

# Towards a sociotechnical framework and maturity model for artificial intelligence-driven supply chain due diligence

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## ABSTRACT

**Objective:** The objective of this article is to develop an integrated sociotechnical framework and a diagnostic maturity model for artificial intelligence-driven supply chain due diligence. It addresses the implementation gap under escalating mandatory regulations by demonstrating how technological capabilities, ethical governance, and cultural adaptation interact, shape each other, and must be developed together.

**Research Design & Methods:** We employed a theory-building approach and conducted a purposive literature synthesis. We applied thematic analysis, grounded in institutional theory, stakeholder theory, and the technology-organisation-environment framework to develop an integrated framework and maturity model, illustrated via analysis of European e-commerce sustainability disclosures.

**Findings:** We identified three critical sociotechnical interfaces (tech-ethics, ethics-culture, and tech-culture) and derived three formal propositions from the analysis. We propose, organisational readiness may function more as a coefficient than an additive factor, where the substantive effectiveness of technological tools depends on cultural commitment. A distinct ‘institutional governance gap’ emerges from the illustrative application.

**Implications & Recommendations:** Organisations, including small and medium-sized enterprises and entrepreneurial ventures operating within mandatory due diligence supply chains, should move beyond technocentric approaches to assess artificial intelligence (AI) readiness simultaneously across operational, institutional, global, and strategic layers. The maturity model enables systematic capability gap identification.

**Contribution & Value Added:** We propose a diagnostic maturity model and formal propositions that bridge the gap between legal theory and organisational implementation. These contributions are conceptual and require empirical validation.

**Article type:** conceptual article  
**Keywords:** artificial intelligence; supply chain due diligence; Corporate Sustainability Due Diligence Directive; EU AI Act; sociotechnical framework; TOE framework; organisational readiness  
**JEL codes:** M14, M16, O33

Received: 5 February 2026

Revised: 12 May 2026

Accepted: 23 May 2026

## Suggested citation:

Welsen, M., & Sułkowski, L. (2026). Towards a sociotechnical framework and maturity model for artificial intelligence-driven supply chain due diligence. *Entrepreneurial Business and Economics Review*, 14(3), 183-203. <https://doi.org/10.15678/EBER.2026.140310>

## INTRODUCTION

Mandatory due diligence legislation marks a paradigm shift in corporate accountability across global value chains (Wilhelm, 2024), with AI increasingly central to its implementation (Shahzadi *et al.*, 2024). The EU Corporate Sustainability Due Diligence Directive (CSDDD), agreed in June 2024 with member state transposition required by July 2027, requires companies to identify and address adverse human rights and environmental impacts across global value chains (European Commission, 2024a, 2025b). In Germany, authorities enacted similar obligations under the Supply Chain Due Diligence Act (LkSG), in force since January 2023, although they have also suspended reporting obligations from 2025 onward due to the upcoming CSDDD (Sinnig & Zetzsche, 2025; Bundesregierung, 2025). This shift demonstrates

the broader trend towards foreign corporate accountability (Rühmkorf, 2023). Early adopters gain legitimacy advantages while laggards face institutional exclusion (Campbell, 2007). To manage such complex requirements, organisations deploy AI systems for supplier monitoring and risk assessment (Shahzadi *et al.*, 2024; Yang *et al.*, 2023). However, the deployment of AI itself is now regulated. The European Union (EU) Artificial Intelligence Act (Regulation 2024/1689) has established risk-based requirements for AI systems, with AI used in employment and worker management classified as ‘high-risk’ (European Commission, 2024b). Organisations that deploy AI for due diligence face overlapping compliance obligations as these frameworks converge. This creates demands to satisfy simultaneously technological, ethical, and cultural requirements (de Oliveira Serra, 2025; Sinnig & Zetzsche, 2025).

AI technologies, such as machine learning, natural language processing (NLP), and predictive analytics all promise to automate supplier data analysis, identify risk patterns, and generate audit-ready documentation (Agrawal *et al.*, 2024; Nweje & Taiwo, 2025; Shahzadi *et al.*, 2024; Shamsuddoha *et al.*, 2025; Yang *et al.*, 2023). Moreover, AI adoption can enhance Environmental, Social, and Governance (ESG) performance (Lin & Zhu, 2025; Vann Yaroson *et al.*, 2025). We argue that there is a gap in the literature on how organisations possess AI tools while lacking readiness to deploy them ethically within complex regulatory environments. This gap reflects the following paradox: The CSDDD demands rigorous evidence, yet data remains qualitative, unstructured, and fragmented across supplier tiers (Brintrup *et al.*, 2023). The volume of information exceeds human processing capabilities and creates a gap between expanding responsibility and capacity to translate data into compliance decisions.

Notably, the existing research examines these AI challenges in isolation: technological capabilities (Shahzadi *et al.*, 2024; Yang *et al.*, 2023), organisational culture (Cannas *et al.*, 2024; Samuels, 2024), and ethical governance (Batool *et al.*, 2025; Stahl & Eke, 2024). This fragmentation obscures the fact that these dimensions dynamically shape one another. Despite growing scholarly attention to both AI governance and mandatory due diligence, research integrating these domains remains scarce.

Recent work addresses these areas only separately. Trindade *et al.* (2025) studied CSDDD design principles but did not address AI implementation challenges. Akbarighatar *et al.* (2023) developed a sociotechnical AI maturity model but did not apply it to mandatory due diligence contexts. Culot *et al.* (2024) reviewed AI in supply chain management but did not engage with emerging regulatory frameworks. Currently, no research integrates institutional theory, stakeholder theory, and the technology–organisation–environment (TOE) framework to explain how organisations respond to the convergent pressures of the CSDDD and EU AI Act.

Single-theory explanations also prove insufficient. Firstly, institutional theory explains why organisations must respond to regulatory pressures (DiMaggio & Powell, 1983), but cannot explain why firms facing identical pressures respond differently and lack mechanisms for priority-setting among competing demands. Secondly, stakeholder theory explains how organisations navigate competing demands (Mitchell *et al.*, 1997), but does not predict implementation success without attention to technological and organisational capabilities. Thirdly, the TOE framework captures why capability variation leads to different outcomes (Tornatzky & Fleischer, 1990), but does not account for the coercive and normative pressures that mandate a response in the first place. The central theoretical contribution lies in reconceptualising organisational readiness as a coefficient instead of an additive factor: technological investments are multiplied and cultural commitment is not just added. This explains why identical AI systems produce divergent outcomes across organisations. The argument is that if cultural commitment is low, even large tech investments bring little benefit; if cultural commitment is high, smaller investments can yield greater impact.

We addressed the literature gaps with our integrated framework by combining all three lenses and revealing dynamics invisible to any single theory, especially the compliance paradox, where structural conformity masks operational divergence (Meyer & Rowan, 1977). The primary objective of this article is to develop an integrated sociotechnical framework for AI-driven supply chain due diligence, synthesising institutional theory, stakeholder theory, and the TOE framework. We derived formal propositions from this framework that specify the interaction mechanisms across dimensions and we developed a diagnostic maturity model that enables systematic readiness assessment. Two research questions guided these contributions:

- RQ1:** How do technological capabilities, ethical governance, and cultural adaptation interact through the integrated lens of institutional theory, stakeholder theory, and the TOE framework in the context of AI-driven due diligence?
- RQ2:** How might organisations systematically assess readiness across all three dimensions?

## RESEARCH METHODOLOGY

### Research Design

We adopted a theory-building approach combining purposive literature synthesis with illustrative case analysis. We began with a literature synthesis to integrate disparate insights (Snyder, 2019), aligning with critical review methodology that provides interpretive analysis to reveal theoretical gaps and develop new frameworks (Paré *et al.*, 2015). Such synthesis is well-suited for an emerging topic where the goal is to combine ideas rather than exhaustively cover all literature. We focused on the intersection of AI and supply chain due diligence – a space of regulation, technology, and ethics. Adopting a problematising review (Alvesson & Sandberg, 2020), we challenged the assumption that technological, ethical, and cultural dimensions can be addressed in isolation. We aimed to develop a conceptual theory, following the approach of prior EBER conceptual studies that synthesise theory and derive propositions (Butkeviciene & Sekliuckiene, 2022). We synthesised institutional theory, stakeholder theory, and TOE framework perspectives into one integrated sociotechnical model and derived formal propositions from the analysis. We complemented this theoretical development with an illustrative analysis of three prominent European e-commerce firms (Amazon, 2025; Otto Group, 2025; Zalando SE, 2025) to demonstrate the framework's applicability in practice. Based on multiple cases, we conducted analytical replication to strengthen theory development by revealing patterns across firms (Eisenhardt & Graebner, 2007; Yin, 2018). We purposefully selected these firms for their market significance and their exposure to emerging due diligence regulations (Bundesministerium für Justiz, 2021; European Commission, 2024a). For each company, we collected recent sustainability reports (2024-2025) and analysed these documents against the AI due-diligence-maturity model criteria. We coded each report to assess the firm's technological capabilities, ethical governance structures, and cultural readiness, using our maturity indicators as a coding scheme (see coding protocol in Appendix B). This analysis provided an illustrative demonstration of the framework rather than a basis for generalisation. It provides real-world context for our theoretical propositions. We acknowledge that our case selection was limited to one industry. Therefore, future studies should examine additional industries and more varied firm types to further test and refine the framework's applicability.

### Literature Selection and Analysis

We searched major databases (Web of Science, Scopus, Google Scholar) using Boolean queries. Representative search strings (Scopus) included: TITLE-ABS-KEY (('supply chain' W/3 'due diligence') AND ('AI' OR 'machine learning')) OR TITLE-ABS-KEY (('supply chain due diligence' OR 'ESG monitoring') AND 'artificial intelligence' AND 'cross-cultural' AND 'technology adoption'). To improve reproducibility, we applied the following inclusion criteria: (1) focus on peer-reviewed articles, regulatory documents or primary corporate disclosures published between 2020-2025; (2) focus on AI applications in supply chain management, due diligence, or ESG compliance; (3) engagement with one of our theoretical foundations (institutional theory, stakeholder theory, or TOE framework) or with AI governance frameworks. Exclusion criteria included: (1) purely technical AI articles without organisational or managerial implications; (2) opinion pieces or practitioner reports without empirical or theoretical grounding; (3) non-English sources. The first author screened titles and abstracts against these criteria, with borderline cases discussed between authors.

Following systematic screening protocols, we filtered the initial pool of approximately 200 articles down to 89 sources based on strict inclusion criteria for relevance to AI in supply chain due diligence and regulatory compliance. Peer-reviewed publications constituted the majority, supplemented by regulatory documents and corporate disclosures. We prioritised conceptual rigour alongside relevance to con-

text and citation impact. This agrees with other literature reviews recently published in related domains (Culot *et al.*, 2024; Samuels, 2024). In addition, we included foundational works on institutional theory (Campbell, 2007; DiMaggio & Powell, 1983), stakeholder theory (Freeman, 2010; Mitchell *et al.*, 1997), and the technology–organisation–environment framework (Tornatzky & Fleischer, 1990).

We conducted thematic analysis for literature selection (Braun & Clarke, 2006) aligned with established guidelines for conceptual research (Snyder, 2019). This involved three stages. Firstly, open coding for identifying emergent themes across the technological, ethical, and cultural dimensions. Secondly, thematic mapping to connect these patterns with constructs from institutional, stakeholder and TOE theories. Thirdly, integrative synthesis for developing the unified framework and maturity model. With this systematic analysis, we ensured that our framework was grounded in the literature and that the themes from different streams of research coherently informed our sociotechnical perspective.

## LITERATURE REVIEW AND THEORY DEVELOPMENT

### Institutional Pressures and Regulatory Transformation

The CSDDD demonstrates a paradigm shift from voluntary corporate social responsibility to legally required due diligence obligations (Leite *et al.*, 2024; Welsen, 2025; Wilhelm, 2024). Organisations face coercive pressures to implement AI systems that will monitor suppliers, identify adverse impacts, and generate compliance documentation (Buhmann & Feld, 2024). This creates three institutional dynamics reshaping organisational responses.

Firstly, normative isomorphism develops as AI ethics standards take shape (DiMaggio & Powell, 1983; Reis & Pinheiro Junior, 2025; Rudko *et al.*, 2025; Singh, 2024), with industry associations promoting explainable AI and creating mimetic pressures (El Mimouni & Bouhdadi, 2025; Kabir *et al.*, 2025). Artificial intelligence functions both as a product and driver of institutional forces.

Secondly, regulatory uncertainty remains, because member states have time until July 2027 to transpose the Directive (European Commission, 2025a), with staggered implementation afterwards (European Commission, 2024a, 2025b). While early movers face higher costs, they gain legitimacy; late adopters risk penalties and reputational deficits (Campbell, 2007).

Thirdly, institutional logic conflict occurs when efficiency-oriented AI clashes with transparency requirements (Milosevic *et al.*, 2023). Algorithms that maximise efficiency may obscure labour rights violations. This creates tensions that no technology can resolve. Empirical research supports these dynamics. Mishra *et al.* (2024) find that coercive pressure influences blockchain adoption, with institutional pressures accounting for substantial variance in adoption decisions among 222 supply chain professionals. These pressures intensify through regulatory convergence. The EU AI Act classifies AI for employment and worker management as ‘high-risk,’ requiring conformity assessments and human oversight or control (European Commission, 2024b). Furthermore, AI for supplier risk assessment likely falls within this classification, creating overlapping obligations with the CSDDD and reinforcing the urgency for explainable AI as a legal requirement (de Oliveira Serra, 2025; Sinnig & Zetsche, 2025).

### Stakeholder Demands and Competing Legitimacy Claims

Stakeholder theory demonstrates how organisations navigate competing demands from constituencies with varying power, legitimacy, and urgency (Mitchell *et al.*, 1997). Artificial intelligence systems must address regulators, investors, consumers, and affected communities simultaneously (Marano *et al.*, 2024), with each shaping design and implementation. This agrees with the concept of stakeholder salience, according to which the urgency of regulatory mandates like the CSDDD combines with the legitimacy of human rights advocates to force a redesign of AI architectures (European Commission, 2024a; Mitchell *et al.*, 1997). When stakeholder power shifts towards mandatory accountability, the Tech-Ethics interface necessitates a move from opaque ‘black-box’ systems to interpretable models (Kabir *et al.*, 2025).

Contemporary applications expand this foundation. Birkstedt *et al.* (2023) identified how diverse stakeholder groups hold conflicting expectations regarding AI transparency and fairness, while Papagiannidis, Mikalef, and Conboy (2025) developed a responsible AI governance framework

that operationalises stakeholder engagement, demonstrating how organisations can integrate stakeholder concerns into AI deployment.

Critical tensions emerge: regulators demand explainability while firms protect proprietary algorithms (Batoool *et al.*, 2025; Radanliev, 2024); investors seek standardised metrics while due diligence requires contextual judgement (Gustafsson *et al.*, 2023a); finally, fairness definitions vary culturally (Han *et al.*, 2025; Roy & Mukherjee, 2022). This complexity reveals why technological capabilities alone prove insufficient.

An AI system may generate documentation satisfying auditors while failing to prevent human rights abuses. Effective systems may produce embarrassing findings, creating incentives to constrain scope (Abhulimen & Ejike, 2024). The challenge lies in aligning incentives with substantive rather than symbolic compliance.

### Technology–organisation–environment Dynamics

The TOE Framework (Tornatzky & Fleischer, 1990) structures analysis across technological readiness, organisational capabilities, and environmental context. Our synthesis revealed that organisational readiness matters more than technological sophistication, consistent with meta-analytic evidence (Pinto *et al.*, 2025), large-scale empirical studies (Arroyabe *et al.*, 2024), and systematic reviews (Romeo & Lacko, 2025; Sánchez *et al.*, 2025).

The technological dimension encompasses advances enabling AI to process supplier databases, identify risk patterns, and generate compliance reports (Brintrup *et al.*, 2023; Shahzadi *et al.*, 2024). Machine learning can detect emission anomalies (Brintrup *et al.*, 2023), predict disruptions (Wong *et al.*, 2022), and analyse disclosures (Li *et al.*, 2024). Natural language processing enables the extraction of relevant information from unstructured supplier communications, audit reports, and media coverage. However, technology availability does not guarantee effective deployment. Data quality challenges persist, and algorithmic bias can systematise discrimination (Akinrinola *et al.*, 2024; Bahangulu & Owusu-Berko, 2025; Belenguer, 2022; Faheem, 2024; Hofmann *et al.*, 2024).

The organisational dimension proves decisive. Cross-functional integration (Cannas *et al.*, 2024), new competencies in algorithm governance (Batoool *et al.*, 2025), and cultural transformation (Samuels, 2024) determine success. Empirical studies validate this: Ioakeimidou *et al.* (2024), Sánchez *et al.* (2025), and Hughes *et al.* (2026) demonstrate that organisational factors outweigh technological sophistication.

The environmental dimension shapes adoption urgency. Firms covered by the CSDDD face legal liability, creating incentives for AI investment (Buhmann & Feld, 2024). Small and medium-sized enterprises (SMEs) experience indirect pressure without proportionate resources, creating asymmetric burdens that threaten viability while creating opportunities for compliance-as-a-service (Gustafsson *et al.*, 2023a). Early adopters gain advantages; late adopters risk legitimacy deficits (Campbell, 2007).

These three perspectives work together but not without tension. Institutional theory emphasises conformity: organisations facing the same pressures should respond similarly. Stakeholder theory suggests that different stakeholder configurations produce different responses. The TOE framework implies that organisational capabilities vary widely and shape implementation outcomes. We addressed the tension by treating the theories as complementary lenses rather than competing explanations. Institutional pressures create the context, stakeholder demands shape choices within that context, and organisational capabilities determine whether those choices succeed. This multi-level complementarity aligns with Herold's (2018) demonstration that institutional theory and stakeholder theory operate at different analytical levels and can be integrated when examining sustainability-related organisational practices. We extend this by adding the TOE framework as a third level. Each theory operates within specific boundary conditions. Institutional theory is most applicable when regulatory pressure is high and compliance norms are crystallising, which are the conditions present in the current CSDDD context. When different parties have valid but contradictory expectations, *e.g.*, authorities demand open data while firms protect their trade secrets, stakeholder theory becomes essential. The TOE framework applies when adoption success varies even when the external pressure is similar, directing attention to internal capabilities. In our framework, we integrated these theories where their bound-

ary conditions overlap: the mandatory due diligence context features high regulatory pressure (activating institutional theory), competing stakeholder demands (activating stakeholder theory), and variable implementation success (activating the TOE framework). The integration of these three perspectives demonstrates a dynamic that is invisible to single-theory analyses: structural isomorphism with operational divergence. Organisations converge (becoming similar) when having similar AI governance structures (satisfying institutional pressures), while they diverge (becoming different) for the implementation (reflecting stakeholder priorities and capabilities) – a compliance paradox where apparent conformity masks substantive variation that determines whether due diligence achieves real or merely symbolic compliance. This compliance paradox aligns with Meyer and Rowan's (1977) concept of institutional decoupling, wherein organisations adopt formal structures for legitimacy while actual practices diverge from espoused policies.

### The Integrated Sociotechnical Framework

This integration shows three dimensions that mutually shape one another: technological capabilities, ethical governance, and cultural adaptation (Akbarighatar *et al.*, 2023; Dey *et al.*, 2023; El Mimouni & Bouhdadi, 2025). The tech-ethics interface captures how ethical demands drive technology choices. The ethics-culture interface shows how cultural context shapes fairness standards. The tech-culture interface reveals how organisational culture determines technological effectiveness. Figure 1 shows the integrated framework with three interfaces. This structure challenges step-by-step implementation models. Organisations cannot first adopt technology, then consider ethics, and then adapt to culture. All three dimensions demand simultaneous attention.

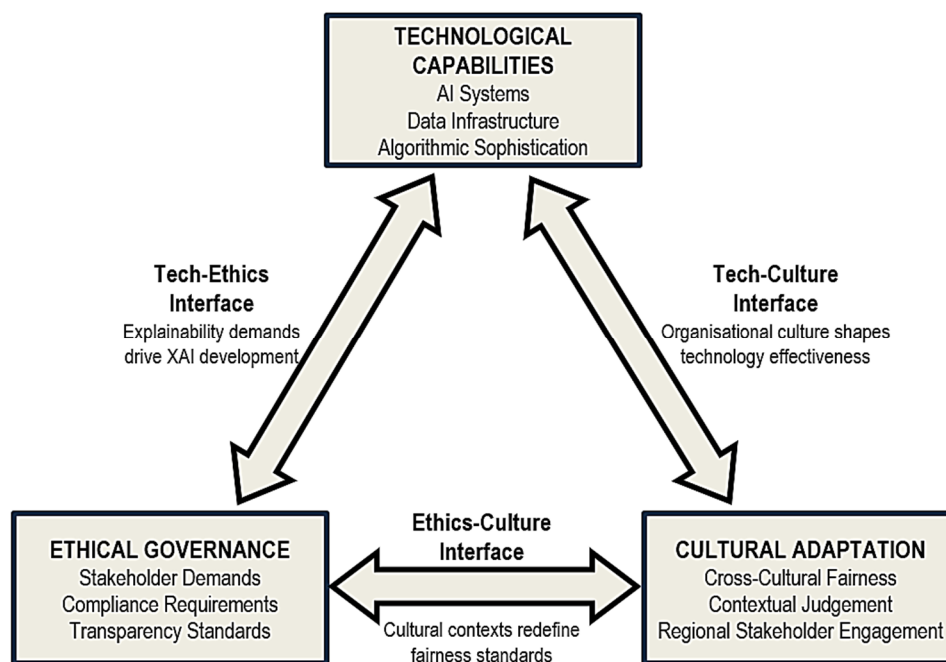


**Figure 1. Integrated sociotechnical framework for AI-driven supply chain due diligence**

Source: own elaboration.

The integrated framework suggests three critical interfaces where dimensions interact, each warranting detailed examination. The tech-ethics interface concerns how ethical demands and technological architectures mutually shape one another. The ethics-culture interface addresses how cultural contexts redefine fairness standards. The tech-culture interface examines how organisational culture determines technology effectiveness.

Sections 3.5-3.7 elaborate on each interface through our integrated theoretical lens, developing formal propositions that specify the interaction mechanisms (addressing RQ1). Section 3.8 then presents the maturity model (addressing RQ2).

### Navigating the Tech-ethics Interface: The Explainability Imperative

Organisations confront the explainability paradox (RQ1). Regulations demand transparency, yet AI often operates opaquely (Batool *et al.*, 2025). The EU AI Act requires high-risk systems to enable oversight and maintain traceability (European Commission, 2024b). Machine learning predicts disruptions accurately, yet stakeholders demand understandable conclusions (Kabir *et al.*, 2025). Under the EU AI Act (Art. 13), ‘transparency’ is not merely an ethical preference but a legal mandate for high-risk systems. This creates a shift in procurement logic: organisations should prioritise ‘global interpretability’ (understanding the whole model) and ‘local interpretability’ (understanding a specific supplier risk score) over marginal gains in predictive accuracy. In a CSDDD audit, a ‘black box’ prediction, no matter how accurate, may count as legal liability, instead of an asset. This tension reflects a fundamental accuracy-interpretability trade-off extensively documented in the machine learning literature: complex models such as deep neural networks and ensemble methods provide accurate predictions but work in ways that humans cannot easily understand. By contrast, interpretable models sacrifice accuracy for transparency (Batool *et al.*, 2025; Chang & Bau, 2025). This evidence demonstrates that ethical demands fundamentally reshape technological architectures.

Practice shows a dual response. Technically, organisations adopt explainable AI using LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), creating audit trails satisfying requirements (Chang & Bau, 2025; Stahl & Eke, 2024; Teixeira *et al.*, 2025). Organisationally, firms establish governance committees ensuring human oversight (Batool *et al.*, 2025). Explainability constitutes both a technical property and an organisational capability.

Systematic reviews confirm explainable artificial intelligence’s (XAI) centrality for regulatory compliance (Chang & Bau, 2025; Kabir *et al.*, 2025), though empirical business management studies examining AI deployment specifically in mandatory due diligence contexts remain scarce. The tech-ethics interface demonstrates mutual influence. Ethical demands reshape technological choices, driving interpretable architectures even when opaque alternatives perform better. Simultaneously, technological capabilities expand ethical possibilities – NLP enables monitoring at previously impossible scales (Marano *et al.*, 2024). Technology and ethics resist independent optimisation.

From this analysis, we derived proposition 1 (tech-ethics interface): Ethical demands for transparency reshape technological architectures, driving organisations towards interpretable AI models even when opaque algorithms offer superior predictive accuracy.

### Reconciling the Ethics-culture Interface: Contextual Fairness

The CSDDD’s global scope creates cultural challenges that technology alone cannot resolve (RQ1, RQ2). Organisations must assess labour practices across countries with different norms (Han *et al.*, 2025). Fairness frameworks developed in Europe may get things wrong in two ways. They may flag acceptable local practices as violations. Or they may treat harmful practices as acceptable local customs. Research shows that people in different cultures understand AI fairness differently (Barnes *et al.*, 2024; Han *et al.*, 2025). Large language models also show cultural biases (Brauner *et al.*, 2024; Starke *et al.*, 2022; Tao *et al.*, 2024; Yuan *et al.*, 2025). The cultural variation literature suggests areas where such differences may arise: working hours considered excessive in Europe may be standard elsewhere; collective bargaining may operate differently across regions; community-based hiring practices may be flagged as nepotism by AI systems trained on Western standards. We believe that those illustrative examples align with Roy and Mukherjee’s (2022) finding that national culture shapes corporate ESG disclosure more than economic factors. Yuan *et al.* (2025) demonstrate that ChatGPT exhibits systematic cultural biases in interpersonal decision-making tasks, while Tao *et al.* (2024) find that cultural prompting can reduce but not eliminate such biases. These findings suggest that AI systems deployed for global due diligence require not merely technical debiasing but an ongoing cultural calibration informed by local stakeholders.

Organisations navigate this through participatory governance. Firms establish regional committees including suppliers, civil society, and workers’ advocates (Marano *et al.*, 2024). These provide cultural context for interpreting outputs. Effective due diligence requires contextual judgement enabled by AI, not replaced by it (Chaudhary, 2024).

From this analysis, we derived proposition 2 (ethics-culture interface): Algorithmic fairness standards are culturally contingent, requiring local stakeholder engagement to prevent the normalisation of harmful practices or the misinterpretation of acceptable local norms.

### **Leveraging the Tech-culture Interface: Organisational Readiness as Primary Determinant**

Organisational culture predicts AI effectiveness better than technical sophistication (Cannas *et al.*, 2024; Milosevic *et al.*, 2023). Evidence suggests that organisations with strong commitment achieve better AI outcomes than technically advanced firms lacking such commitment (Cannas *et al.*, 2024; Neumann *et al.*, 2024). Technology amplifies existing tendencies rather than transforming them.

This logic suggests that organisational readiness may function rather as a coefficient than an additive factor. If cultural commitment is low, the substantive impact of even sophisticated technology remains minimal. Artificial intelligence does not create a due diligence culture. It scales the one that already exists. This coefficient logic draws on resource complementarity theory (Amit & Schoemaker, 1993), which establishes that strategic resources generate value through synergistic combination rather than independent contribution. Empirical research supports this pattern. Neumann *et al.* (2024) state that internal capabilities prove far more influential for AI adoption than external support. Studying 280 Vietnamese SMEs, Dey *et al.* (2023) found that AI capabilities enhance supply chain resilience only when supported by appropriate cultural and governance mechanisms – AI adoption alone proved insufficient. Similarly, Hughes *et al.* (2026) demonstrate that organisational factors consistently outweigh technological sophistication in determining generative AI adoption success. The same technology produces different outcomes depending on organisational values: committed firms invest in supplier improvement while cost-focused firms may simply switch suppliers without solving the problem (Abhulimen & Ejike, 2024). Best practice favours cultural transformation before technological deployment. Organisations establish committees, develop protocols, and create incentives rewarding ESG outcomes before deploying AI at scale (Shahzadi *et al.*, 2024). The tech-culture interface inverts conventional logic: cultural readiness determines technological effectiveness, not the reverse.

From this analysis, we derived proposition 3 (tech-culture interface): Organisational readiness acts as a primary determinant of AI effectiveness, in which technology may function as a coefficient that amplifies existing cultural tendencies rather than transforming them independently of context. Together, propositions 1-3 address RQ1 by specifying the mutual influence mechanisms across dimensions through the integrated theoretical lens, revealing interaction effects invisible to single-theory approaches.

### **Practical Implications: The AI Due-diligence-maturity Model**

Research shows that AI maturity, not just technical sophistication, predicts whether organisations succeed with AI (Hansen *et al.*, 2024). Several maturity models already exist in related areas. Akbarighatar *et al.* (2023) developed a sociotechnical AI maturity framework focused on responsible AI. Vann Yaroson *et al.* (2025) examined responsible AI capabilities in supply chains. Sadiq *et al.* (2021) and Colangelo *et al.* (2022) addressed AI maturity for data management and production systems. However, none of these models addresses the specific needs of mandatory due diligence compliance under the CSDDD and EU AI Act. Our model differs from these existing frameworks in three key respects. Firstly, while Akbarighatar *et al.* (2023) generally focus on responsible AI practices, our model specifically targets mandatory due diligence contexts where regulatory convergence (CSDDD and EU AI Act) creates unique compliance challenges. Secondly, unlike Sadiq *et al.* (2021) and Colangelo *et al.* (2022) who emphasise technical maturity, our model foregrounds the institutional and cultural layers that our theoretical framework identifies as primary determinants of effectiveness. Thirdly, our four-layer structure (operational, institutional, global, strategic) operationalises the compliance paradox, enabling organisations to diagnose why structural conformity may coexist with operational divergence.

We built on earlier work, including the corresponding author's prior analysis of organisational responses to sustainability directives (Welsen, 2025), as well as recent validation studies of readiness assessment approaches (Elhady & Shohieb, 2025). Our AI due-diligence-maturity model has four organisational layers. Three layers map directly to the framework dimensions: the operational layer addresses technological capabilities, the institutional layer covers ethical governance structures, and the

global layer reflects cultural adaptation across borders. The fourth layer, namely the strategic one, captures leadership commitment as a cross-cutting enabler that determines whether the other three dimensions achieve substantive rather than symbolic compliance. The four maturity levels, *i.e.*, crawl, walk, run, fly, follow common maturity model practice (Sadiq *et al.*, 2021). They represent progress from initial ad-hoc approaches (crawl), through developing awareness (walk), to integrated practice (run), and finally optimised strategic leadership (fly). By structuring the assessment across four layers and four maturity levels, we provide diagnostic granularity that enables targeted interventions.

We operationalised this multidimensional progression in the AI due-diligence-maturity model. Table A1 in the Appendix provides a detailed breakdown of maturity levels and indicators across the four layers, capturing the progression from reactive compliance to strategic leadership. Maturity progression differed across firm types. Platform multinational enterprises (MNEs) may advance rapidly; SMEs may go directly to Level 3 through AI-as-a-service or require extended early phases. For resource-constrained firms, the maturity model suggested a potential 'leapfrog' strategy. By adopting AI-as-a-service compliance tools, an SME might bypass level 2 (walk) and advance directly to level 3 (run), provided that the firm's institutional governance mechanisms are established in parallel. This leapfrog potential extends Steinmueller's (2001) concept of technology leapfrogging to organisational contexts, enabling resource-constrained organisations to bypass in-house AI development through platform-based solutions. This re-frames mandatory due diligence as a catalyst for digital professionalisation rather than an entry barrier.

Organisations should assess maturity against size-appropriate benchmarks. This model requires empirical validation beyond the illustrative application presented here; we offer it as a theoretically grounded but exploratory diagnostic tool inviting future empirical testing. Until validated, the model functions as a conceptual framework for structuring analysis rather than a prescriptive assessment instrument. The three-firm analysis in Section 4.1 demonstrates applicability but cannot establish validity. Future research should test the model across larger samples and diverse industry contexts.

Progression follows iterative improvement logic (Deming, 1982). Organisations may use the model as a preliminary self-assessment tool for identifying potential gaps across layers, though practitioners should note that the model requires empirical validation before prescriptive application. A firm strong in technology but weak in culture should prioritise stakeholder engagement; a firm with governance but limited capacity should invest in infrastructure. The model enables targeted development.

## DISCUSSION

This section applies the integrated framework and maturity model developed in Section 3 to examine AI-driven due diligence in practice. Section 4.1 presents an illustrative analysis of three European e-commerce firms, explores the framework's applicability, and reveals patterns across cases. Section 4.2 discusses the significance of these findings for theory and practice.

### Illustrative Application

To demonstrate the practical applicability of the proposed maturity model, we conducted systematic qualitative content analysis of sustainability reports from Amazon (2025), Otto Group (2025), and Zalando SE (2025). Otto Group and Zalando operate under LkSG; Amazon faces indirect pressure through European operations and forthcoming CSDDD obligations. We coded the documents for explicit mentions of AI, machine learning, and algorithmic systems, applying conservative coding rules where capabilities were not inferred from absence of evidence. Pattern-matching analysis tested observed evidence against the three theoretical propositions. Appendix B summarises the coding protocol and key evidence; complete evidence matrices are available from the corresponding author upon request.

The analysis revealed pronounced variation across firms. At the operational layer, Amazon demonstrated explicit AI deployment across sustainability functions, including 'AI-powered robots to automate sorting recyclable materials' (p. 20), predictive leak detection (p. 24), and 'AI machine learning to determine the safest and most efficient packaging' (p. 22). Otto Group deployed 'AI-powered forecasting tools, including demand forecasting and return rate prediction' (p. 81) and op-

erated an ‘AI Forecasting solution since 2019’ (p. 81). Zalando’s reports contain no explicit mention of AI, machine learning, or algorithmic systems for due diligence purposes.

**Table 1. Summary of AI due-diligence maturity assessment: Three European e-commerce firms (2024-2025)**

| Firm       | Business model  | Operational | Institutional | Global | Strategic | Overall |
|------------|-----------------|-------------|---------------|--------|-----------|---------|
| Amazon     | Hybrid          | Fly         | Run           | Fly    | Fly       | Fly     |
| Otto Group | Hybrid          | Run         | Walk          | Crawl  | Walk      | Walk    |
| Zalando    | Platform/Hybrid | Crawl       | Crawl         | Crawl  | Crawl     | Crawl   |

Source: own study based on systematic content analysis of publicly available sustainability reports (2024-2025).

A pronounced institutional governance gap emerged. Only Amazon achieved ISO/IEC 42001 certification for responsible AI (p. 49) and maintained board-level oversight where committees ‘reviewed the Company’s approach to responsible AI development and AI governance’ (p. 47). Otto Group provided AI awareness training to ‘around 17 000 white-collar employees’ (p. 80) but lacked formal AI governance structures. Zalando demonstrated comprehensive sustainability governance but no AI-specific policies or roles.

Pattern-matching analysis suggested differential proposition support. Proposition 1 (tech-ethics) found preliminary support only in Amazon’s certification-driven approach, suggesting that the transparency-architecture relationship operates primarily in technology-intensive contexts. Proposition 2 (ethics-culture) received universal support: all three firms deployed multi-language stakeholder tools, suggesting that global governance requires culturally accessible interfaces regardless of AI maturity. Proposition 3 (tech-culture) received the strongest cross-case support: Zalando’s explicit acknowledgement of data quality limitations suggests that organisational readiness may function as a coefficient – technology cannot bypass foundational data gaps. Several validity limitations apply. The assessment relied exclusively on public disclosures, which may have understated actual capabilities. The coding was conducted by the researchers who developed the model. As a safeguard against author bias, conservative coding rules required explicit textual evidence and treated absence as absence of capability; this rule produced the lowest maturity assessment for the firm employing the corresponding author. The illustrative analysis demonstrated exploratory framework application but did not constitute validation. Nevertheless, the analysis revealed an important gap between operational AI deployment and institutional governance warranting further investigation.

### Discussion of Findings

The preceding illustrative analysis addressed both research questions and revealed patterns warranting further reflection. Regarding RQ1, the three interfaces demonstrate that technological capabilities, ethical governance, and cultural adaptation do not merely coexist but actively reshape one another. The tech-ethics interface shows that regulatory demands for transparency alter AI architectural choices, even when opaque models offer superior performance. The ethics-culture interface reveals that fairness cannot be universally defined but requires continuous local calibration. The tech-culture interface inverts conventional assumptions: rather than technology driving organisational change, cultural readiness determines whether technological investments yield substantive outcomes.

Regarding RQ2, the AI due-diligence-maturity model provides a diagnostic tool for systematic readiness assessment. The illustrative application to European e-commerce firms demonstrates both the model’s applicability and a concerning finding: even firms with advanced operational AI capabilities exhibit significant institutional governance gaps. This pattern, *i.e.*, operational sophistication without corresponding governance maturity, exemplifies the compliance paradox identified in our theoretical framework. Organisations may satisfy surface-level regulatory requirements while lacking the governance structures necessary for substantive due diligence.

These findings carry implications for both theory and practice. Theoretically, they suggest viewing AI-driven due diligence as fundamentally sociotechnical rather than purely technological. The coefficient logic of proposition 3 that organisational readiness multiplies rather than adds to technological

capability suggests that investments in AI systems without parallel investments in governance and culture may yield minimal returns. The illustrative analysis also provides partial support for proposition 1 (in Amazon's transparency-driven architecture choices) and proposition 2 (in all firms' multi-language stakeholder tools). Practically, the findings indicate that organisations facing CSDDD compliance should resist the temptation to pursue technology-first strategies. The institutional governance gap observed across all three firms, regardless of their operational maturity levels, suggests that this is a systemic challenge, which requires deliberate attention.

## CONCLUSIONS

### Research Results Summary

Addressing RQ1, our integrated framework synthesising institutional theory, stakeholder theory, and the TOE framework demonstrates that dimensions operate as mutually constitutive interfaces: tech-ethics (transparency demands drive XAI adoption), ethics-culture (fairness standards are culturally contingent), and tech-culture (organisational culture determines technology effectiveness). The three derived propositions specify these interaction mechanisms, revealing effects invisible to single-theory approaches and reconceptualising compliance as a sociotechnical transformation. Addressing RQ2, we propose the AI due-diligence-maturity model across four layers (operational, institutional, global, strategic) with four maturity levels (crawl to fly). This enables identification of capability gaps and prioritised development. Appendix A provides the full operationalisation.

### Theoretical Contributions

The compliance paradox identified in our framework, where structural conformity masks operational divergence, explains why the illustrative analysis revealed institutional governance gaps even among firms demonstrating operational AI maturity. This insight anchors our four theoretical contributions.

Firstly, we demonstrated mutual influence across dimensions that the existing research treats as related but separate, showing how changes in one dimension reshape possibilities in others. Prior sociotechnical work on AI (Akbarighatar *et al.*, 2023; Dey *et al.*, 2023) recognises that technology and organisation interact, but does not specify how this interaction occurs in mandatory due diligence contexts. Our framework identifies three interfaces (tech-ethics, ethics-culture, tech-culture) as the specific sites where dimensions shape one other. Ethical demands drive technological architectures, which enable new ethical possibilities, which encounter cultural variation requiring further adaptation. This extends sociotechnical theory from general recognition of interdependence to specification of interaction mechanisms.

Secondly, we integrated institutional theory, stakeholder theory, and the TOE framework within a unified framework. These lenses typically compete for explanatory primacy. We argue for their complementarity: institutional theory explains regulatory pressures, stakeholder theory illuminates competing demands, and the TOE framework structures analysis of barriers and enablers. Integration reveals dynamics invisible to single-theory approaches.

Thirdly, our AI due-diligence-maturity model extends recent advances in measuring organisational readiness. Dey *et al.* (2023) found that AI capabilities enhance organisational agility only when supported by cultural and governance mechanisms, confirming our mutual influence thesis. By structuring assessment across four layers with four maturity levels, we provide diagnostic granularity that enables targeted interventions.

Fourthly, we advanced the understanding of regulatory transformation as a sociotechnical process. The CSDDD literature largely focuses on legal compliance and liability frameworks (Buhmann & Feld, 2024; Gustafsson *et al.*, 2023b). We argue that compliance requires simultaneous technological, organisational, and cultural transformation. Legal obligations catalyse sociotechnical change whose outcomes depend on organisational responses. Regulatory effectiveness depends not merely on legal design but on organisational capacity for adaptation.

### Final Reflections and Limitations

This research reconceptualised AI in supply chain due diligence as a sociotechnical challenge rather than a purely technological solution. By showing that technological capabilities, ethical governance, and cultural adaptation dynamically shape one another, we challenged assumptions in both academic literature and practitioner discourse. Organisations cannot address CSDDD compliance through technology alone. Effective AI-driven due diligence requires transformation across all three dimensions, with cultural readiness often more important than algorithmic sophistication. The integrated framework synthesises fragmented perspectives into a unified model, while the maturity model provides diagnostic tools for systematic readiness assessment.

Several limitations qualify our contributions. Firstly, this conceptual framework requires empirical validation through systematic case studies. Secondly, our purposive literature review cannot claim to be comprehensive. Thirdly, applicability may vary across industries with different supply chain complexities. Fourthly, while we emphasised SME relevance, our illustrative analysis focused on large MNEs. Fifthly, rapidly evolving AI technology and regulations mean that specific details may have changed before the article's publication. The illustrative analysis provides early evidence of framework usefulness but cannot support statistical generalisation; it does reveal an important gap between technical deployment and institutional governance warranting further study.

Sixthly, we based the above analysis exclusively on publicly available sustainability reports. Actual AI capabilities may exceed what is disclosed in these documents. The conservative coding approach (explicit AI/ML/Algorithm terms only) may understate deployment, particularly for Zalando, where advanced digital tools are utilised but not explicitly labelled as AI-driven. The assessment was conducted by the researchers who developed the maturity model. Seventhly, as a conceptual article, the propositions require empirical testing through quantitative studies with larger samples to establish generalisability.

The main implication is important and clear: technology alone cannot resolve fundamental tensions between efficiency and accountability, or between symbolic compliance and substantive impact. Moreover, AI-driven due diligence will succeed only when organisations recognise that algorithms are tools enabling human judgement, not substitutes for it. The challenge lies not in building more sophisticated AI but in building organisational cultures capable of using AI wisely. Such cultures treat compliance as an opportunity rather than a burden, engage stakeholders as partners, and understand technology as an amplifier of values rather than a replacement for them. For entrepreneurial firms and SMEs in supply chains subject to mandatory due diligence, this finding suggests potential pathways. While our illustrative analysis focused on large MNEs, the framework implies that strong commitment and stakeholder relationships may partially compensate for limited technological resources – a proposition requiring empirical testing with SME samples.

### Research Agenda

Future research should pursue three directions. Empirically, scholars should investigate how organisations navigate the three interfaces through comparative case studies. Longitudinal research could test whether cultural transformation before technological deployment produces better outcomes. Quantitative studies could examine whether advancement in one maturity layer enables or constrains progress in others. The CSDDD implementation period beginning July 2027 offers an opportunity to study regulatory transformation in real time (Sinnig & Zetzsche, 2025).

Theoretically, researchers should examine boundary conditions. Does mutual influence operate differently in highly versus lightly regulated industries? Do firm size, ownership structure, or governance quality moderate relationships between dimensions? These investigations would refine framework applicability. Furthermore, SMEs face different resource constraints than large MNEs (Sánchez *et al.*, 2025). They may need collaborative compliance models or AI-as-a-service approaches to meet requirements. Understanding whether entrepreneurial firms achieve compliance through innovative mechanisms would inform regulatory design for diverse organisational forms.

Methodologically, scholars should operationalise the maturity model by developing Likert-scale items from the Appendix A indicators, testing inter-rater reliability with coders blind to firm identity,

and validating constructs against compliance outcomes such as audit findings and supplier remediation rates. Such instruments would enable systematic comparison across organisations and jurisdictions. The concurrent CSDDD and AI Act implementation creates a natural experiment for examining how overlapping regulations shape AI adoption.

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## APPENDIX A: AI DUE DILIGENCE MATURITY MODEL – DETAILED INDICATORS

This model enables organisations to assess AI readiness for supply chain due diligence, based on Welsen (2025).

**Table A1. AI due-diligence-maturity model: Indicators across four organisational layers and maturity levels**

| Organisa-tional layer                                                    | Level 1. Crawl (ini-tial & ad-hoc)                                                                                                              | Level 2. Walk (de-veloping & aware)                                                                                                                           | Level 3. Run (inte-grated & proactive)                                                                                                                                     | Level 4. Fly (optimised & strategic)                                                                                                                                                                                          |
|--------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1. Operational (day-to-day processes, workflows, and tools)              | Data are siloed and require manual ex-traction. The use of AI is experimental and lacks formal risk checks or ethi-cal guidelines in workflows. | Standalone AI tools are used for spe-cific tasks. Basic bias checks and data quality proto-cols are introduced but applied incon-sistently.                   | Artificial intelligence risk assessments and ethical reviews are a standard, required part of the project lifecycle. Data govern-ance is automated and robust.             | A predictive, AI-driven sys-tem illuminates the multi-tier supply chain. Generative AI acts as a ‘co-pilot’ for ex-perts, with continuous, auto-mated monitoring for perfor-mance and ethical drift.                          |
| 2. Institu-tional (inter-nal govern-ance, policies, roles, and training) | Compliance is a manual, checklist-based exercise. No formal AI policies or dedicated gov-ernance roles exist.                                   | An ethics commit-tee is formed. The first AI governance policies are writ-ten, but enforce-ment is ad-hoc. Awareness training is offered.                     | A robust, cross-func-tional AI governance framework is estab-lished with clear roles (e.g., AI Ethics Of-ficer). Training is man-datory for relevant teams.                | AI governance is fully inte-grated into the enterprise GRC (governance, risk, com-pliance) framework. Ethical performance is a formal key performance indicator (KPI), continuously audited and re-ported.                    |
| 3. Global (cross-border coordination and adapta-tion)                    | Each country or business unit oper-ates in isolation. There is no central coordination of AI compliance, creat-ing inconsistency and risk.      | Headquarters be-gins issuing basic global AI guide-lines. Subsidiaries in high-regulation zones (e.g., EU) re-act to local laws, but knowledge is not shared. | A unified global AI governance program exists, balancing cen-tral standards with re-quired local adapta-tion. Best practices are actively shared across the MNEs net-work. | The firm uses its global foot-print as a strategic ad-vantage, leveraging insights from advanced regulatory markets to pre-emptively raise standards worldwide. Responsible AI is required of global partners and suppli-ers. |
| 4. Strategic (top-manage-ment over-sight and business strategy)          | Top management is largely unaware or uninvolved in AI governance; it is viewed purely as a technical IT issue.                                  | Leadership recog-nises AI compliance as a necessary cost and risk-mitigation issue. Budgeting is reactive, often fol-lowing an incident or new regulation.    | Leadership actively di-rects AI governance as a key part of corpo-rate responsibility. Responsible AI is inte-grated into strategic planning and resource allocation.      | The Board of Directors pro-vides active oversight. Re-sponsible AI is a core part of the corporate brand and a source of competitive ad-vantage, shaping new busi-ness models and market en-try decisions.                    |

Note: The levels are grounded in our prior work (Welsen, 2025). The operational layer progresses from data challenges (Shahzadi *et al.*, 2024) to AI-driven platforms. The institutional layer matures from reactive postures (Brintrup *et al.*, 2023) to robust governance (Batoool *et al.*, 2025). The global layer addresses cross-border requirements (Gustafsson *et al.*, 2023a; Wilhelm, 2024). The strategic layer evolves to a point where responsible AI becomes a competitive advantage (Hansen *et al.*, 2024).

Source: own study based on Welsen (2025).

## APPENDIX B: ILLUSTRATIVE ANALYSIS CODING PROTOCOL

This appendix documents the systematic approach that we used for the illustrative maturity assessment presented in Section 4.1

### B.1 Documents analysed

Amazon (2025): 2024 Amazon Sustainability Report Otto Group (2025): Annual Report 2024/25 – Sustainability Strategy Zalando SE (2025): Carbon Disclosure Project (CDP) Questionnaire 2025, Corporate Sustainability Reporting Directive (CSRD) Digest 2024, Sustainability Progress Report 2023

### B.2 Coding approach

We systematically searched the documents for explicit mentions of AI, machine learning, and algorithmic systems across four organisational layers. Conservative coding rules were applied: (1) only explicit AI/ML/Algorithm terminology was coded; (2) general digitalisation or non-AI automation was excluded; (3) capabilities were not inferred from absence of evidence; (4) when uncertain about maturity level, the lower level was assigned. Pattern matching analysis then tested observed evidence against the three theoretical propositions.

### B.3 Evidence summary by company (2024-2025) Table B.3

| Amazon Layer  | Evidence                                                                           | Page  | Maturity Level |
|---------------|------------------------------------------------------------------------------------|-------|----------------|
| Operational   | 'AI-powered robots to automate sorting recyclable materials'                       | p. 20 | Fly            |
| Operational   | 'AI machine learning to determine the safest and most efficient packaging'         | p. 22 | Fly            |
| Operational   | 'Detecting water leaks' via AI                                                     | p. 24 | Fly            |
| Operational   | 'Deep learning-based algorithm provides real-time best-fit recommendations'        | p. 36 | Fly            |
| Institutional | 'Review of the Company's approach to responsible AI development and AI governance' | p. 47 | Run            |
| Institutional | 'ISO/IEC 42001 certification... establishes requirements for responsible AI'       | p. 49 | Fly            |
| Global        | 'Joined the Frontier Model Forum to advance AI safety and security'                | p. 49 | Fly            |
| Strategic     | 'Accelerated its investments in generative AI'                                     | p. 4  | Fly            |
| Strategic     | 'Architecture that will simultaneously support next-generation AI capabilities'    | p. 10 | Fly            |

| Otto Group Layer | Evidence                                                                                                                | Page  | Maturity Level |
|------------------|-------------------------------------------------------------------------------------------------------------------------|-------|----------------|
| Operational      | 'AI-powered forecasting tools, including demand forecasting and return rate prediction'                                 | p. 81 | Run            |
| Operational      | 'AI Forecasting solution since 2019'                                                                                    | p. 81 | Run            |
| Operational      | 'Sorting for Circularity' project harnesses artificial intelligence'                                                    | p. 77 | Run            |
| Institutional    | 'Explanatory learning path on how to use our internal AI chat function (ogGPT) to around 17 000 white-collar employees' | p. 80 | Walk           |
| Global           | No explicit AI-specific global guidelines found                                                                         | N/A   | Crawl          |
| Strategic        | 'Responsible use of artificial intelligence ... will remain priorities'                                                 | p. 79 | Walk           |

| Zalando Layer | Evidence                                               | Page | Maturity Level |
|---------------|--------------------------------------------------------|------|----------------|
| Operational   | No explicit AI/ML/Algorithm mentions for due diligence | N/A  | Crawl          |
| Institutional | No AI-specific governance structures found             | N/A  | Crawl          |
| Global        | No AI-specific cross-border coordination found         | N/A  | Crawl          |
| Strategic     | No AI positioning in sustainability strategy           | N/A  | Crawl          |

**B.4 Pattern matching results – Table B.4**

| Proposition         | Amazon     | Otto Group   | Zalando      |
|---------------------|------------|--------------|--------------|
| P1 (Tech-Ethics)    | Consistent | Inconsistent | Inconsistent |
| P2 (Ethics-Culture) | Consistent | Consistent   | Consistent   |
| P3 (Tech-Culture)   | Consistent | Consistent   | Consistent   |

Source: own study.

### B.5 Limitations

Assessments relied exclusively on public disclosures. Sustainability reports may underrepresent AI capabilities reported in other corporate communications. The conservative coding approach may understate actual AI deployment, particularly for Zalando, which uses advanced tools but does not explicitly label them as AI-driven.

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The contribution share of authors was equal and amounted to 50% each. MW – conceptualisation, literature review, framework development, illustrative analysis, and writing; ŁS – methodology design, theoretical supervision, and critical revision.

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### Acknowledgements and Financial Disclosure

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

### Use of Artificial Intelligence

Artificial intelligence tools, specifically Google Gemini Pro and Anthropic Claude 3.5, were used during the preparation of this manuscript exclusively for language editing, proofreading, and text condensation to meet submission length requirements. These tools assisted with a grammar check, sentence refinement, and structural organisation. They were not used to generate original scientific concepts, data, or findings. The authors reviewed and edited all AI-assisted output and take full responsibility for the integrity and content of the final publication.

### Conflict of Interest

The corresponding author is employed by Zalando SE, one of the firms included in the illustrative analysis. This employment informed the selection of e-commerce as the illustrative context but did not influence the maturity assessment, which was based solely on publicly available sustainability reports. No other potential conflicts of interest are declared.

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Published by Krakow University of Economics – Krakow, Poland

