From Reporting to Transformation: A Review of AI Tools Enabling Sustainability Governance Across Multi-Tier Supply Chains

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This paper deals with the topic of artificial intelligence tools that have the capacity to assist with sustainability governance in multi-tier supply chains. These tools in the sustainability sector in general are meant to cut costs and enable small and medium enterprises and lower-tier suppliers to get access to best practices, streamline their sustainability efforts, and create universally comparable outputs. The added value of our research is to categorize existing tools, to identify potential gaps, and to enable users to understand the tools with the highest impact. We collect available solutions by a combination of desk research and interviews of industry experts from various levels of supply chain. We evaluate them by their capability to overcome five main challenges – data beyond simple reporting and manual collection, reach beyond Tier 1 suppliers, usability by small enterprises, involvement of artificial intelligence, and tools having an accessible cost. Having such an overview will assist low-key users with less resources to easily tap on existing solutions without large barriers.

Keywords:
AI tools,
supply chains,
sustainability reporting,
sustainability governance,
AI in logistics,
global value chains

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1 Introduction

There have been visible signs of accelerating climate change in Europe, most visibly temperature in Southern European countries such as Greece has been breaking records in past years (Giannaros et al., 2023) or precipitation and drought extremes in other parts (Matanó et al., 2024). Such changes have a fundamental impact on multiple dimensions of the economy and people's lives. For example, agriculture output in multiple EU countries has been impacted by droughts, and larger impacts are yet expected to come (Bolla et al., 2024). Excessive use of electricity during hot summers is taking a toll on aging energy infrastructure (Semmelmann, vom Scheidt, 2025). The impact of climate change in Europe is expected to be roughly double as compared to the global average (UN, 2023).

Hans Joachim Schellnhuber, the founder of Potsdam Institute for Climate Impact Research noted that implementing artificial intelligence (AI) will be critical in combating climate change (Rockström et al., 2017, Fan et al., 2025; Rolnick et al., 2019). While there have been tremendous efforts to combat climate change, the recent rise in AI has given new hope to this powerful tool in the area of climate adaptation and mitigation while it also brings about certain drawbacks like energy consumption (Klesel and Messer, 2026). According to Schellnhuber (1999), there is a tipping point in climate change soon to come. AI tools can help to detect this tipping point (Bury et al., 2021). Due to the non-linear nature of the earth system, modelling of this system has been prohibitively expensive, unless the emergency of AI gives people hope to be able to calculate it at a reasonable cost (Pathak et al., 2018). With new AI tools, it became possible to realistically estimate benefits of renewable energy as compared to maintaining the status quo and propose a replacement plan (Algburi, 2025; Khan, 2026).

Global supply chains are the building block of the world economy and similarly, the joint strength of the actors within them can serve to combat climate change (Vieira et al., 2024). It is therefore very important to be able to implement AI solutions in the supply chains to combat climate change (Ren et al., 2025). Yet, the main difficulty lies in the fact that the world economy is getting increasingly fragmented with more complex supply chains spanning sectors, continents and independent entities which deal with each other at arm's length (Li et al., 2025). One particular problem stands out in these fragmented supply chains; that is, different firms along the supply chain have become digitally uneven. Large corporations with large resources have access to a plenty of digital tools including AI at their disposal, while lower tier smaller firms struggle to cope with the pace. For example, manual entry of data becomes a bottleneck for system optimization (Ayinaddis, 2025; OECD, 2025). Asymmetry prevents the supply chains as a whole from achieving their full potential in combating climate change. Similarly, companies dealing at arm's length have limited motivation to share their internal data as doing so creates risks to expose their know-how (Zaheer, Trkman, 2017).

In this paper, we aim to exploit this research gap. We intend to find avenues to enable AI usage across supply chains to handle sustainability transformation. That means, utilizing AI not only to collect data and undergo reporting processes, but also to help the actions to be performed. Secondly, we go beyond the simple notion of Tier 1 suppliers that can be directly controlled by the buyers. We rather understand supply chains as entire complex units of analysis where all involved parties play a role. Thirdly, we explore how AI tools can help to reduce reporting and transformation costs to lower-tier suppliers and small and medium enterprises (SMEs).

The paper is structured as follows. In the literature review, we explore the situation within today's supply chains, identify the hurdles and issues associated with sustainability reporting at transformation at multiple levels of supply chains, and check in which tasks could AI tools help the entities to reduce costs and enable action. In the analysis, we identify eleven main categories of AI tools and see how the best tools in each category can do to overcome the five main issues associated with categories of AI tools and see how the best tools in each category can do to overcome the five main issues associated with sustainability reporting and transformation across supply chains. Methodologically, after collecting data on available tools, we seek expert opinions and independent grading of three different supply chain student groups to double check the evaluation.

2 Literature review

2.1 Complex supply chains and requirements propagation/cascading

The complexity inherent for today's supply chains generate important barriers for any innovation adoption, reduce information flows and its speed, and increase transaction costs. Moreover, the incentives are misaligned as each tier of supply chain can be controlled by a separate business entity. In modern multi-tier supply chains, its total carbon footprint is largely decided by energy intensive lower tiers (Tachizawa & Wong, 2014; Wilhelm et al., 2016; Sauer & Seuring, 2023). In other words, Scope 3 of the emissions as mandated by the Greenhouse Gas Protocol (World Resources Institute, 2011). Therefore, the supply chain governance needs a reliable and robust propagation toolbox to go beyond the Tier 1 often dominated by large corporations. This toolbox consists of cascading the code of conduct (Jiang, 2009), monitoring the conduct with regular auditing (Locke et al., 2007) and legally binding sustainability related clauses in written contract (Hoejmose & Adrien-Kirby, 2012). However, despite all the efforts, data acquisition continues to be a major hurdle to achieve full potential of the system (Busch et al., 2022; Matthews et al., 2008). Kim et al. (2022) have also discovered that the lower in the supply chain we go the less green supply chain management practices are applied unless resources and/or incentives are available. These important transaction costs are one of the arguments we aim to address.

2.2 Main hurdles or issues

Low completeness and inconsistent quality of sustainability data is frequently reported as a major issue (Kolk, 2008; Ioannou & Serafeim, 2015). The lack of various resources has caused many SMEs to be unable to effectively participate in the digital transformation (Johnson & Schaltegger, 2016, Mittal et al., 2018; Eller et al., 2020), which also results in lack of standardised data essential for involvement (Rai et al., 2006; Sanders, 2007).

Johnson & Schaltegger (2016) explained how SMEs with limited resources face considerable internal costs when implementing sustainability reporting. This includes data collection, costs of analysis, but also transaction costs – getting advisory services on legal requirements, training, communicating with clients who are requesting such information, and many others. Where large companies have specialized people handling these tasks, SMEs tend to manage everything centrally within the general management team (Desouza and Awazu, 2006). In addition, duplication of data due to lack of harmonizing standards becomes an external cost burden for these companies (Locke et al., 2007; Soundararajan & Brown, 2016) while there are seldom universal authorities who would control the reporting among various entities and ensure there is no double counting or analysis loopholes. Choi & Hong (2002) and Borgatti & Li (2009) illustrated that governance in multi-tiered supply chains is lagging precisely where it is needed the most.

Among the largest issues, we have identified the following: associated internal and external costs (Rudzioniene, Bazdzius, 2023), topics and issues requested are actually not material for SMEs (Setyaningsih et al., 2024; Steidle et al., 2025), multi-tier analysis is not enabled (Grimm et al., 2023), data is sometimes collected and input manually which brings additional administrative costs (Troshani, Rowbottom, 2024) and AI and other automated systems might or might not be involved in the operations of the SMEs (Mustafa et al., 2025). We see an opportunity for the SMEs to search for tools that enable them to report sustainability data easier so they become more reliable players in the supply chains and partners to their larger clients.

2.3 Overcoming hurdles with AI

The issues mentioned above can now be effectively addressed because with AI, automated data extraction and reliable estimations where data is missing have both become feasible (Baryannis et al., 2019; Busch et al., 2022). AI also lowers participation cost for SMEs (Brynjolfsson et al., 2018)

AI can be useful and reduce costs mostly in the following cases, or tasks: data extraction (Spillias et al., 2025), supply chain mapping (Adegboye et al., 2024; Belu, Marinoiu, 2025), sustainability reporting (Ameh, 2024; Mustafa et al., 2025), dashboards (Akter, Kudapa, 2024), footprint calculation in logistics or in general (Frikha, Mrad, 2025; Huang, Mao, 2024), future prediction (Nweje, Taiwo, 2025), risk assessment (Boone et al., 2025, Zigiene et al., 2022), supplier selection process (Agarwal et al., 2019; Lau et al., 2006, Nida, 2025), logistics optimization (Boute, Udenio, 2022; Shawon et al., 2025), supplier communication and training (Boison et al., 2025) and audit targeting (Rainy, Chowdhury, 2024; Vaghani, 2024). These can be summarized in three main categories: data intelligence and visibility (data extraction, supply chain mapping, sustainability reporting, dashboards, calculation tools), risk identification and prioritization (prediction tools, risk management), and governance and accountability (supplier selection, logistics optimization, supplier communication and training, audit targeting). Overall, we build the conceptual model of AI involvement as specified in Figure 1 below.

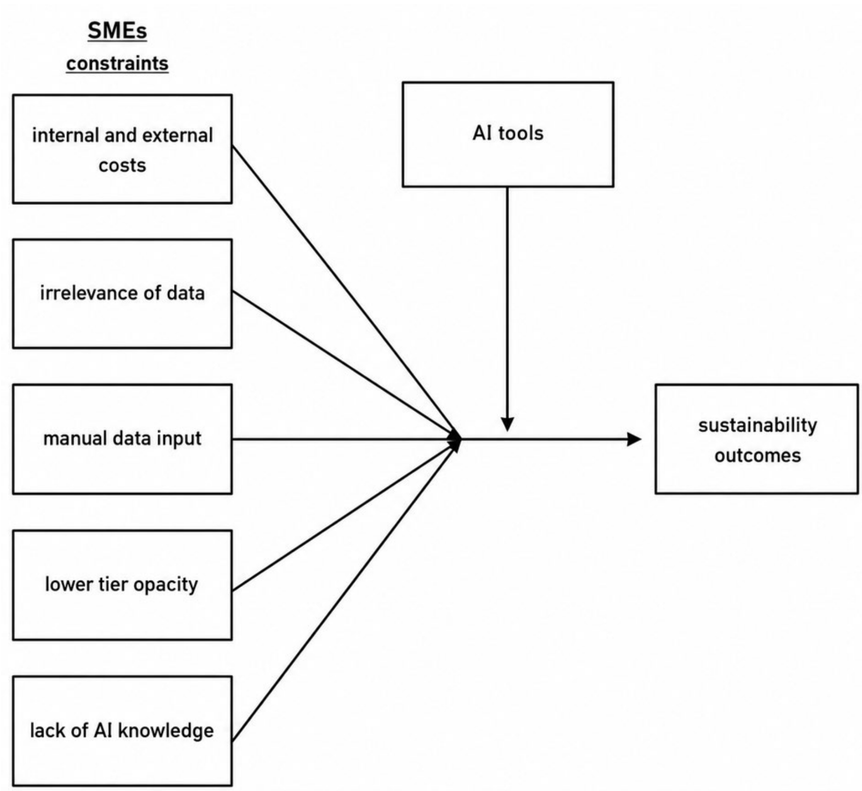

Figure 1: Relationship of SME constraints, AI tools and sustainability outcomes
Source: own elaboration

We listed potential settings where AI can be used to reduce the barriers and improve the sustainability outcomes at lower costs than ever before. Especially in situations where the transaction costs mean a large proportion of the final cost (i.e. for one-off requests and small-scale endeavors, which is all typical for SME settings), the moderating effect of an effective use of AI tools can be enormous.

3 Methodology and data

The methodology of this paper is a desk review of available AI tools. The data themselves are organized in 11 categories of tools (as reviewed in Table 1 below). The categories refer to the main tasks that AI can perform based on literature review. For each category, sample size refers to the number of individual tools, mostly in the form of software solutions offered to sustainability professionals and companies handling sustainability information.

Table 1: List of categories for tool evaluation

Category	Content	Sample size (n)
1	Data extraction	9
2	Supply chain mapping	6
3	Sustainability reporting in supply chains	9
4	Dashboards	9
5	Calculation tools	8
6	Prediction tools	9
7	Risk management	8
8	Supplier selection	9
9	Logistics optimization	9
10	Supplier communication and training	9
11	Audit targeting	10

Source: own elaboration

For each of the tools, five basic questions were asked to our student analysts to evaluate its fit (as shown in Table 2). The questions relate to the issues that SMEs normally face, and results from the literature review above (cost, relevance for SMEs, multi-tier analysis is enabled, automated data input, AI involvement). For each question, we already demonstrate the average score attained in our research (on a scale 1, meaning lowest/non-existent to 10, meaning highest/fully available).

Table 2: List of questions for tool evaluation

Question	Content	Average score
1	Are there discounts for SMEs? (1-10)	5,00
2	Is it suitable for small suppliers? (1-10)	6,43
3	Is the data input manual or automatic? (1=fully manual, 10=fully automatic)	8,12
4	Can we analyze data on more supply chain levels? (1-10)	7,43
5	What is the level of AI involvement? (1-10)	8,02

Source: own elaboration

We collected the data through an expert network in the area of sustainability reporting and supply chain professionals over the period 2024-2026. Secondly, an additional source of data was a collective research event handled on 25th February 2026 in Prague, Czechia, by three independent groups of university students in the courses of Supply Chain and International Business Operations – a total of 66 students participated in the evaluation. These groups are diverse culturally as they include Czech students, foreign students mostly from Eastern Europe studying in Czech, and U.S. exchange students studying in English. Yet, they already possess a certain understanding of supply chain management. Each of the groups were working on an independent document, pairs of students worked on various categories. After the collection of data, they graded the results of another pair to strengthen the evaluation. The collected data were structured and filtered for quality by the research team, with specific focus on feasibility. The average scores were assigned to each of the tools so we could evaluate the best three in each category.

4 Results

In Table 3, we can note average scores for each of the categories involved and the questions evaluated. Each company has received at least 2 different scores. On some occasions even up to six scores were assigned in cases where the same AI tool was listed by various pairs of students. We see that Question 1 received ambiguous results, where some companies offer significant discounts or even free usage for SMEs, while others use the same pricing. Similarly, the tools did not receive a very high score on the suitability for SMEs use (Question 2), especially in the categories of calculation tools, prediction tools, risk management and audit targeting where it scored below 6. The highest scores were for Questions 3 and 5, i.e. data is usually input automatically and AI is very much involved in the process. Interestingly, on Question 4 about the ability to handle multiple tiers of suppliers at the same time, calculation tools, which are one of the most prominent category with a large spotlight by the users, received the lowest scores.

Table 3: Average scores for each category and question.

Category	Q1	Q2	Q3	Q4	Q5
Data extraction	6,17	7,19	7,44	7,63	7,75
Supply chain mapping	4,36	6,81	9,49	7,52	8,11
Sustainability reporting in supply chains	5,72	7,00	9,39	7,00	7,89
Dashboards	6,67	6,94	9,56	7,28	7,89
Calculation tools	4,35	5,95	7,78	6,39	7,00
Prediction tools	4,28	5,72	6,61	7,94	8,22
Risk management	3,84	5,59	8,94	7,63	8,28
Supplier selection	4,93	6,50	7,74	7,22	7,87
Logistics optimization	5,17	6,44	7,50	7,44	8,44
Supplier communication and training	4,94	7,17	6,39	7,81	8,44
Audit targeting	4,58	5,45	8,45	7,83	8,28
OVERALL	**5,00**	**6,43**	**8,12**	**7,43**	**8,02**

Source: own calculation

Below in Table 4, we note the best three tools for each of the categories. Overall, the tool Flowgenius received the highest score of all – 9,20. It was nominated for the category of dashboards. 10 more tools received a score above 8,00 and overall, the best scores were also in the category of dashboards (overall, 7,67), mostly caused by the fact that these tools offer the most friendly prices to SMEs. On the other hand, calculation tools received the worst scores (on average, 6,29), followed by prediction tools (6,55) and supplier selection (6,85).

There were some tools which appeared repeatedly (demonstrated in Table 5). That means they are able to handle multiple tasks within one platform which could create opportunities for SMEs to reduce transaction costs, specifically for training, onboarding and initial data collection or integration with their internal systems, even though they were not necessarily graded as the most useful in individual categories. IntegrityNext was listed in five categories and Ecovadis in four of them. This does not mean that the other tools cannot handle more tasks than listed, it just means they were not named among the top three for the given category by anyone. This is a nice demonstration that our study's categorization, while robust, may not fully capture the functional integration offered by certain platforms, which could be a fruitful stream for future research.

Table 4: Top three tools for each category and score.

Category	1st	2nd	3rd
Data extraction	Prewave 8,30	Parseur 7,80	Sourcemap 7,60
Supply chain mapping	Everstream 7,80	Ecovadis 7,75	Resilinc 7,50
Sustainability reporting in supply chains	Normative 8,90	Greenomy 8,20	Greenly 8,10
Dashboards	Flowgenius 9,20	MS Power BI 8,30	Novata 8,10
Calculation tools	Normative 7,80	Worldfavor 7,70	IntegrityNext 7,55
Prediction tools	GMDH Streamline 8,10	DATUP 7,70	KINAXIS 7,20
Risk management	Sardine 7,90	IntegrityNext 7,60	Lasso Security 7,20
Supplier selection	FairSupply 7,67	GEP Smart 7,50	Worldfavor 7,30
Logistics optimization	Slimstock 8,00	PTV Logistics 8,00	Sourcemap 7,50
Supplier communication and training	SmartCat 8,40	Inventive AI 7,90	Kodiak Hub 7,70
Audit targeting	BeSirius 8,00	Prewave 7,80	Versed AI 7,60
OVERALL	**Flowgenius 9,20**	**SmartCat 8,40**	**MS Power BI 8,30**

Source: own calculation

Table 5: Most versatile tools.

Tool	Number of categories
IntegrityNext	5
Ecovadis	4
FairSupply	3
SourceMap	3
Interos	3
Everstream Analytics	2
Makersite	2
Prewave	2
Sweep	2
Resilinc	2
Wordfavor	2

Source: own calculation

5 Conclusion

The objective of the paper was to evaluate existing AI tools relevant for sustainability reporting and transformation within complex supply chains. We have identified three main areas of tools engagement – data intelligence and visibility, risk identification and prioritization, governance and accountability – with eleven main tasks where AI can importantly serve as an enabler to overcome five main challenges – costs, information irrelevance, manual data input, lack of visibility beyond Tier 1, and lack of AI implementation.

Results show that most tools use automated data collection and enable large deployment of AI. The results are fairly optimistic, but not entirely conclusive when it comes to the capability to analyze a full supply chain at all its tiers. The lowest scores were seen on the usefulness of the tools in SME contexts and their availability when it comes to costs. Therefore, some barriers to AI implementation in SMEs still remain. Thematically, it looks like calculation and prediction tools are the least suitable for usage by SMEs and lower tier suppliers, while on the other hand dashboards, sustainability reporting and data extraction tools received the best scores – all in the area of data intelligence and visibility. This implies that the largest potential for use by SMEs still lies in the area of descriptive tasks rather than analytical and decision support tools.

There are important business implications of our paper. Any company regardless of its size can refer to our overview and get the best tool that is relevant for their needs. Some tools even have the ambition to cover multiple sustainability-related tasks at a time. The transaction costs that the user firm needs to sacrifice and the time needed to set up the system can be reduced this way. Overall, using the tools might bridge the communication and expectation gaps between lead firms and their supply chain regardless of the tier in which the supplier is located.

Limitations of our research are clear – the mentioned tools are subject to economic development and might change in quality over time, or they might be removed from the market. However, we believe that our analysis serves as an important snapshot of the AI tool scene in the sustainability reporting and sustainability transformation in 2026. For future research, we would recommend diving deeper into the specific features of each tool, and to understand what is the best practice or necessary functionality for a given category. Also, it would be worthwhile to expand the evaluation process to increase its robustness. Lastly, SMEs needs in the area of sustainability should be explored to tailor potential innovation in the market to their needs.

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