacturers depend on globally distributed networks of component and material suppliers, and the performance of these networks rests on how well sourcing, warehousing and delivery are coordinated (Chopra & Meindl, 2016). Sourcing and procurement sit early in this chain. The choice of supplier, and of the geography from which a part is obtained, shapes lead times, inventory buffers and delivery reliability further downstream. Global sourcing can give access to specialised manufacturing capability, but it is also associated with longer lead times and greater exposure to logistics and currency risk, which is why manufacturers periodically revisit the balance between global and local supply.

These decisions rest on data. In ERP environments such as SAP, material master, vendor master and purchase-order records underpin every transaction and every report built on them, and incomplete or inconsistent records weaken supplier evaluation and sourcing analysis. Master data therefore needs to be validated before it can support the monitoring of supplier lead time and delivery-date adherence, or the assessment of which globally sourced parts might be sourced from suppliers within India, an exercise referred to in this paper as Master Data Localization. Digital tools, from spreadsheet-based dashboards to more recent AI-enabled assistants, are increasingly discussed as ways of making this information easier to reach, although they can only be as reliable as the data beneath them.

This paper draws on a one-year on-the-job training in the sourcing function (Category: CT) of Atlas Copco (India) Pvt. Ltd., Pune, a global industrial equipment manufacturer. It describes procurement data validation and cleansing, supplier and purchase-order monitoring through an Excel-based Sourcing Dashboard, and participation in a Master Data Localization project. It also outlines a proposed AI-enabled Sourcing Assistant, which remains a concept and was neither built nor piloted. The study is descriptive and applied: it documents work carried out and draws practical lessons from

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it, rather than testing hypotheses or reporting measured savings. In line with the host organisation's confidentiality requirements, supplier identities, commercial terms and internal performance figures are not disclosed.

II. LITERATURE REVIEW AND THEORETICAL BACKGROUND

A. Literature Review

Supply chain management treats materials, information and funds as flows that must be coordinated across suppliers, manufacturers and customers, and sourcing is one of the decisions that shapes the others (Chopra & Meindl, 2016). Standard purchasing texts describe sourcing and procurement as core supply management functions, covering supplier selection, the purchasing process and performance measurement (Monczka et al., 2016; Van Weele, 2018). The supplier-selection literature increasingly evaluates suppliers against several criteria rather than price alone (Ho et al., 2010). Total cost of ownership follows the same logic by counting purchase-related costs beyond the unit price (Ellram, 1995).

Frameworks for measuring supply chain performance offer structured sets of measures and guidance on choosing among them (Beamon, 1999; Gunasekaran et al., 2001). Delivery reliability and lead time are among the operational measures such frameworks include. These measures depend on the records behind them. Data quality is multidimensional and is commonly defined as fitness for use (Wang & Strong, 1996). Poor master data is reported as a significant cost for firms, which must weigh the effort of maintaining data against the cost of errors (Haug et al., 2011).

Localization is one way of managing sourcing risk. Reviews of supply chain risk management discuss how sourcing arrangements can be used to reduce supply risk (Tang, 2006). A survey of manufacturing location decisions found firms giving more weight to supply chain issues alongside cost (Ellram et al., 2013). That study concerns plant location rather than component sourcing, so it is used here only as a parallel.

On the digital side, supply chain analytics is commonly grouped into descriptive, predictive and prescriptive forms (Wang et al., 2016). A spreadsheet dashboard that reports lead time and delivery adherence belongs to the descriptive group; this classification is the author's own. The digitisation of procurement is shaped by several influencing factors (Bienhaus & Haddud, 2018), and applications of artificial intelligence in supply chain management have been reviewed since at least Min (2010). This literature serves only as background. The proposed Sourcing Assistant is the author's own concept and has not been tested.

B. Theoretical Background

The study rests on the procure-to-pay logic, in which a requirement becomes a purchase requisition, then sourcing and an RFQ, then a purchase order, goods receipt and payment. The internship work sat mainly in the earlier stages of this cycle. In SAP Materials Management, the material master and vendor master are the reference records beneath requisitions and orders, so their accuracy limits the reliability of any analysis built on them.

Supplier performance is examined through two measures: lead time, and delivery-date adherence, meaning whether an order arrives by its promised date. Localization is treated as a screening decision. Globally sourced parts are assessed against technical feasibility, local supplier capability, lead-time improvement, indicative cost competitiveness and quality or certification alignment, in the spirit of total cost of ownership.

Digital capability is viewed as a progression from digitised records, to integrated data, to analytics, and then to AI-assisted support, with the Excel dashboard in the first stages and the proposed assistant as an early idea for the last. Any such assistant is framed as human-in-the-loop: it retrieves information and sends reminders, while supplier selection and negotiation stay with the sourcing team.

III. MATERIALS AND METHODS

A. Research Objectives

This study examines the author's sourcing and procurement placement at Atlas Copco (India) Pvt. Ltd. through five objectives: (1) to understand the company's sourcing, procurement and warehouse operations, and how sourcing decisions affect downstream inventory availability and supply continuity; (2) to gain practical exposure to SAP-based procurement processes and apply data collection, validation and cleansing to support sourcing analysis; (3) to examine supplier performance and purchase-order status, using lead time and delivery-date adherence, through a structured Sourcing Dashboard; (4) to contribute to the Master Data Localization project by screening globally sourced parts for local sourcing potential, issuing RFQs and supporting preliminary supplier discussions; and (5) to develop a conceptual framework for an AI-enabled Sourcing Assistant that tracks supplier delivery performance, pending purchase orders and sourcing follow-ups, while defining the human oversight it would require.

B. Research Design, Data and Methods

This is a descriptive, applied study based on the author's participation, as a Sourcing Intern, in the sourcing function (Category: CT) of Atlas Copco (India) Pvt. Ltd., Pune, from November 2025 to November 2026. It documents work carried out and draws practical lessons from it; no hypotheses were tested.

Primary data came from direct observation during orientation and a warehouse visit, structured exposure to SAP Materials Management (purchase requisitions, purchase orders, vendor and material master), and participation in data validation, dashboard development and the localization project under the industry mentor's guidance. Secondary data comprised the author's progress notes, periodic mentor updates, non-confidential company and sector information, and the literature reviewed above. Procurement data from SAP and internal records were consolidated, checked for missing, inconsistent or badly formatted fields, and corrected against SAP where possible. Supplier performance and purchase-order status were analysed through lead time and delivery-date adherence and reported in a Microsoft Excel Sourcing Dashboard. For Master Data Localization, globally sourced parts were screened on technical feasibility, local supplier capability, potential lead-time improvement, indicative cost

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competitiveness, and quality or certification alignment; the resulting candidate list was approved by the mentor before RFQs were issued to Indian suppliers. The Sourcing Assistant concept was developed by comparing the current manual follow-up process with a proposed one.

Under the host organisation's non-disclosure requirements, supplier identities, commercial terms and actual performance figures are withheld, and the paper therefore reports no numerical results. Records are fuller for the earlier part of the placement; the localization and Sourcing Assistant accounts draw partly on periodic notes and recollection. The author's role in localization ended at candidate consolidation, RFQ issuance and preliminary negotiation support; final supplier decisions rested with the sourcing team.

IV. DATA ANALYSIS AND DISCUSSION

Actual supplier names, prices and performance values are confidential, so this section presents the work qualitatively. It sets out what was done, what was produced, and what each activity showed. Where a table row is a proposal, it is marked as such.

A. Sourcing and Warehouse Exposure, and the Work Performed

TABLE I
ACTIVITIES, TOOLS AND OUTPUTS BY OBJECTIVE

Obj.	Activity performed (tool / source)	Output	Status
1	Orientation; warehouse visit; observation of the sourcing–inventory link (observation; mentor discussions)	Understanding of the sourcing-to-warehouse flow	Actual
2	SAP exposure; collection, validation and cleansing of procurement data (SAP MM; internal records)	Cleansed, validated procurement dataset	Actual
3	Supplier and purchase-order analysis; lead-time and delivery-date tracking (Microsoft Excel)	Sourcing Dashboard	Actual
4	Localization screening; RFQs; preliminary negotiation support (SAP master data; RFQ template; candidate tracker)	Candidate list; RFQ documentation; response tracking	Actual
5	AS-IS/TO-BE comparison; risk and oversight definition (concept document)	Conceptual proposal	Proposed (not built or piloted)

Table I shows that the practical work ran from foundational exposure to applied tasks, with only the fifth objective remaining at concept stage. The warehouse visit gave the clearest view of why sourcing matters downstream. Parts with longer supplier lead times were generally held at higher safety-stock levels, while parts with shorter, more reliable lead times needed less buffer. This was an observation, not a measured relationship, but it explains why lead time was chosen as a core dashboard measure.

B. Data Validation and the Sourcing Dashboard

TABLE II
DATA-QUALITY DIMENSIONS ADDRESSED DURING VALIDATION

Dimension	Action taken	Example
Accuracy	Inaccurate entries corrected or flagged	Values checked against the authoritative SAP source, not assumed
Completeness	Incomplete records identified	Missing dates in order and delivery fields
Consistency	Inconsistent formatting standardised	Differing supplier naming conventions

Validation checked that material identifiers, supplier references, order dates and delivery dates were present, correctly formatted and internally consistent (Table II). The cleansed data then supported the supplier and purchase-order analysis behind the dashboard, which tracks lead time and delivery-date adherence. This sequence matters: the reliability of any dashboard figure is bounded by the quality of the records beneath it. The point is consistent with the view that data quality means fitness for use (Wang & Strong, 1996) and that poor master data carries real costs (Haug et al., 2011). The improvement is described qualitatively, as better-quality input for sourcing analysis. It was not measured, and the dashboard's effect on team efficiency was not assessed.

C. Master Data Localization

TABLE III
LOCALIZATION WORKFLOW AND THE AUTHOR'S INVOLVEMENT

Stage	Activity	Status / limit
Review of master data	Globally sourced parts reviewed, with SAP as the primary reference	Actual
Feasibility screening	Five criteria applied: technical feasibility, local supplier capability, lead-time improvement, indicative cost competitiveness, quality/certification alignment	Actual
Candidate consolidation	List prepared and approved by the mentor before RFQs	Actual; count confidential

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Stage	Activity	Status / limit
RFQ issuance	RFQs sent to Indian suppliers; responses tracked	Actual; counts confidential
Preliminary negotiation	Discussions with a subset of responding suppliers, under mentor guidance	Actual; outcomes confidential
Supplier selection, commercial finalisation, PO transition	Handled by the sourcing team	Outside the author's scope

Localization emerged as a staged process, not a single decision (Table III). Each stage depended on a complete and comparable master-data view, and building that view meant cross-referencing several SAP fields and internal records. The criteria treat cost as one consideration alongside lead time and quality, which is in keeping with the total-cost view in the literature (Ellram, 1995). The expected benefits, shorter lead times and lower exposure to international logistics and currency risk, remain expectations. The paper reports no localization outcomes, and the final decisions rested with the sourcing team.

D. Proposed Sourcing Assistant

TABLE IV
OBSERVED PROCESS AND PROPOSED SOURCING ASSISTANT

Process	Current practice (observed)	Proposed (concept only)
PO status check	Manual filtering of the Excel dashboard or an SAP report	Natural-language query returning filtered results
Supplier delivery review	Compiled manually before each review meeting	Summary produced on demand from the same data
Meeting follow-up	Tracked manually by calendar and email	Reminders generated by the assistant

The gap behind the proposal was observed in practice (Table IV). Even with the dashboard in place, routine questions, such as which orders from a given supplier were overdue, still required manual filtering each time. The proposed assistant would draw on the same approved data and be limited to information retrieval and reminders. Anything affecting a supplier relationship or commercial term would stay with a human decision-maker. The risks identified were exposure of sensitive data, misread queries, outdated data, and over-reliance on tool output. None has been tested, since the assistant was never built or piloted. Any benefit, such as less manual searching, is a hypothesis for a future pilot and not a finding.

V. FINDINGS, CONCLUSIONS AND SUGGESTIONS

A. Findings

The placement produced five findings, all qualitative and grounded in observation and participation rather than measured outcomes. First, data quality proved to be a precondition for analysis: validation and cleansing of procurement records had to precede any supplier or purchase-order reporting, because errors such as missing dates and inconsistent supplier names would otherwise carry straight into the results. Second, lead time and delivery-date adherence worked as practical, easily tracked indicators of supplier reliability and gave the Sourcing Dashboard a workable basis. Third, the warehouse visit showed that sourcing decisions reach inventory directly, since parts with longer supplier lead times were generally held at higher safety-stock levels than those with shorter, more reliable ones. Fourth, Master Data Localization proved to be a staged process of master-data review, screening, candidate consolidation, RFQ and preliminary negotiation, and not a single decision; each stage called for assessment against technical, supplier-capability, quality, lead-time and commercial criteria, supported by a complete and comparable master-data view. At the time of writing, the project had reached preliminary negotiation with a subset of responding suppliers, and its final outcomes rested with the sourcing team. Fifth, open and overdue purchase orders created recurring manual tracking work even with a dashboard in place, which supports the rationale for the proposed Sourcing Assistant. That support is a rationale only: the assistant has not been built, tested or piloted, and the study offers no evidence of its effect.

B. Conclusions

This study set out, through five objectives, to document what a year in the sourcing function of Atlas Copco (India) Pvt. Ltd. showed about supply chain operations, master data and early digital support. The first four objectives were met through practical work: the author came to understand how sourcing connects to warehouse availability, gained working familiarity with SAP-based procurement, built and maintained a dashboard around lead time and delivery adherence, and took part in the early stages of a localization initiative. The fifth objective was met only at concept level, as a bounded framework for a Sourcing Assistant. Taken together, the work suggests an order of dependence: reliable master data first, simple supplier measures second, and only then more ambitious steps such as localization screening or AI-assisted retrieval. Skipping the first step weakens everything built on it. The reach of the study is limited. It is descriptive, rests on one placement in one function, and reports no measured outcomes, so it cannot show that localization shortens lead times or that the dashboard or assistant saves effort. What it offers is a practical account of how these tasks fit together and where careful, human-supervised digital support might come next, a question for the sourcing team to test and not for this paper to assert.

C. Suggestions

To act on these findings, a phased and modest approach is suggested.

For Sourcing and Procurement: run procurement data validation as a recurring routine, for example monthly, with a named owner; keep lead time and delivery-date adherence as the core dashboard measures; and apply the localization criteria consistently to future candidates.

For Suppliers: confirm promised delivery dates and RFQ responses in a standard format, so that tracking and comparison are straightforward.

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For Warehouse and Inventory: review safety-stock levels alongside supplier lead-time records.

For Management and IT/Data Teams: set data-access rules and a narrow query scope before any assistant touches live SAP data, and pilot it first on pending-purchase-order queries for one category.

For all users: keep supplier selection, negotiation and localization decisions with the sourcing team; the assistant should only retrieve information and send reminders.

D. Implications of the Study

The findings carry practical implications for several groups, though none of them rests on demonstrated benefits.

Sourcing and Procurement Teams: Reliable master data and a consistent set of supplier measures give a firmer basis for supplier reviews and follow-ups; the study does not show that this saves time.

Suppliers: A documented, criteria-based localization process may give capable Indian suppliers a clearer route to qualification, while all suppliers can expect delivery to be monitored against promised dates.

Warehouse and Inventory Teams: Better visibility of supplier lead times could inform safety-stock decisions, although this link was observed, not measured.

Management: Data governance appears to be the groundwork for both localization and AI-assisted tools, and human oversight should be settled before any wider use; no savings are demonstrated.

IT and Data Teams: An assistant would need access controls, a data-refresh process and a narrow scope, which these teams would have to define.

E. Future Scope of the Study

Several directions remain open for future work, none yet undertaken.

Pilot Testing: A narrowly scoped pilot of the Sourcing Assistant on pending-purchase-order queries could test accuracy, usability and effort saved, with human review and data-access governance in place.

Dashboard Expansion: Once lead time and delivery adherence are well embedded, measures such as supplier responsiveness, quality incidents and order ageing could be added; a tool such as Power BI could be considered later if sharing or data-volume needs justify it.

Supplier-Performance Analytics: With enough accumulated data, formal time-series analysis could separate sustained trends in lead time and delivery adherence from normal variation.

Localization Assessment: Globally sourced parts could be revisited periodically against the criteria, and any parts that are localized could be followed over time to assess lead-time and cost effects.

Data-Quality Monitoring: Completeness, consistency and validity rates could be tracked routinely to show whether data quality is holding.

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REFERENCES

[1] Beamon, B. M. (1999). Measuring supply chain performance. *International Journal of Operations & Production Management, 19*(3), 275–292. https://doi.org/10.1108/01443579910249714

[2] Bienhaus, F., & Haddud, A. (2018). Procurement 4.0: Factors influencing the digitisation of procurement and supply chains. *Business Process Management Journal, 24*(4), 965–984. https://doi.org/10.1108/BPMJ-06-2017-0139

[3] Chopra, S., & Meindl, P. (2016). *Supply chain management: Strategy, planning, and operation* (6th ed.). Pearson.

[4] Ellram, L. M. (1995). Total cost of ownership: An analysis approach for purchasing. *International Journal of Physical Distribution & Logistics Management, 25*(8), 4–23. https://doi.org/10.1108/09600039510099928

[5] Ellram, L. M., Tate, W. L., & Petersen, K. J. (2013). Offshoring and reshoring: An update on the manufacturing location decision. *Journal of Supply Chain Management, 49*(2), 14–22.

[6] Gunasekaran, A., Patel, C., & Tirtiroglu, E. (2001). Performance measures and metrics in a supply chain environment. *International Journal of Operations & Production Management, 21*(1/2), 71–87.

[7] Haug, A., Zachariassen, F., & van Liempd, D. (2011). The costs of poor data quality. *Journal of Industrial Engineering and Management, 4*(2), 168–193. https://doi.org/10.3926/jiem.2011.v4n2.p168-193

[8] Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research, 202*(1), 16–24.

[9] Min, H. (2010). Artificial intelligence in supply chain management: Theory and applications. *International Journal of Logistics Research and Applications, 13*(1), 13–39. https://doi.org/10.1080/13675560902736537

[10] Monczka, R. M., Handfield, R. B., Giunipero, L. C., & Patterson, J. L. (2016). *Purchasing and supply chain management* (6th ed.). Cengage Learning.

[11] Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics, 103*(2), 451–488.

[12] Van Weele, A. J. (2018). *Purchasing and supply chain management* (7th ed.). Cengage Learning.

[13] Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics, 176*, 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014

[14] Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems, 12*(4), 5–33. https://doi.org/10.1080/07421222.1996.11518099

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