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ARTIFICIAL INTELLIGENCE AS A DRIVER OF CORPORATE SUSTAINABILITY METRICS AND TRIPLE BOTTOM LINE ENGAGEMENT IN SUPPLY CHAINS

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Abstract. Despite global attention and increased investment, the implementation of digital technologies, for instance, artificial intelligence (AI), and its impact on sustainability metrics (SMII) and triple bottom line awareness (SEI) within large global supply chain companies, remains unclear. Digitization does not always promote sustainability due to high energy use and social inequality; ESG goals may also pose hurdles to further digital transformations. In contrast, long-term digitization is a driver of achieving sustainable goals. Due to a lack of consensus, this study researches the impact of implemented AI technology on SMII (operational level) and SEI (strategic level) within large, global supply chain firms. The study includes a literature review of 817 sources on the main theories and possible variable relationships. Secondary data from Fortune 500 industrial companies and their integrated, annual, and sustainability reports were collected and analyzed, yielding 10 digital technologies and 12 sustainability metrics as a basis for the subsequent survey of 106 participants. PLS-SEM modeling is used to test and interpret two hypotheses and to validate results. This study reveals a positive and significant relationship in implementing AI and a global supply chain company's SEI. This is explained by Institutional theory - external pressures and competition, also, that the large international companies have greater resource availability per the Resource Orchestration theory. Further studies could examine why AI affects sustainability at the strategic level but has little impact on the operational level.

Keywords: Artificial Intelligence; Digital Transformation, Sustainability; Triple-Bottom Line; Global Supply Chain Management; PLS-SEM

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JEL Classifications: O33, M11, M14, Q56

1. Introduction

Even though global spending and attention on the symbiosis of digitization and sustainability are growing, perceptions of digital transformation (DX) towards sustainability are mixed. It is expected that spending on digital transformation will increase from 2,58 trillion US dollars in 2025 to 3,88 trillion US Dollars by 2028 globally, as digital transformation includes technological advancements such as cloud computing and artificial intelligence (AI) (*Global Digital Transformation Spending 2028* | Statista, n.d.).

In Industry 4.0, digital technologies are the core for advancing manufacturing and the production of goods, and include AI, additive manufacturing, robotics, the internet of things (IoT), and virtual and augmented reality (VR/AR), and other technological advancements (*Industry 4.0: In-Depth Market Analysis* | Statista, n.d.).

Industrial manufacturing is mentioned as a primary industry that has been investing in digital transformation since 2021 (*Global Investment in Industrial Digital Transformation 2021* | Statista, n.d.). Digital transformation

does not necessary brings sustainability, there are concerns about high energy usage and social inequality associated with it. Actually, meeting ESG goals for environmental, social, and governance is one of the most common hurdles preventing global digitization initiatives (*Factors Preventing Digital Transformation Worldwide 2023*| Statista, n.d.).

However, previous research also shows that, when it comes to long-term organizational sustainability goals, digital and emerging technologies are believed to accelerate them significantly or play a largely positive role (*Companies' Sustainability Impact of Technology 2024*| Statista, n.d.).

As there is no clear consensus in past research and the arguments are quite contradictory, this study aims to provide insights into whether the implementation of digital transformation tools, such as artificial intelligence, can be considered as a positive driver of corporate sustainability measurement adoption and engagement in the triple bottom line within global supply chain companies. The research hypotheses are the following:

- H1: Artificial intelligence, if implemented within the company, may positively impact the use of sustainability metrics.
- H2: Artificial intelligence, when implemented within the company, positively impacts sustainability awareness by increasing engagement across all three pillars: environmental, social, and economic.

To reach this objective and test the hypotheses, the main research questions (RQ1-RQ4) are the following:

1. What are the most common digital transformation initiatives being implemented or already have been implemented within the global supply chain companies, based on the information provided in their integrated, annual, or sustainability reports?
2. What are the most common sustainability metrics within global supply chain companies, based on the information provided in their integrated, annual, or sustainability reports?
3. How does the most common digital transformation tool (AI) relate to the sustainability engagement within global supply chain companies, based on the survey results of 106 participants?
4. How does the most common digital transformation tool (AI) relate to sustainability measurement within global supply chain companies, based on survey results from 106 participants?

This study seeks to broaden the contemporary literature on the interplay between digital transformation, particularly artificial intelligence, and sustainability, while focusing on the adoption of the triple bottom line and sustainability measurement within global supply chain companies. It suggests a novel approach by providing insights into international, large-scale supply chain companies, analyzing 106 survey responses that will guide future research on the topic.

The article is structured in several sections. Section 1 begins with an introduction and provides the rationale, objective, hypotheses, and four research questions (RQ1-RQ4) regarding the implementation of digital transformation tools (artificial intelligence), the possible impact on corporate sustainability measurement adoption, and organizational engagement in the triple bottom line within global supply chain companies. Section 2 analyzes the theoretical background and recent literature analysis on digital transformation, sustainability, and supply chains, which serve as the basis for the hypotheses analyzed further. Section 3 provides details on the methodology and procedural steps taken, including: literature review; secondary data collection and analysis; survey design and data collection; PLS-SEM modeling and hypothesis testing; and interpretation and validation of the results. Section 4 provides results and discussion on RQ1-RQ4 and testing the hypotheses (H1, H2). Finally, the article concludes with suggestions for further research in Section 5.

2. Literature analysis

Based on the literature analysis, both digital transformation and sustainability are multidimensional. However, the results did not provide a dominating theory. At the end of 2024, the Web of Science (WOS) Core Collection and Scopus databases were analyzed for keywords related to supply chain, digital transformation, sustainability, and their implementation.

Dynamic capability theory is mentioned a few times for analyzing digital transformation and green supply chains in Egypt (Hamdy, 2024); digital transformation and corporate sustainability within listed companies in China (Ji et al., 2023); as well as big data, green lean six sigma, sustainable supply chains, and economic performance (Fayyaz et al., 2025). The Dynamic capability theory relates organizations' attention to internal and external competencies to a response to a dynamic environment (Alkaraan et al., 2024).

Other authors research dynamic capabilities together with manufacturing, sustainability, digital transformation, sustainable competitive advantage, economic, environmental, and social aspects (Felsberger et al., 2022). This could be used to explain the successful implementation of digital transformation tools such as artificial intelligence and the use of sustainability metrics as an operational task within the company (H1).

Wang et al. base digital transformation, sustainability in manufacturing, and motivation for adopting green supply chains on Institutional theory, which is mainly concerned with external factors (Wang et al., 2023). Institutional theory is commonly used for digital transformation topics and driving forces analysis, but less so for supply chains (Tiwari et al., 2024). However, institutional normative, mimetic, and coercive pressures could be sufficient for large, global companies to increase sustainability engagement and measure their sustainability indicators, as this became an international standard (Saida & Hasbaoui, 2024; Petera et al., 2021).

This theory could be used to explain the implementation of digital transformation technologies such as AI in response to external pressures from competitors and the market, while also influencing sustainability awareness under regulatory or stakeholder demands, as a strategic move within the company (H2).

Resource orchestration theory is used to analyze digital transformation, supply chain capabilities (such as agility, adaptability, and alignment), and sustainable performance (Mohaghegh et al., 2025). Sharma et al. provide positive relations with lean practices and sustainable operational outcomes (Sharma et al., 2024). In some cases, sustainability is mentioned only as secondary to digital transformation across operations, production, manufacturing, sourcing, customers, and sales in the oil and gas industry (Panduru et al., 2021). The theory of Resource orchestration could also explain whether increasing digital capabilities through AI positively impacts the company's sustainability awareness as a strategic orientation (H2).

Even though the digital transformation and sustainability engagement relationships are mentioned, they are not specifically aligned. For instance, there is focus on broader topics such as supply chain, sourcing, production, digital transformation, digitization barriers, and sustainability, as per the Sustainable Development Goals (SDGs) (Dadsena et al., 2024). The SDGs are also studied alongside digitization, digital accessibility, sustainability, and sustainable transformation in production as the digitization sustainability matrix (Gupta et al., 2020).

The circular economy is mentioned in the publications in relation to supply chain and production, digital transformation and the impact of digitization on circularity (Agnusdei et al., 2023). Giudice et al. analyze data-driven decision-making based on big data in circular supply chains and logistics as the moderating effect (Del Giudice et al., 2020). Or energy saving, sustainability, digitization, and digital documentation in railway infrastructure (Raco, 2023). Also, production, manufacturing, digital transformation, digitalization, and sustainable digital economic growth receives scholarly interest as well (Yin et al., 2022).

Bashynska et al. focuses on analyzing digital transformation and sustainability, and the outcomes of digital smartization projects across the supply chain, factories, industrial enterprises, production, and supplier dimensions (Bashynska et al., 2023). It is followed by waste production and conscious resource usage, digital planning and digital manufacturing, digital transformation, digitization, and sustainability (Nölle, 2020). Also, authors focus on lean manufacturing, production, and digital transformation, digitization, and sustainability by integrating digital twins and artificial intelligence to optimize production (Piras et al., 2024).

González Chávez et al. use a specific term, twin transition or twin transformation, that encompasses both digital and sustainable aspects across manufacturing, production, the supply chain, and the value chain (González Chávez et al., 2023). Or twin transformation for circular supply and value chains, smart manufacturing, and

digital transformation for reaching sustainability goals within production (Hong et al., 2024). Other researchers, such as Patalas-Maliszewska & Łosyk, focus on transition to digital production, sustainable solutions, sustainable development, and supply chain management, production, sales, digital manufacturing, followed by sustainable supply chain management practices, sustainable supplier selection (SSS), and resilient manufacturing strategy (RMS) while incorporating additive manufacturing (Patalas-Maliszewska & Łosyk, 2024).

There are some mentions of the relationship between digital transformation and sustainability metrics. It includes Industry 5.0-4.0, supply chain, manufacturing, production, digital transformation, sustainability, circular economy, ESG, and circularity indicators (Payer et al., 2024) or decision-making models on technology selection (Erbay & Yıldırım, 2019).

These topics cover a variety of industries, including digital transformation, digitalization, and the sustainability objectives of organizations within shipbuilding supply chains (Diaz et al., 2020). IoT is followed by big data models, cloud computing, precision technologies, and sustainability (including environmental footprint) in food production (Moysiadis et al., 2020).

Digital transformation tools related to sustainability and supply chains are provided, including additive manufacturing, automation, digital retrofitting, the Internet of Things, building information modeling, geographic information systems, machine learning, big data, cloud computing, virtual and augmented reality, artificial intelligence, and more. For instance, additive manufacturing is mentioned as a way to enhance the digital value chain and sustainability in manufacturing, industrial production, the digital supply chain, logistics, inventory management, and decentralized manufacturing (Araújo et al., 2021).

As for other common digital transformation tools, automation is mentioned alongside production, manufacturing, sustainable manufacturing, value chain, supply chain, suppliers, and sustainability (Cerezo-Narváez et al., 2018). Digital retrofitting of legacy industrial machines, Industrial Internet of Things (IIoT), and manufacturing include such topics as sustainable manufacturing, production, lean production, purchasing, logistics, and sales (Tantscher & Mayer, 2022). Combined effects of digitization (e.g., digital twin, BIM, and GIS), sustainability (e.g., zero energy district, renewable energy systems for sustainable mobility), and energy efficiency measures are explored within zero energy port areas (Agostinelli et al., 2022).

Detailed digital transformation tools (e.g., digital twin, enabled by cloud computing, artificial intelligence, machine learning, big data, and BIM) and sustainability within the supply chain are also mentioned by scholars (Ruperto & Strappini, 2021). It is followed by BIM and GIS, automation, urban sustainability within the construction supply chain, procurement, suppliers, warehousing, and production processes (Uzairuddin & Jaiswal, 2022).

Digital twins, together with topics of manufacturing, production, supply chain, supplier, consumers, and economic, environmental, and social sustainability performance indicators within the ceramic industry (Contini et al., 2023). In some cases, 3D printing is also mentioned as a technology in construction, manufacturing, and production projects (Chang & Antwi-Afari, 2023).

Based on the literature analysis, a structural equation model is developed, positing that artificial intelligence may affect the use of sustainable metrics within large, global supply chain companies (H1), grounded in the Dynamic Capability Theory. While the second hypothesis (H2) proposes that artificial intelligence may foster greater strategic sustainability awareness within large global supply chain companies, it is grounded in Institutional theory and Resource orchestration theory.

3. Methodology

This chapter provides information based on the research procedures conducted in this study. The main objective of this study is to analyze the implementation of digital transformation tools, such as artificial intelligence, which can be considered as a positive driver of corporate sustainability measurement adoption and engagement

in the triple bottom line within global supply chain companies. Therefore, a mixed-methods approach combining secondary (company report analysis) and primary quantitative data (survey results) is chosen. The research phases and related tasks are presented in a procedural diagram and are summarized in Figure 1 (Moubarac et al., 2012).

Phase	Steps	Procedures	Products
1.	Literature review	Literature review of Web of Science and Scopus databases publications. (n = 817). Content analysis of academic publications.	Extracted data and annotated references.
2.	Secondary data collection and analysis	Secondary data: 14 industrial company annual, sustainable or integrated reports, companies selected based on Fortune 500 report (<i>Fortune Global 500 – The Largest Companies in the World by Revenue Fortune</i> , n.d.). (n = 103) Content analysis of secondary data (company reports), descriptive statistics. <i>Digital transformation tools (n=10); sustainability metrics (n=12)</i>	Extracted, coded and categorized data with MAXQDA software, annotated references. The diagrams with most common digital transformation tools and sustainability metrics created with MAXQDA software.
3.	Survey design and data collection	Survey questionnaire distributed through LinkedIn: public post (n=1) and private messages (n = 2409). Obtained sample size: 106, including: 1) quota for employees of fourteen industrial companies based on the Fortune 500 report (for data triangulation), 2) similar company employees (for a broader understanding of the phenomenon). (n = 106, with the response rate of 4,4%)	Survey dataset collected via Google Forms.
4.	PLS-SEM modelling and hypothesis testing	Testing hypotheses significance by using partial least squares structural equation modeling (PLS-SEM)	Tested significance of H1 and H2, and mediation by using SmartPLM 4 software.
5.	Interpretation and validation	Concluding the findings, validation of the model.	Validated model.

Figure 1. A Procedural diagram of research activities.

Source: authors

In the first phase, the Web of Science Core Collection and Scopus databases are used for the literature review. The specific keywords used for the search are: supply chain (“supply chain” OR “operation*” OR “procur*” OR “production” OR “inventory” OR “sale”), followed by digitization (“twin transition” OR “twin transformat*” OR “digital transition” OR “digital transformat*” OR “digitization” OR “digitalization”); sustainability (“green transition” OR “green transformat*” OR “sustainable transition” OR “sustainable transform*” OR “sustainab*” OR “triple bottom line” OR “ESG”) and implementation (“project” OR “invest*” OR “CAPEX” OR “capital expenditur*”). Comparing similar publications yielded a final list of 817 sources.

In the second phase, as per the Procedural diagram (Figure 1), the secondary data sample is selected from Fortune Global 500 companies in the Industrial sector, as this sector primarily relates to supply chain management. Each company’s website is searched for integrated, annual, or sustainability reports from 2020 to

2024, resulting in total of 103 reports for further content analysis. The reports are analyzed by using MAXQDA software for data extraction, coding, and categorization. The data is coded by one of the authors according to literature analysis and provides information on the most commonly used 10 digital transformation technologies: Internet of Things (IoT), Cloud computing, Blockchain, Big data, Artificial Intelligence (AI), Digital twin, Building information modeling (BIM), Geographic information system (GIS), Life cycle analysis (LCA), and Data analytics.

Also, the most common 12 sustainability metrics are extracted, coded by one of the authors and categorized by the MAXQDA software, into such groups as: Water withdrawal, Energy consumption (GWh), Renewable energy consumption (%), GHG emissions scope 1 and 2 (kilotons CO₂e), Total waste sent to landfill (kilotons), Number of nationalities, Women in workforce (%), Women in senior management positions (%), Lost-time injury frequency rate, Average hours of training per year and employee, Employee engagement score, and Community spending (volunteering). Both digital technologies (n=10) and sustainability metrics (n=12) were included as survey options (Table 1).

Table 1. The questions distributed via online survey

No.	Question	Options
1.	How many employees does your organization have?	○ 1–9 employees ○ 10–49 employees ○ 50–249 employees ○ 250+ employees ○ Not applicable / Don't know ○ Other
2.	Please select all the regions where your company operates. (Select all that apply)	○ North America ○ South America ○ Europe ○ Africa ○ Asia ○ Oceania ○ Not applicable / Don't know ○ Other
3.	Three pillars of sustainability are environmental, economic, and social. Please select in which sustainability aspects your company is actively engaging in. (Select all that apply)	○ Environmental - my company focuses on protecting the natural environment, conserving resources, and minimizing pollution ○ Social - <...> emphasizes the well-being of people and communities ○ Economic - <...> focuses on creating long-term economic prosperity and stability ○ Not applicable / Don't know ○ Other
4.	Please indicate which of the following digital transformation activities are currently being implemented or have been implemented in your company. (Select all that apply)	○ Internet of Things (IoT) ○ Cloud computing ○ Blockchain ○ Big data ○ Artificial Intelligence (AI) ○ Digital twin ○ Building information modeling (BIM) ○ Geographic information system (GIS) ○ Life cycle analysis (LCA) ○ Data analytics ○ Not applicable / Don't know ○ Other
5.	Which of the following sustainability metrics does your company currently calculate or track? (Select all that apply)	○ Water withdrawal ○ Energy consumption (GWh) ○ Renewable energy consumption (%) ○ GHG emissions scope 1 and 2 (kilotons CO₂e) ○ Total waste sent to landfill (kilotons) ○ Number of nationalities ○ Women in workforce (%) ○ Women in senior management positions (%) ○ Lost-time injury frequency rate ○ Average hours of training per year and employee ○ Employee engagement score ○ Community spending (volunteering) ○ Not applicable / Don't know ○ Other

Source: authors

As for the third phase of the Procedural diagram (Figure 1), the survey was distributed by one of the authors to 2409 participants via private LinkedIn messages and one public LinkedIn post in August-December 2025. As per Table 1, the questionnaire includes questions on the organization's demographics, such as company size (the primary interest is large companies with 250+ employees) and the regions in which the company operates (the primary interest is global companies - companies that operate in more than one continent - are considered global).

It is followed by questions related to RQ1 - digital transformation activities being implemented or successfully implemented in the past (as the primary interest is to figure out the pattern with the report results of 14 companies). Then RQ2 and RQ4 - sustainability metrics calculated within the companies (as the primary interest is to figure out the pattern with the report results of 14 companies). And finally, about the RQ3 - pillars of sustainability that the company engages in (as the primary interest is all three triple bottom line pillars).

The main focus of phase four is on developing the structural model for the PLS-SEM (Figure 2). Partial least squares structural equation modeling (PLS-SEM) is chosen and relevant for understanding complex interactions among AI and SEI, AI and SMII, and SEI and SMII (Y. Chen et al., 2024). PLS-SEM analysis method, which is commonly found in the social sciences research, allows researchers to assess the relationships among latent variables, also the direct and indirect effects between variables by performing calculations with SmartPLS software, which is considered reliable by the scholars (Salam et al., 2017; Gelashvili et al., 2022).

First, artificial intelligence (AI) is used as an independent variable, and the triple bottom line pillars serve as a sustainability engagement index (SEI), followed by the sustainability metric index (SMII). Second, the company size (LARGE_COMPANY) and operating across more than one continent (GLOBAL) are treated as latent variables.

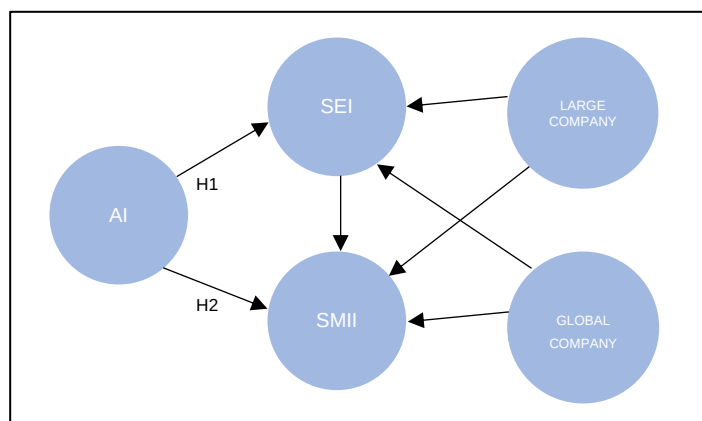


Figure 2. Structural model of the PLS-SEM.

Source: authors

In this research, SmartPLS 4 software and the PLS-SEM method are used to analyze data from 106 respondents, as PLS-SEM is sufficient for small sample sizes (100-150) (Saeed et al., 2019). First, the data is manually cleaned in the Excel spreadsheet by assigning binary values to each variable: 1 is assigned as “yes” and 0 is assigned as “no”. The separate columns are created in order to indicate whether the organization has engaged in activities related to environmental, social, or economic sustainability or only two, one or none of triple bottom line activities.

The numerical values are also assigned to the sustainability metric results (12 variables), each are listed as a separate column with binary values as well. New columns are created with calculated sums for SEI and SMII each by using the previously mentioned simplification of data by assigning binary values and creating separate columns. The cleaned data were loaded into SmartPLS, and latent variables and connections were assigned, allowing the use of the calculation function (with standard parameters).

The last phase (phase five) is closely related to the bootstrapping function used for non-normal data and to testing the hypotheses (H1 and H2) (Sadeli et al., 2023). According to the standardized path coefficient (β), values greater than zero indicate a positive effect, values less than zero indicate a negative effect, and values equal to zero indicate no effect (Salam et al., 2017). According to the p-value, results are statistically significant if the p-value is < 0.05 ; if > 0.05 , the data is statistically insignificant (Sadiq, 2022).

5. Results and Discussion

According to the results for RQ1, artificial intelligence is the most commonly used digital transformation tool across 14 global supply chain companies analyzed from the Fortune 500 list and the content analysis of their 103 integrated, annual, or sustainability reports from 2020 to 2024 (Figure 3). Digital twin, data analytics, and Internet of Things follow it. These results are similar to the literature analysis that is based on publication data from the databases of Web of Science Core Collection and Scopus.

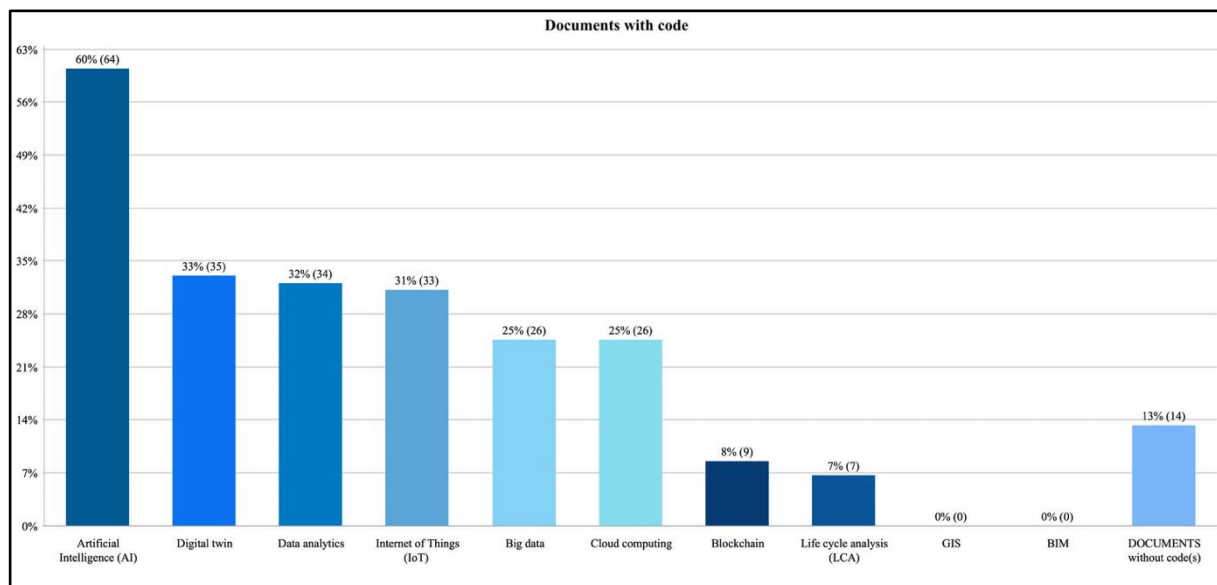


Figure 3. The most commonly mentioned digital technologies within Fortune Global 500 Industrial companies.

Source: authors'

Based on the survey results of 106 participants, the second most common digital transformation tool is also artificial intelligence (Figure 4). Contrary to the Fortune 500 company report analysis, the most common DX tool is data analytics, followed by artificial intelligence, the internet of things, and cloud computing. The difference may be that the company develops reports for external use and is influenced by institutional pressures and a strategic perspective. At the same time, company employees answer the surveys and may provide insights from a more personal perspective.

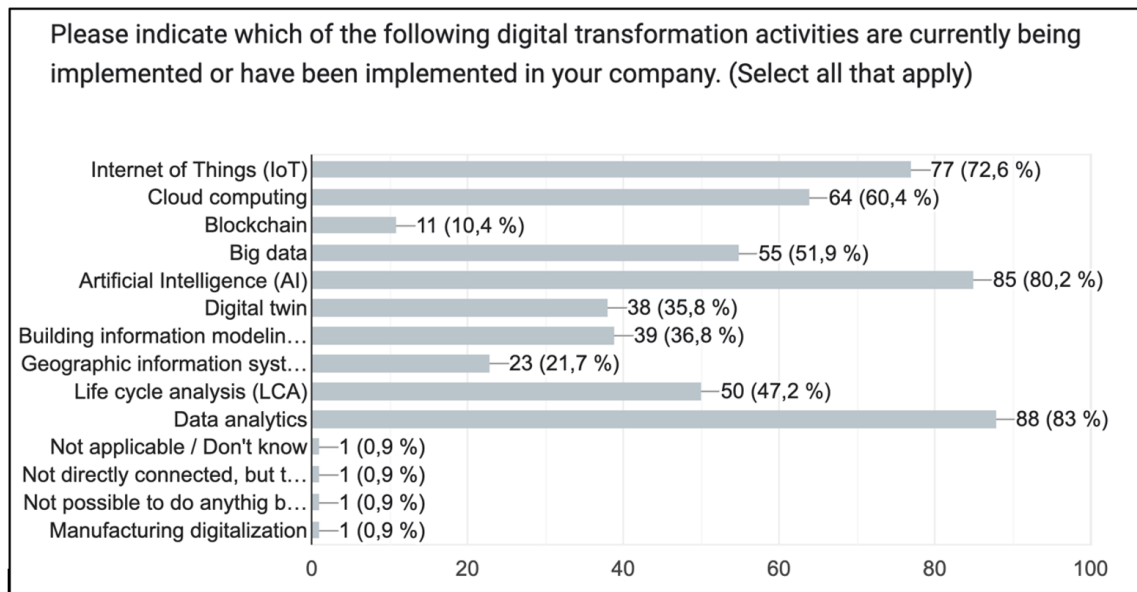


Figure 4. The most commonly used digital transformation tool.

Source: authors

As per RQ2, the greenhouse gas (GHG) emission scope 1 and scope 2 calculations (environmental pillar of three bottom line) are the most common sustainability metrics across 14 global supply chain companies analyzed from the Fortune 500 list and the content analysis of their 103 integrated, annual, or sustainability reports from 2020 to 2024 (Figure 5). It is followed by employee engagement (social pillar), community spending – volunteering (social pillar), and water withdrawal (environmental pillar).

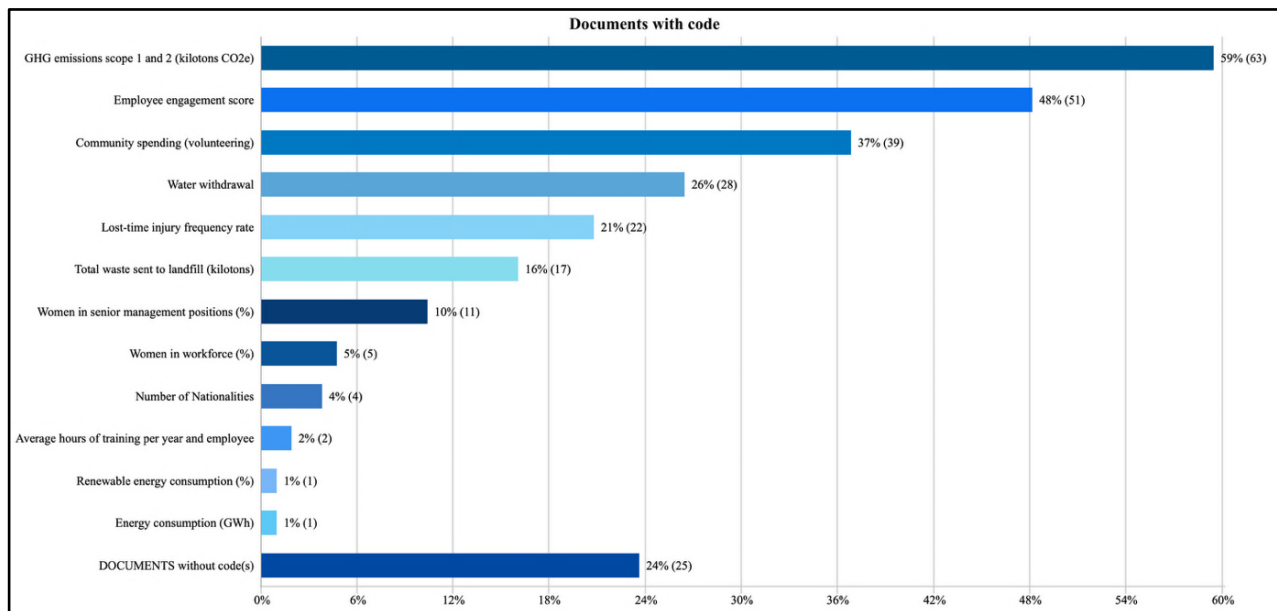


Figure 5. The most commonly mentioned sustainability metrics within Fortune Global 500 Industrial companies.

Source: authors

Based on the survey results of 106 participants, the fifth most common sustainability metric is GHG emissions calculation (Figure 6). Contrary to the Fortune 500 company report analysis, the most common sustainability metric is energy consumption (GWh), followed by the percentage of women in the workforce and employee engagement score.

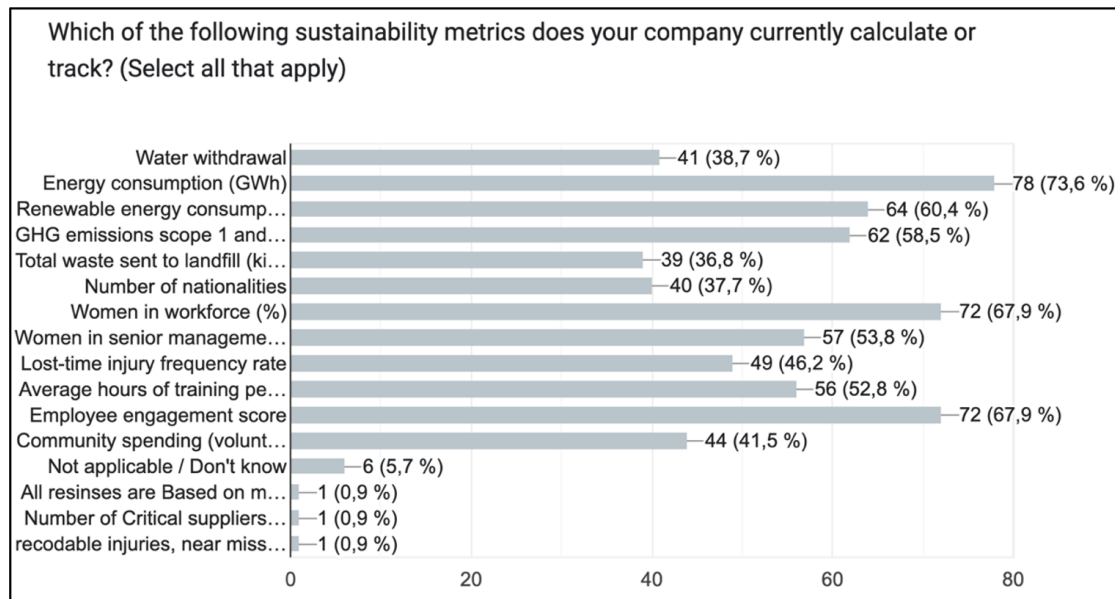


Figure 6. The most commonly used sustainability metrics.

Source: authors

As per RQ3, the survey participants indicate that the environmental pillar is the most common that their company engages in (Figure 7). It may be related to the perception that sustainability is sometimes tied only to environmental issues, while the social and economic pillars may not always be considered as common.

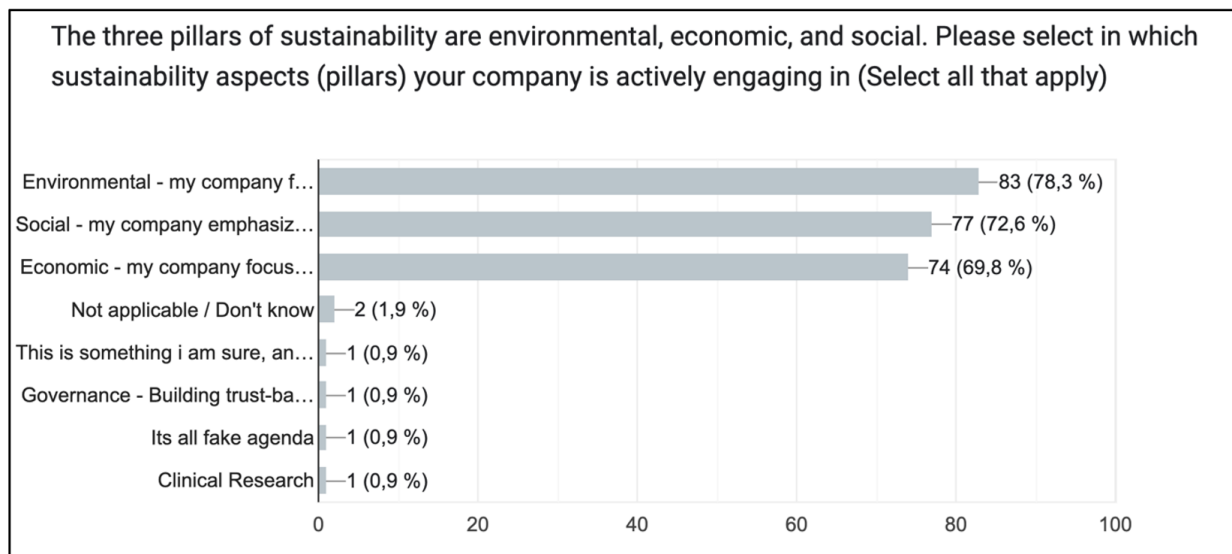


Figure 7. The company's engagement in the sustainability aspects (pillars).

Source: authors

The collected data were loaded into SmartPLM, and the results indicate several relationships among the variables (Figure 8, Table 2). First of all, artificial intelligence (AI) and the sustainability engagement index (SEI) show a positive ($\beta = 0.663$), statistically significant relationship ($p = 0.006$), as the standardized path coefficient is greater than zero and the p-value is less than 0.05. This supports the H2 hypothesis that AI, when implemented within a global supply chain company, positively impacts sustainability engagement by strategically raising awareness of all three pillars. Also, this relates the findings to the Institutional theory and Resource orchestration theory.

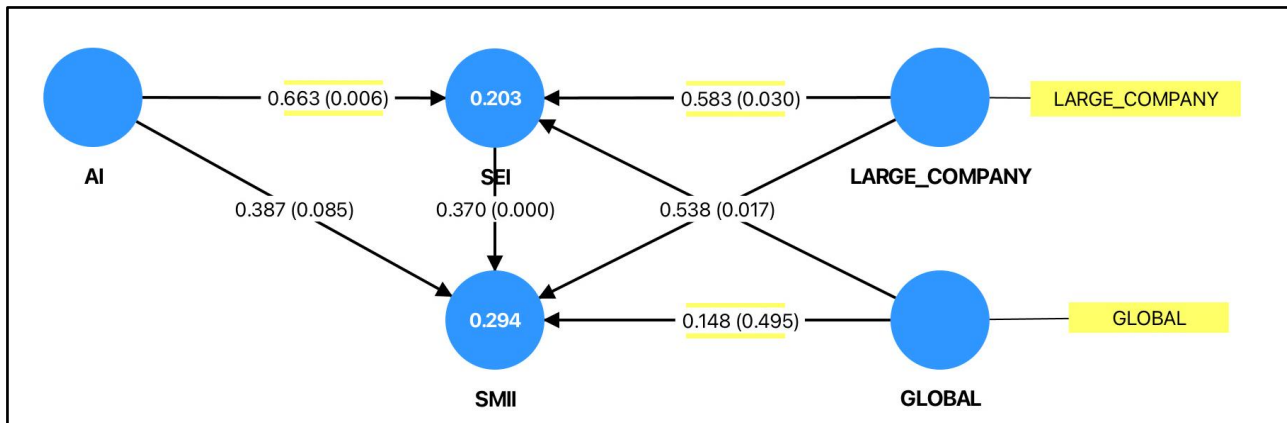


Figure 8. Structural model of the PLS-SEM with calculated results.

Source: authors

Also, there is a positive effect ($\beta = 0.370$) and a significant relationship ($p = < 0.001$) between the sustainability engagement index (SEI) and the sustainability metric index (SMII) in global supply chain companies. Large-sized (>250 employees) companies (LARGE_COMPANY) and the sustainability engagement index (SEI) show a positive effect ($\beta = 0.583$) and a significant relationship ($p = 0.030$). This could be explained by the greater resources in large companies, which also aligns with the Resource orchestration theory. Similarly, large-sized companies (LARGE_COMPANY) and the sustainability metric index (SMII) show a positive effect ($\beta = 0.566$) and a significant relationship ($p = 0.027$). Also, companies operating in more than one continent (GLOBAL) and the sustainability engagement index (SEI) also show a positive effect ($\beta = 0.538$) and a significant relationship ($p = 0.017$), this may also be explained by higher variety and availability of resources.

Table 2. Calculated results of structural path, values, and results interpretation.

Structural path	β -value	t-value	p-value	Results interpretation
AI -> SMII	0.387	1.722	0.085	Positive effect, not significant (H1 not supported)
AI -> SEI	0.663	2.729	0.006	Positive effect, significant (H2 supported)
SEI -> SMII	0.370	3.965	<0.001	Positive effect, significant
LARGE_COMPANY -> SEI	0.583	2.166	0.030	Positive effect, significant
LARGE_COMPANY -> SMII	0.566	2.219	0.027	Positive effect, significant
GLOBAL -> SEI	0.538	2.380	0.017	Positive effect, significant
GLOBAL -> SMII	0.148	0.682	0.495	Positive effect, but not significant

Source: authors

Although there is a positive effect ($\beta = 0.387$), the relationship between artificial intelligence (AI) and the sustainability metric index (SMII) is insignificant ($p = 0.085$) among global supply chain companies. Therefore, H1 is also not supported: AI, if implemented within the company, may not positively impact the use of sustainability metrics at the operational level of the supply chain company, and there is insufficient empirical evidence for the Dynamic Capabilities Theory; therefore, the theory cannot be supported by using this dataset. Moreover, companies operating in more than one continent (GLOBAL) and the sustainability metric index (SMII) show a positive effect ($\beta = 0.148$). Still, the relationship is insignificant ($p = 0.495$); this may be due to differences in regulations across continents, so the operational measurement is not as standardized as general awareness of sustainability.

Therefore, future studies may conduct more in-depth analyses of why implemented artificial intelligence enhances sustainability awareness at the strategic level but does not have a significant impact on sustainability

metric usage at the operational level within large global supply chain companies. This may raise questions for other researchers about strategic-operational differences in the sustainability aspects of AI use in supply chain companies, particularly regarding the implementation gap in sustainability metrics.

Conclusions

As there is no clear consensus on digital transformation and sustainability metrics measurement (operational level) and sustainability awareness (strategic level) within large global supply chain companies, this study aims to analyze the impact of implemented artificial intelligence technology on sustainability metrics and triple bottom line awareness. As two hypotheses are tested and four research questions are answered, the study concludes with the confirmed hypothesis (H2) that implementing AI within a global supply chain company has a positive impact on sustainability engagement in the triple bottom line pillars of environmental, social, and economic aspects.

From a theoretical perspective, this aligns with Institutional theory, given the high external pressures on large and global companies from both stakeholders and competitors. Also, as large international companies tend to have better access to various resources, they can allocate them to topics such as AI implementation and increased sustainability awareness, in line with the Resource Orchestration theory. The main contribution of the study is the empirical identification of strategic and operational differences: AI significantly influences strategic sustainability awareness but shows no statistically significant influence on operational sustainability metrics. This study can also provide directions for future analysis, as the empirical results suggest that artificial intelligence is the most commonly used digital transformation tool among Fortune 500 global supply chain companies, and these results are consistent with the literature. However, the survey of 106 participants found that it is the second-most-common digital transformation tool, behind data analytics. Future investigators may analyze the differences, as they may provide explanations for the differences between the company-developed reports for external use, which are influenced by institutional pressures and a strategic perspective, and the employees' survey responses, which may offer insights from a more personal perspective.

Also, there are differences between the company's reported sustainability metrics and those of survey participants, which could be further analyzed. As per the company's integrated, annual, and sustainability reports, the greenhouse gas (GHG) emissions calculations (the environmental pillar of the triple bottom line) are the most common metrics. At the same time, the survey results suggest that GHG emissions calculation is only the fifth most common sustainability metric. Contrary to the company report analysis, the most common sustainability metrics are energy consumption, the percentage of women in the workforce, and employee engagement score. This may suggest that the specifics of greenhouse gas calculation are more within the sustainability expert's responsibility, rather than broader topics such as gender- and employee-related matters or technical and environmental aspects that are more evident within the company, such as energy use in offices or manufacturing facilities.

Moreover, the results of the PLS-SEM analysis indicate that there may be even more opportunities for further research, as a positive effect and significant relationship exist between the sustainability engagement index and the sustainability metric index in global supply chain companies, which could be further explained by other empirical studies focusing solely on the sustainability matters. Large companies and the sustainability engagement index show a positive relationship and a significant association, which may stem from the requirement to disclose sustainability performance under country- or regional-level regulations, as well as from more employees focusing on such topics as their primary function. This could be further explored by analyzing not only from the standpoint of Institutional theory and Resource orchestration theory, but also including other theories. As this study uses PLS-SEM as the primary analysis method, an alternative, such as Bayesian structural equation modeling (BSEM) for complex models and small samples, could be suggested instead (Q. Chen et al., 2024).

From a managerial perspective, the study could provide valuable insights to top management and their decision-making on resource utilization regarding digital technologies, such as AI implementation, and the expectation that it will positively affect their sustainability metrics, which may not be the case. Therefore, managers should

allocate additional resources specifically to sustainability metric calculations rather than expecting sustainability awareness to yield the actual results. Also, the company reports do not always indicate the most commonly used digital transformation technologies, or at least some employees may not be aware of their use, or they may be used only fragmentarily, even though a lot of attention is given to external communication, probably due to external pressures of the stakeholders and by seeking a competitive advantage. Therefore, employees should also be given specific training and information on their management's preferred adoption of novel technologies. This study is subject to several limitations as well. By focusing only on large, global supply chain companies, future studies may include companies of different sizes (micro, startups, small or medium), and more regional companies (focusing only on one operating region instead of global, for instance, Europe), and from other industries (e.g., services or consulting). Also, the survey data collection may be considered limited, as the response rate was 4,4% (103 participants out of 2409 sent requests). This could be solved in future studies by conducting a more widespread study of a broader population, rather than focusing solely on large and global supply chain companies. As this study exclusively focused on AI, as the solely digital transformation technology, other technologies (for instance, data analytics, the internet of things, BIM, GIS, robotics, automation, and virtual and augmented reality), could be researched in relation to sustainability awareness and metrics in the future.

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