Bridging the Gap: End-User Programmers in Modern Supply Chain Analytics

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***Abstract*—This paper examines the role of end-user programmers in enhancing data-driven decision-making within supply chains, particularly for Small and Medium-sized Enterprises (SMEs). End-user programmers increasingly use low/no code software and platforms to improve their organization's analytical capability. Low/no code provides less technical users access to analytical tools, thereby enabling them to address supply chain challenges. While low/no code simplifies the (data) modeling process, end-user programmers do hold assumptions about the modeling process that lack scientific support. This paper examines three such assumptions: 1) their confidence in producing models with few errors, 2) assumptions regarding in which context to use machine learning, and 3) assumptions regarding the complexity of making statistical results applicable. By reflecting on these assumptions, this paper provides directions organizations can adopt to support low/no code adaption within logistic SMEs.**

Keywords–Supply chain management; low code/no code; Analytics Maturity Curve

I. Introduction

Today's supply chains encounter major challenges, often experiencing disruptions in their intricate networks. These disruptions lead to significant consequences and expenses [1]. Smaller businesses are especially vulnerable, with 40%-60% of them failing to endure significant disruptions [2] via [1]. Logistics service providers are coping with workforce issues due to labor shortages [3]. Furthermore, various groups advocate for greater sustainability within supply chains (e.g., [4]).

Industry 4.0 technologies are seen as potential solutions to these issues [5]. These technologies include cyber-physical systems, the Internet of Things (IoT), and Big Data Analytics (BDA) [5][6]. Several authors have outlined how these technologies can address supply chain challenges, which we will refer to as the Industry 4.0 Promise (I4.0P). By accessing substantial data in supply chains, better decision-making is possible through BDA methods [6][7], and AI could even drive complete automation [5][8]. A research by McKinsey highlights how AI seems particularly promising in the logistics sector [9]. Given the ambiguity of what exactly is meant by "AI" [10], we imply the usage of Machine Learning (ML) tools techniques, which we therefore abbreviate as AI/ML.

Despite the high potential promoted by BDA vendors and consultants [11], companies struggle to translate their data efforts into value [12]. This challenge extends to logistics service providers, many of which are small and medium enterprises (SMEs): they continue to face difficulties with digitalization. Organizations not only handle their own logistics and IT systems, but also cope with the complexities of logistic networks and its underlying processes, creating additional barriers for digitalization [13]. This interconnectedness in logistic networks might explain why some studies suggest that the logistics sector lags behind in digitalization, compared to other industries [14] via [13]. SMEs encounter challenges when using data for analysis, including insufficient executive support, limited skills and IT-support, and they express a need for well-defined business problems [15].

Although these challenges are significant, ongoing advancements in data & AI could offer solutions to (some of) these challenges. There is a growing trend in organizations adopting low code and no code platforms [12], and this trend is likely for good reason. These platforms bring notable advantages, especially by creating a new layer of abstraction for novice users of data/AI technology. This accessibility is valuable for users with limited IT and data science expertise.

However, there are some caveats to the wide adoption of data technology by less experienced users, which in the remainder of this paper we will refer to as end-user programmers. Some of this stems from assumptions about BDA in the Industry 4.0 Promise, which might create expectations that lack scientific evidence. Additionally, there are human biases in modeling and programming that professional programmers are trained to capture but which low code users are often unfamiliar with. By exploring these caveats, we aim to contribute to the discussion about which skills these new low/no code users should acquire before creating and managing data solutions. While many findings may apply more broadly, we specifically focus on low/no code usage in logistics SMEs. The following research questions are formulated:

RQ1: How are low code development platforms relevant for SMEs within the logistics sector and what are the challenges and necessary guidelines?

RQ2: How does the actual usage of BDA in decision-making differ from end-user programmers' expectations when utilizing low/no code software for data modeling and what are the implications of this disparity?

This paper is organized as follows. In Section II, we explore the potential and challenges of low code platforms. In addition we highlight guidelines that are particularly important in the logistics sector. In doing so we answer RQ1. RQ2 addresses some of the challenges end users will have when applying these low/no code platforms to implement AI. Section III will address the assumption of the analytical maturity curve

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present at a lot of organizations and section IV scrutinizes the assumption that "data can speak for itself". Both sections are aimed at addressing RQ2. Finally, we summarize the paper's findings in Section V.

II. Low code for SMEs (RQ1)

This section will discuss the emergence of low code development platforms and their relevance to SMEs in the logistics sector. In addition, it will discuss challenges of these platforms and proper guidelines.

A. The data quality in logistics

Decisions made by supply chain managers cover inventory, warehouse layout, procurement and routing. Most of these decision problems have been studied extensively in OR literature but there exists a gap between theory and application. Syntetos et al. analyze the gap between theory and practice in supply chain forecasting and conclude that for example data is often recorded at different frequencies (say daily) than decision makers require (say weekly). Aggregating this data can be complex and software packages often do not support this 'temporal aggregation' [16].

Adding to the complexity of supply chain management is the frequently encountered issue of poor data quality at SMEs [17]. Furthermore, planning and scheduling often rely on decentralized spreadsheets. Supply chain managers often find themselves manually collecting data, such as inventory levels and order status, in an ad hoc manner. The decision making that then follows is often done based on the intuition and business knowledge of the manager.

B. The rise of low and no code platforms

While modern data technology can address data quality concerns, SMEs might not be able to apply it directly as they lack the necessary skills and IT support [15]. Enhancing data quality is also expensive. According to Anaconda's 2022 "The state of data science" survey, respondents spend around 22% of their time on data preparation and 16% on data cleansing [18]. An earlier survey suggested that up to 70% of time is consumed by tasks related to data cleansing [19]. However, recent studies propose that this knowledge gap is closing, partly due to the rising popularity of low/no code platforms [20]. Gartner predicts a 19.6% growth in the low code market for 2023, attributed to a scarcity of tech talent and an increasing hybrid and borderless workflow [21].

Low/no code empowers companies to create, deploy, and maintain applications through drag-and-drop visual components. This method avoids the need to master intricate coding languages, making it easier for a broader range of users. No code goes even further by eliminating coding completely [22]. Both low code and no code can aid in Extract, Transform and Load (ETL), cutting significant time previously devoted to these tasks [18]. It simplifies these tasks for non-technical staff. With its comprehensibility to a broader range of professionals, low code is said to have a democratizing effect, engaging business experts too. This characteristic also makes it more suitable for SMEs [23].

Low/no code brings numerous benefits. A survey of IT-professionals highlighted that key advantages including ease of use, resource savings, easy prototyping and increased productivity [24]. A study in the logistics sector found that low code platforms reduce the reliance on skilled programmers [25]. Li and Wu [20] also confirmed user preference for low code/no code solutions.

Expanding employee involvement in data/AI projects is just one benefit. Bridging the gap between data scientists and business specialists also makes projects more meaningful for organizations. Engaging domain experts in the data/AI development process is crucial, especially for tasks like data annotation, augmentation, and interpretation [23].

C. Challenges of low code platforms

While low/no code platforms offer exciting opportunities for smaller firms, there are still several challenges companies face when trying to put them to use. Setting proper guidelines is key when trying to address these challenges.

The concern most mentioned by IT professionals is platform dependence [24]. When an organization adopts a low code platform, it relies on the platform's vendor. Tied into this challenge is the fragmentation of the low code landscape. Each platform has its own low code developing paradigm. Using the tool effectively requires the user to get acquainted with the specific tool in question [26].

Another challenge mentioned in the literature is scalability and interoperability [23][26]. Most low code platforms are well suited for designing small applications but lack the ability to support bigger infrastructures. For SMEs this is their number of users is likely small. Interoperability is a challenge however, since the IT infrastructure at small firms can still be scattered.

Lastly, there is the risk of inadequate maintenance and testing. Although low code software is easily maintainable [27], it might not be done in practice. Since the literature on low code is still lacking in this area, it can be worthwhile to look at evidence from studies on spreadsheet modeling. They reveal that end-user programmers make considerably more errors in modeling than professional programmers [28]. While spreadsheets are often tested, many end-user programmers do not follow structured testing methods that are typical in software development [29]. Improper testing is often caused by an overconfidence in end-users programmers' ability to identify errors in spreadsheets [30]. Spreadsheet modeling also shows a lack of documentation: Hermans et al. [31] find that only approximately one in three spreadsheets contains documentation. As a consequence, spreadsheets are frequently explained by inefficient and inconsistent 1-1 communication between employees, such as via e-mail [32].

D. Guidelines for low code platforms

In order to address the aforementioned challenges, setting proper guidelines can be helpful. Some literature already exists on this topic. Rokis and Kirikova [27] mention seven challenges based on a systemic literature review and Sundberg and Holmström [23] mention specific guidelines when using low code platforms in ML operations. In the context of SMEs in the logistics sector, we propose the following guidelines:

Have an overarching organizational AI strategy

While low code platforms are user-friendly, merely providing them to professionals in the organization doesn't ensure their adoption and effective use [23]. A study which focused on the application of low code platforms in supply chain management concluded that the lack of an adoption strategy

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is a major barrier in organizational adoption [33]. We propose that organizations should not forget employee skill enhancement as part of such a strategy. By adequately training users, maintenance and testing can be improved.

Limiting platform dependence and increasing interoperability

Vendor lock-in is one of the main concerns surrounding low code development platforms and mitigating it is challenging. However, Ihirwe et al. [34] via [27] mention that ensuring interoperability can help mitigate this dependence. Low code applications should at least be able to communicate with the external world using for example APIs. This is especially important in supply chain management as information sharing within the value chain is important [35].

Ensuring adequate testing and maintenance

Each low code development platform has specific ways of maintenance and testing. Although maintenance of an application might be easier compared to traditional programming code, creating awareness within the organization is still needed. Companies should also consider the ease of setting up testing procedures as a criterium for vendor selection. The ability to test applications varies across the different platforms [36].

III. On the role of machine learning in planning and forecasting in supply chains (RQ2)

The analytical maturity assumption (AMA) is often used to illustrate the typical roadmap towards becoming more data-driven, and is therefore adopted in the I4.0P. Best known is the analytics maturity curve by Gartner, though several adaptations exist [37]. In this section we will challenge the validity of this assumption and why machine learning might be benificial to companies that have low levels of ”data-readiness”.

A. The Analytics Maturity Assumption

The AMA is found in numerous reviews on the role of BDA in I4.0P (e.g., [6][7][37]). As illustrated in Figure 1, the AMA outlines different stages that organizations go through to enhance their analytical maturity, progressing from descriptive (“What happened”) and diagnostic (“Why did it happen?”), to predictive (“What will happen”) and prescriptive (“How can we make it happen?”). With each stage, the complexity of the (statistical) models increases. Where descriptive analytics is mainly concerned with reporting from existing data sources, i.e., the use of descriptive statistical techniques, predictive and prescriptive analytics employ AI/ML to make accurate forecasts and make data-driven decisions.

Advancing in the AMA relies largely on the availability and quality of data sources. However, as mentioned earlier, data quality is problematic in supply chains. Furthermore, even if data quality is improved, there is no guarantee that this data will lead to more accurate predictions [38]. In fact, current academic literature is indecisive on whether ML is preferred over traditional statistical methods for forecasting [39][40]. So why, according the the AMA, does the usage of ML in forecasting lead to better predictions? And if it does not improve forecasting, what is then the business rationale for ML, beyond forecasting?

B. Machine-learning for improving data quality

Analytical maturity models suggest that ML models are aimed to “predict what will happen” (forecast) and to decide the best course of action under such forecast [41]. Practical applications of ML, however, show a different purpose. ML is commonly employed to enhance ”data-readiness,” a concept that goes beyond just data quality, but also ensures that data is suitable for a specific context of forecasting and decision-making [42].

Academic literature shows many examples where ML enhances data-readiness. For instance, although Karkouch et al. [43] present different data quality challenges in IoT, they also list different strategies to contest these. Many of these are ‘model-based’ algorithms that use ML to detect outliers. Perhaps it should therefore be no surprise that outlier detection is a common application of active learning [44].

ML is frequently used for data imputation, which under certain conditions improves the further forecasting/optimization task, even if this ‘downstream’ task uses more traditional statistical models [45]. Given the multimodality of many datasets, the ML community has put its attention to techniques such as ‘data fusion’ [46]. This allows integrating different data sources for further downstream tasks. Also, recent Large Language Models such as GPT-4 find their application in what could be considered data preparation/data cleaning and feature engineering tasks, such as data augmentation, text classification, named entity recognition, and translation [47].

In other words, ML has become a method that offers a clearer understanding of “what happened”, perhaps more than “what will happen”. Here, the term ‘predict’ is ambiguous. While the AMA seems to imply it is about time-based predictions (i.e., forecasts), the previous examples (predicting outliers, missing data, missing labels, etc.) show that this is often to improve data-readiness.

IV. On data-driven decision-making (RQ2)

Data Analytics and Data Science have long been presented as solutions for mitigating biases in decision-making (e.g., [48, Ch. 1], [49, Ch. 2], [50]). This section will firstly address that there exist other methods for reducing biases (such as wisdom of the crowds). Secondly, it will question whether decision makers within SMEs have the necessary skills to use data driven methods such as machine learning.

A. Data-driven decision-making is not the only method for reducing judgemental biases

This perspective is supported by findings from behavioral economics, which identify decision biases, like the hindsight bias or confirmation bias, which can lead to irrational choices [51]. In the light of the scientific method, data and statistical methods can be used to validate ones believes. By reducing judgemental biases, improved decision-making may lead to some “value”, whether economic or social [52, p. 6]. While some studies indicate that companies that implement data-driven decision-making outperform companies that do not [7], many companies, including SMEs, struggle with data-driven decision-making [53]. Decision are often based on personal experience [50, Ch. 7].

What is frequently overlooked in the argument favoring data science and analytics against judgmental biases is that decision sciences have also introduced alternative methods for bias reduction, or have studied when intuition can be trusted and when not [54]. These methods, partially or fully relying on

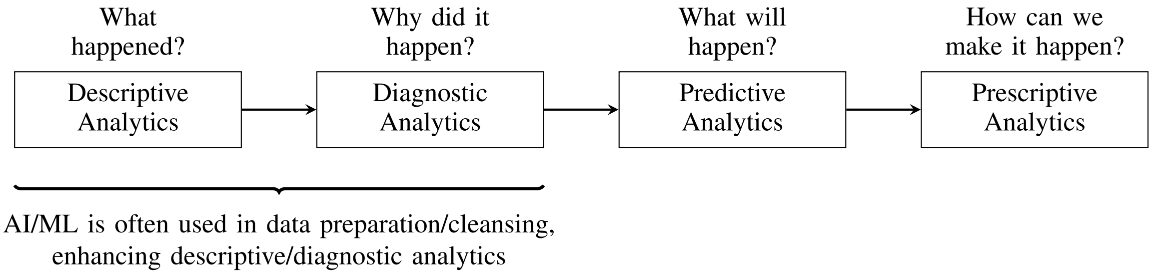

Figure 1. Gartner analytics maturity as presented by [37], where does AI/ML contribute value?

expert knowledge, differ from a complete reliance on 'letting the data speak for itself'. Rather, they provide guidelines that assist forecasters and decision-makers in reducing judgemental bias. For example, the usage of Wisdom of the Crowds (WoC), or variations such as "surprisingly popular" [55], are scarcely mentioned in the I4.0P, nor the different guidelines forecasters may use to eliminate judgemental biases [56].

End-user programmers and decision-makers could benefit from these results in the decision sciences. They provide methods for reliable decision-making in data-poor environments, which are prevalent in supply chains. Also, they are easier to implement compared to methods that heavily depend on data. Especially combining supply chain data with expert judgement, following guidelines from the decision sciences, may be fruitful. Although, as indicated by Syntetos et al. [16], data may not be on the right decision-making level, it does provide boundaries and conditions to which estimates from expert judgement should adhere.

Only recently has the AI community shifted its perspective from model-centered to data-centered AI [57][58], and has thereby increased its attention on the human aspect in data sources, models and decision-making. As Balazka and Rodighiero [59] pointed out, it is a person who decides what data is collected, who gets access to the data, what data gets labeled and how it is labeled. In essence, even if data is used to support decision-making, it remains susceptible to human judgement. However, this shift towards human-centeredness has not been noticed in the review by Silva et al. [37] on the role of BDA in Industry 4.0, hence, remains absent in the I4.0P.

B. Can decision-makers interpret empirical results?

Decision-makers seem to neglect that the data and subsequent conclusions used for data-driven decision-making does not have to be data or findings within their own context (e.g., within their own organization). When decision-makers are asked about evidence-based practice (which does not only base its decisions on own analysis, but also on other sources such as experts and scientific literature), one finds that decision-makers rarely consult scientific evidence that may generalize to their own organization. Decision-makers report lack of time, lack of understanding of scientific research, and the unreadability of academic writing as reasons for not using empirical evidence from the (scientific) community [50].

This reveals a paradox: if decision-makers, in SMEs or elsewhere, lack the time and expertise to interpret scientific (that is, data-driven) results, how can they accurately interpret results from empirical evidence within their own organization, which employ the same statistical principles? In terms of skills end-user programmers and decision-makers require, it becomes clear that although low/no code assists data modeling, there remains a skill gap in how to interpret the outcomes of these models and how to reflect these to existing literature.

V. Conclusion and Future Work

As low/no code platforms become more popular in organizations, more professionals without formal IT/data science education will engage in data modeling. These platforms can help improve organizations' data-readiness in supply chains, while also making data modeling easier for non-technical users. This could therefore also benefit SMEs. Overall, low/code software and platforms might help address various data challenges in modern supply chains, such as IoT data quality problems and the mismatch between data measurement and decision-making levels.

However, there are several risks involved in this increase in end-user programmers. In order to address the risks and find potential guidelines we provide answers to the following research questions:

RQ1: How are low code development platforms relevant for SMEs within the logistics sector and what are the challenges and necessary guidelines?

RQ2: How does the actual usage of BDA in decision-making differ from end-user programmers' expectations when utilizing low/no code software for data modeling and what are the implications of this disparity?

(RQ1) Guidelines on for low code platforms: While research on the usage of different low/no code platforms and solutions for analytical purposes is still in its infancy, research from spreadsheet modeling suggests that end-user programmers are more likely to make errors in modeling. Therefore, SMEs should adhere to guidelines in order to reduce this risk. Firstly, developing a comprehensive organizational AI strategy that emphasizes employee skill enhancement is needed. Secondly, reducing platform dependence and promoting interoperability (via APIs) is key, especially when sharing information within the supply chain. Lastly, ensuring proper testing and maintenance is needed.

(RQ2) The Analytical Maturity Assumption: When end-user programmers use low/no code software for modeling, they hold certain expectations on how the models and algorithms will support decision-making. These expectations often align with the analytics maturity curve and underlying assumptions, which in this paper we have called the Analyical Maturity Assumption (AMA). However, evidence suggest that AMA is flawed. In practice, predictive (machine learning (ML))

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models are typically used to improve one's understanding of "what happened". This by employing methods like outlier detection, filling missing values, and data fusion. In contrast, the literature is inconclusive on whether ML models should be preferred over traditional statistical models in forecasting. This observation may be especially relevant to actors in supply chains: instead of using ML directly to improve forecasting and decision-making, it may be wiser to use these techniques to improve data-readiness. The refined data could then be employed for forecasting/decision-making, where conventional methods might be more fitting, .

(RQ2) Can end-user programmers/decision-makers interpret statistical results?: There seems to be a paradox in how organizations try to become more data-driven, and how they use scientific evidence. Research towards evidence-based practice shows that decision-makers rarely consult scientific evidence that may well generalize to their own context. Reasons include lack of time, lack of understanding scientific research, and unreadability of research reports. If decision-makers struggle with using research outcomes, how can they grasp results from in-house data analysis rooted in the same statistical principles? Put differently, while low/no code solutions simplify the modeling part of data analysis, end-user programmers and decision-makers should still be trained in how to interpret results from statistical models, whether these originate from in-house analysis or elsewhere. Organizations should also acknowledge existing scientific evidence before delving into their own data, to guide and benchmark their own efforts.

Considering the growing adoption of low/no code platforms, more research is needed in this area. In this paper we found that low/no code platforms promise to democratize AI solutions. However, there is a skill gap present at SMEs which could form a potential risk when these platforms gain in popularity. Research should focus on how both companies and the low/no code platforms themselves address this skill gap.

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