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Impact of human resource training on supply chain efficiency in Guiyang's enterprises: a structural equation modelling (SEM) analysis

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ABSTRACT
This study investigates the impact of human resource (HR) training on supply chain efficiency (SCE) among enterprises in Guiyang, China. A quantitative approach was used to analyse data from 316 respondents across ten key industrial sectors. Structural equation modelling (SEM) was applied to analyse the relationships between HR training, organisational culture, technological adaptability, and supply chain efficiency. The measurement model demonstrated adequate convergent validity (average variance extracted > 0.50) and internal consistency (composite reliability > 0.70). Discriminant validity was confirmed through the Fornell-Larcker criterion and HTMT ratio (< 0.85). The structural model revealed a positive influence of HR training on organisational culture (β = 0.664, $p < 0.01$), technological adaptability (β = 0.399, $p < 0.01$), and SCE made directly (β = 0.262, $p < 0.05$) and indirectly through organisational culture and technological adaptability (β = 0.272, $p < 0.05$). The model fit indices (χ^2/df = 1.295; CFI = 0.984; TLI = 0.976; RMSEA = 0.031) confirmed its robustness. The findings suggest that HR training enhances SCE by improving employee skills, fostering technological integration, and cultivating an adaptive organisational culture. This research contributes to the theoretical understanding of HR development in supply chain management. It provides policymakers and business leaders with practical insights on leveraging workforce training as a strategic tool to enhance supply chain performance in regions such as Guiyang.

KEY WORDS
human resource training, organisational culture, technological adaptability, supply chain efficiency, structural equation modelling (SEM)

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Introduction

Supply chain efficiency (SCE) has become a critical determinant of enterprise success in an era of globalisation and digital disruption, where firms must optimise costs, reduce lead times, and ensure resilience against market volatility (Christopher, 2016; Bowersox et al., 2020, Sakharina et al., 2020). In China, particularly in emerging industrial centres like Guiyang, SCE is essential for driving regional economic growth amid rapid modernisation and integration into global value chains (Govindan et al., 2020). However, the human dimension - specifically,

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how human resource (HR) training influences SCE - remains a pressing issue. While technological and infrastructural investments dominate discussions, the role of workforce development in enhancing or undermining efficiency raises key questions: does HR training foster sustainable operational gains or does it risk creating inefficiencies if not correctly aligned with organisational factors? In transitional economies, skill mismatches that lead to supply chain bottlenecks and other high-profile challenges underscore these concerns, prompting debates over whether HR initiatives promote mutual benefits or exacerbate vulnerabilities (Sanders, 2016; Zhu et al., 2023).

Existing research highlights controversies surrounding the impact of HR training on SCE. On one hand, proponents argue that targeted training builds adaptive skills, enabling better process coordination and innovation, as seen in studies linking employee development to improved lean practices and digital integration (Gunasekaran et al., 2015; Fu et al., 2023). For instance, in manufacturing contexts, HR programmes have been credited with boosting productivity and reducing waste, mirroring benefits in broader resource management frameworks (Huo et al., 2021). On the other hand, critics contend that without supportive mechanisms, training can lead to misallocated resources or underutilised capabilities, akin to "inefficiency trap" scenarios in strategic investments where initial gains give way to long-term strains (Queiroz et al., 2019; Hasan et al., 2022). Cases from developing regions, where firms face cultural resistance or technological gaps, illustrate these tensions, though some attribute failures to pre-existing weaknesses rather than training itself (Lee & Park, 2024; Song et al., 2021).

Despite these insights, prior studies exhibit notable shortcomings, often treating HR training in isolation from mediating factors such as organisational culture and technological adaptability, thereby limiting a comprehensive understanding of its pathways to SCE (Tripathi & Talukder, 2020; Zen et al., 2023). This oversight is especially evident in regional contexts like Guiyang, where empirical evidence on human-centric drivers remains scarce amid industrial transitions. To address these gaps, this study examines the influence of HR training on SCE in Guiyang enterprises, identifies mediating mechanisms, such as organisational culture and technological adaptability, and offers policy insights to optimise HR strategies in regional supply chains. Specifically, it investigates the impact of HR training on SCE in Guiyang, how organisational culture and technological adaptability mediate this relationship, and what recommendations can enhance HR-SCE synergies for stakeholders. Employing structural equation modelling (SEM) on data from 316 respondents across ten firms, the analysis provides regionally grounded evidence (Alrazehi et al., 2025; Silic et al., 2020).

This paper makes two key contributions to existing literature. First, it applies a structural equation modelling (SEM) framework to examine the mediating roles of organisational culture and technological adaptability in the relationship between HR training and SCE in Guiyang's enterprises. Second, by integrating these factors into the analysis, the study offers novel insights into the broader policy discourse on human resource development - specifically, whether it serves as a vehicle for mutual supply chain enhancement or constitutes an inefficiency trap. While HR training, in principle, mirrors developmental inflows from other organisational investments by providing capabilities for growth, its operational implications and effects on supply chain sustainability depend on how effectively enterprises allocate and manage these resources - a process inherently shaped by organisational culture and technological adaptability.

The remainder of this paper is organised as follows. Section 1 reviews the literature on HR training, SCE, and mediating factors. Section 2 introduces the theoretical framework and hypotheses. Section 3 describes the data and empirical methodology. Section 4 presents the estimated effects of HR training on SCE through mediators. Finally, Section 5 concludes the study with a summary and policy recommendations.

1. Literature review

1.1. HR training and supply chain efficiency

Human resource (HR) training equips employees with critical skills, knowledge, and competencies to streamline supply chain processes, directly boosting efficiency through reduced errors, enhanced coordination, and promoted innovation. Mechanistically, training in lean and agile methodologies enables workers to pinpoint inefficiencies, optimise workflows, and minimise waste and delays (Christopher, 2000; Sanders, 2016). Technology-oriented programmes, such as those on Enterprise Resource Planning (ERP), Radio Frequency Identification (RFID), and blockchain, further improve data accuracy, traceability, and decision-making (Queiroz et al., 2019). Similarly, Total Quality Management

(TQM) and Kaizen initiatives cultivate continuous improvement and defect minimisation (Deming, 1986; Imai, 1986).

Based on empirical evidence, targeted HR interventions enhance learning and performance, yielding cost savings and responsiveness gains (Haq et al., 2021). Green HR training integrates sustainable practices and environmental collaboration, amplifying firm outcomes (Agyabeng-Mensah et al., 2020). Systematic reviews highlight HR's role in bridging skill gaps to achieve operational excellence (Hohenstein et al., 2015), while recent studies on high-involvement HRM show that it fosters resilience and adaptability through employee participation and versatility (Gu et al., 2023; Kumar et al., 2020). Organisations that merge HR training with digital transformation achieve superior resilience and efficiency (Hasan et al., 2022; Fu et al., 2023). These mechanisms - skill augmentation, process refinement, and adaptive innovation - solidify the direct, positive impact of HR training on supply chain efficiency.

1.2. Technological adaptability between HR training and supply chain efficiency

Technological adaptability (TA) mediates the relationship between HR training and supply chain efficiency (SCE) by enabling employees to integrate emerging technologies, such as ERP systems and AI, into operations. Mechanistically, HR training builds digital literacy, reducing resistance to change and facilitating seamless adoption, thereby enhancing data accuracy, forecasting, and resilience (Cascio & Montealegre, 2016; Ivanov et al., 2019). Studies show that technology-enabled capabilities, nurtured through training, mediate performance gains in dynamic environments, like healthcare, where integration and resilience lead to sustainable efficiency (Junaid et al., 2023). ERP implementation, often supported by knowledge-focused training, similarly mediates organisational performance by bridging skill development to operational outcomes (Karim et al., 2023). This pathway - training fostering adaptability, which optimises technological utilisation - amplifies SCE in volatile markets (Teece et al., 1997).

1.3. Organisational culture between HR training and supply chain efficiency

Organisational culture (OC) mediates the impact of HR training on supply chain efficiency by embedding shared values and norms that align behaviours with operational goals. Mechanistically, training reinforces collaborative and innovative cultures, reducing silos and promoting continuous improvement, thereby enhancing coordination and reducing costs (Schein, 2010; Denison & Mishra, 1995). Evidence from the banking sector indicates that HR practices shape culture, mediating employee performance and efficiency (Khaskheli et al., 2025). Innovation-driven cultures, cultivated via training, further mediate organisational outcomes, linking cultural alignment to performance (Imran et al., 2022). Learning-oriented cultures, supported by knowledge management training, serially mediate intelligence and efficiency gains (Meher et al., 2023). This intermediary role - the moulding culture of training, which sustains efficient practices - strengthens SCE in competitive settings (Cameron & Quinn, 2017).

The following hypotheses were proposed to address this gap:

H1: HR training positively influences organisational culture.

H2: HR training positively influences technological adaptability.

H3: HR training positively influences supply chain efficiency.

H4: Organisational culture positively influences supply chain efficiency.

H5: Technological adaptability positively influences supply chain efficiency.

2. Research methods

2.1. Conceptual framework and empirical model

Human resource (HR) training serves as a foundational mechanism for enhancing organisational performance by developing employee competencies, aligning them with strategic goals, and promoting adaptive behaviours (Armstrong & Taylor, 2014). Theoretically grounded in social learning theory (Bandura, 1977), it facilitates knowledge acquisition through observation and practice, while andragogy (Knowles et al., 2005) emphasises self-directed learning for practical application. The Kirkpatrick Model (Kirkpatrick & Kirkpatrick, 2006) provides a mechanistic evaluation of training outcomes, linking individual reactions and behaviours to organisational results (Fig. 1).

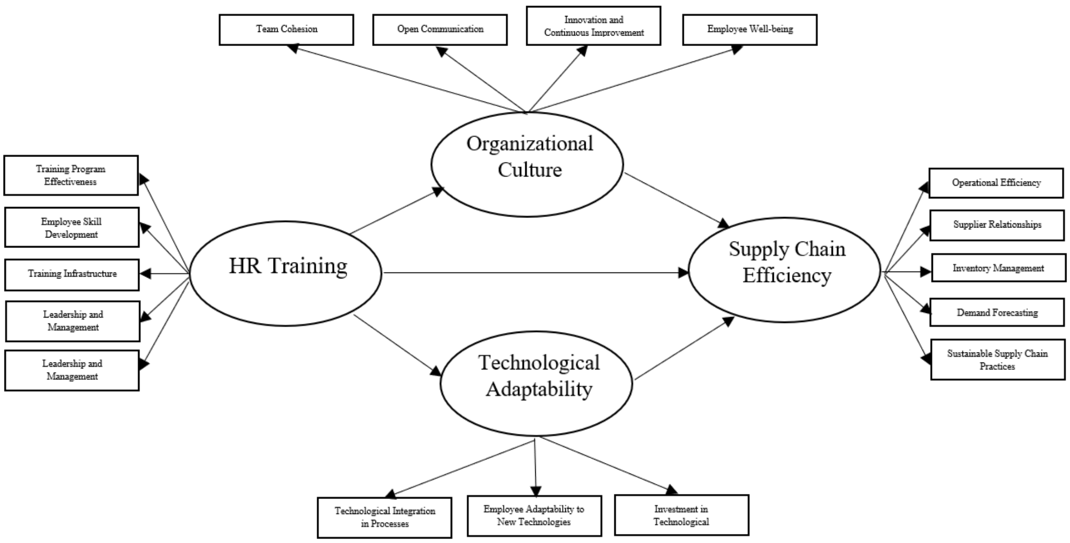

Fig. 1. Conceptual framework

Supply chain efficiency (SCE) operates through optimisation mechanisms that reduce inefficiencies and enhance value creation, drawing from lean principles (Womack et al., 1990) to eliminate wastes such as overproduction and defects. This theory posits that coordinated processes minimise costs and delays, supported by digital tools for real-time coordination (Christopher, 2016; Emon et al., 2024), ultimately fostering responsiveness and sustainability.

Building on the literature review, HR training directly boosts SCE by equipping employees with skills for process refinement and innovation, while indirectly amplifying it via organisational culture and technological adaptability. As per Schein's (2010) model, organisational culture acts as a mediating mechanism by embedding shared norms that reinforce the effects of training, enabling collaboration and resilience (Zen et al., 2023). Technological adaptability, rooted in dynamic capabilities theory (Teece et al., 1997), mediates by translating trained skills into effective technology integration, improving decision-making and agility (Bowersox et al., 2020; Fu et al., 2023).

Thus, the conceptual framework hypothesises that HR training positively influences organisational culture and technological adaptability, which in turn drive SCE. This integrated model underscores the mechanistic interplay of human capital development within cultural and technological contexts for sustainable supply chain outcomes (Gowen & Tallon, 2003; Huo et al., 2021).

$$SCE = \beta_1 HRT + \beta_2 OC + \beta_3 TA + \epsilon.$$

2.2. Data and sample

This study used a mixed-methods approach, integrating quantitative survey data with qualitative interviews to provide a comprehensive analysis of the impact of HR training on SCE. Quantitative data were collected over two months via online questionnaires. Participants were informed of the study's purpose, the voluntary nature of their participation, and confidentiality. Next, qualitative interviews were scheduled to build on the quantitative findings, ensuring method integration. Preliminary quantitative analysis used SPSS 26 for descriptives and normality checks (skewness and kurtosis within ±2). CFA and SEM were conducted in AMOS 26 to assess measurement and structural models. Qualitative data were transcribed, coded, and triangulated with quantitative results to enhance validity and depth.

For the quantitative component, the study subjects were employees of supply chain-related enterprises in Guiyang, covering manufacturing, logistics, and service industries. The target population was approximately 1,600 employees from ten enterprises. The sample size was estimated using G*Power software, requiring at least 300 participants to achieve a moderate effect size and a statistical power of 0.95. Stratified random sampling was used to ensure representativeness across industries (e.g., 40 % manufacturing, 30 % logistics, and 30 % services) and organisational levels (operations, management, and supervisory). Questionnaires were distributed online to 400 potential respondents, yielding 303 valid responses (a response rate of 75.75 %). The sample structure in Tab. 1.

Tab 1. Participant demographics

Category	Description	Percentage
Gender	Female	58.2
	Male	39.2
	Undisclosed	2.6
Age	Under 30	2.1
	Between 31 and 35	14.6
	Between 36 and 40	55.2
	Over 40	28.1
Education	Bachelor's degree	3.8
	Master's degree	84.4
	Doctoral degree	11.8
Monthly Income	Below RMB 6,000	1.6
	6,001- 8,000	10.4
	8,001-10,000	40.0
	Over RMB 10,001	48.0
Occupation	Administrative management	47.3
	Operations	35.0
	Financial accounting	9.3
	Management	4.7
	Self-employment	2.0
	Supervisory roles	1.7

2.3. Variables and measurement

Variables for the quantitative component were measured using a structured questionnaire divided into Part I (demographics) and Part II (constructs), with responses rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Items were adapted from validated scales:

HR training (HRT): 4 items focusing on development, effectiveness, and support (Bandura, 1977; Armstrong & Taylor, 2014).

Organisational culture (OC): 4 items on teamwork, communication, innovation, and engagement (Schein, 2010; Cameron & Quinn, 2011).

Technological adaptability (TA): 3 items on integration, literacy, and readiness (Teece et al., 1997; Garavan, 2007).

Supply chain efficiency (SCE): 5 items on coordination, responsiveness, cost management, and sustainability (Christopher, 2016; Womack et al., 1990).

Content validity was ensured through the item-objective congruence (IOC) index (> 0.50) assessed by three experts (Rovinelli & Hambleton, 1977). A pilot test (n = 30) yielded Cronbach's α > 0.70 for all constructs. Confirmatory factor analysis (CFA) confirmed factor loadings ranging from 0.62 to 0.89 ($p < 0.001$, no loadings at 1.0); convergent validity (composite reliability [CR] > 0.70, average variance extracted [AVE] > 0.50; Fornell & Larcker, 1981); and discriminant validity (square root of AVE > inter-construct correlations, heterotrait-monotrait [HTMT] ratio < 0.85; Henseler et al., 2015). Two correlated error terms (between OC innovation and TA readiness) were included, justified theoretically by overlapping constructs (e.g., innovation often requires technological readiness), and kept minimal to avoid artificially inflating fit indices (Kline, 2015). Detailed correlation analyses for observed and latent variables are provided in Appendix A, as they support preliminary checks but do not directly advance the main SEM argument.

3. Research results

Preliminary data analysis was performed using SPSS version 26, followed by confirmatory factor analysis (CFA) and structural equation modelling (SEM) using AMOS version 26. The specific steps were as follows: descriptive statistics were used to summarise the basic characteristics of the respondents (see Section 3.2 for sample details). Skewness and kurtosis values were within ±2, validating the normality of the data. Reliability was assessed using Cronbach's α coefficient and CR values. CFA was performed to evaluate the measurement model, including factor loadings and model fit indices.

3.1. Measurement model

The measurement model was assessed through CFA to evaluate its quality, including convergent and discriminant validity (Fornell & Larcker, 1981; Henseler et al., 2015). Factor loadings for all items ranged from 0.62 to 0.89 ($p < 0.001$), with no loadings at 1.0, indicating no issues with model specification or data processing. Convergent validity was confirmed by composite reliability (CR) values exceeding 0.70 for all constructs and average variance extracted (AVE) values above 0.50. Discriminant validity was established as the square root of AVE for each construct was greater than its correlations with other constructs, and the heterotrait-monotrait (HTMT) ratio was below 0.85. The model included two correlated error terms (between organisational culture innovation and technological adaptability readiness), justified theoretically by conceptual overlap (e.g., innovation often requires technological readiness;

Kline, 2015). These were kept to a minimum to prevent artificial inflation of fit indices. The measurement model showed good fit ($\chi^2/df = 1.30$, CFI = 0.98, RMSEA = 0.03), providing a solid foundation for the structural model.

3.2. Structural model

The structural model, presented in Fig. 2 with standardised coefficients, examines the direct and indirect effects of HR training on supply chain efficiency through organisational culture and technological adaptability. As shown in Table 2, HR training exerts a significant positive total effect on organisational culture ($\beta = 0.664$, $p < 0.01$) and technological adaptability ($\beta = 0.399$, $p < 0.01$). Its total effect on supply chain efficiency is 0.534 ($p < 0.05$), comprising a direct effect of 0.262 and an indirect effect of 0.272 through the mediators. Organisational culture has a direct effect on supply chain efficiency of 0.268 ($p < 0.05$), while technological adaptability has a direct effect of 0.236 ($p < 0.05$). Mediation analysis confirms partial mediation: HR training influences supply chain efficiency indirectly through organisational culture

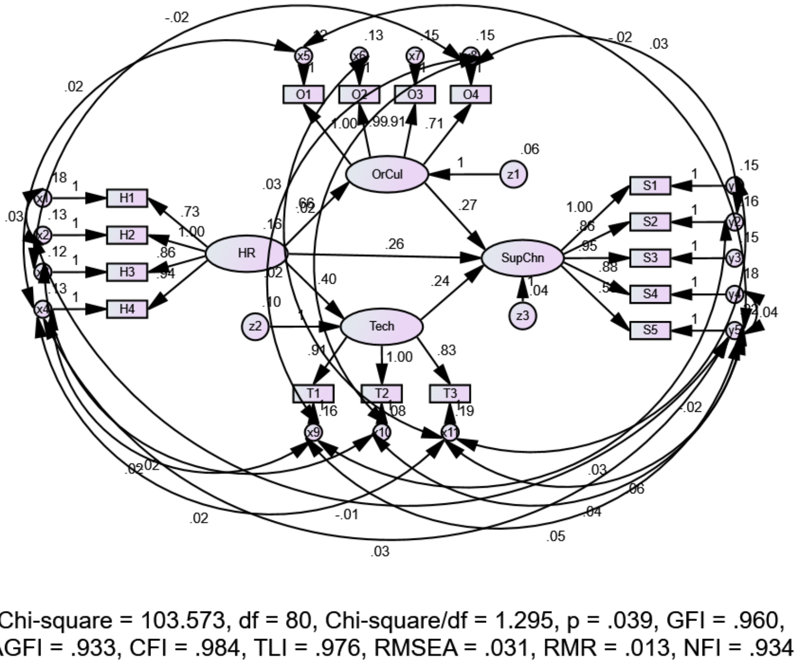

Fig. 2. Structural equation modelling of the impact of human resource training on supply chain efficiency in Guiyang's enterprises

Tab. 2. Model summary

Dependent variables	Organisational culture			Technological adaptability			Supply chain efficiency		
Independent variables	TE	DE	IE	TE	DE	IE	TE	DE	IE
HR training	0.664**	0.664**	-	0.399**	0.399**	-	0.534*	0.262*	0.272*
Organisational culture	-	-	-	-	-	-	0.268*	0.268*	-
Technological adaptability	-	-	-	-	-	-	0.268*	0.268*	-
R-square		0.528			0.203			0.567	

Note: p < 0.05 (*), p < 0.01 (**)

Model fit statistics:
$\chi^2 = 103.573$, $df = 80$, $\chi^2/df = 1.295$, $p = 0.039$, GFI = 0.960, CFI = 0.984, TLI = 0.976, NFI = 0.934, RMSEA = 0.031, RMR = 0.013.

(indirect effect = 0.178, $p < 0.05$) and technological adaptability (indirect effect = 0.094, $p < 0.05$). The model's explanatory power is robust, with R^2 values of 0.528 for organisational culture, 0.203 for technological adaptability, and 0.567 for supply chain efficiency. Model fit statistics indicate a well-specified model (χ^2 = 103.573, df = 80, χ^2/df = 1.295, p = 0.039, GFI = 0.960, CFI = 0.984, TLI = 0.976, NFI = 0.934, RMSEA = 0.031, RMR = 0.013). Detailed correlation analyses for observed and latent variables are provided in Appendix A, as they support preliminary checks but do not directly advance the main SEM argument.

3.3. Qualitative results

Qualitative data from 15 semi-structured interviews were analysed using thematic analysis (Braun & Clarke, 2006) and coded in NVivo software. The analytic framework was grounded in the conceptual model, linking themes directly to the research questions and constructs (HR training, organisational culture, technological adaptability, and supply chain efficiency). The coding procedure involved open coding to identify initial patterns, axial coding to establish relationships, and selective coding to refine core themes. Three key themes emerged: (1) skill enhancement through training: respondents emphasised the role of training in boosting efficiency, with one noting that "Training helped us reduce inventory errors by 20 %" (Manager A), linking the result to HR training and supply chain efficiency; (2) cultural alignment: participants highlighted improved collaboration post-training, e.g., "Our team culture improved post-training, leading to better supplier coordination" (Supervisor B), connecting the result to organisational culture as a mediator; (3) technological integration: adaptability was seen as critical; one participant commented that "Digital tools are useless without trained staff" (Manager C), tying training to technological adaptability's role in enhancing supply chain outcomes. These themes corroborate the quantitative findings, illustrate practical mechanisms, and reinforce the model's validity. For space constraints, a coding tree, exemplar quotes, and an analysis outline are provided in Appendix B.

Conclusions

This study employed a mixed-methods design, utilising structural equation modelling (SEM) for quantitative analysis and thematic analysis for qualitative insights, to investigate the impact of human resource (HR) training on supply chain efficiency (SCE) in enterprises located in Guiyang, China. The quantitative results confirmed that HR training exerts direct and indirect positive effects on SCE through the mediating roles of organisational culture and technological adaptability. Specifically, HR training significantly enhances organisational culture ($\beta = 0.664$, $p < 0.01$) and technological adaptability ($\beta = 0.399$, $p < 0.01$), thereby contributing to improved SCE (direct effect: $\beta = 0.262$, $p < 0.05$; indirect effect: $\beta = 0.272$, $p < 0.05$). The model's explanatory power is robust, with R^2 values of 0.528 for organisational culture, 0.203 for technological adaptability, and 0.567 for SCE, underscoring the pivotal role of employee development and technological readiness in driving operational excellence within supply chains. Qualitative findings from semi-structured interviews with 15 managers and supervisors confirmed these outcomes, revealing key themes such as skill enhancement, cultural alignment, and technological integration that illustrate the practical mechanisms underlying these relationships.

The findings advance the literature by integrating HR training, organisational culture, and technological adaptability into a unified empirical model of supply chain performance, addressing gaps in prior research that often examined these variables separately (Huo et al., 2021; Fu et al., 2023). This study contributes novel insights into socio-technical systems theory (Trist & Bamforth, 1951), demonstrating how human capital development interacts with cultural and adaptive factors to enhance efficiency and competitiveness in transitional economies.

From a managerial perspective, the results suggest that enterprises in Guiyang and similar regions should prioritise strategic investments in HR training programmes aligned with organisational values and technological priorities to foster collaboration, innovation, and resilience. Policymakers could support this through public-private partnerships, tax incentives, and industry-wide initiatives to promote workforce upskilling and regional supply chain sustainability.

Although this study offers robust evidence, several limitations warrant acknowledgement. The cross-sectional quantitative design limits causal inferences, while the qualitative sample of 15 interviews may constrain broader perspectives. Data collection relied on self-reported surveys, potentially introducing common method bias, and online distribution may have excluded participants who were less digitally accessible. Analytically, the SEM assumptions of normality and linearity were met, but could be sensitive in expanded datasets; the two correlated error terms, though justified, highlight possible conceptual overlaps. These constraints inform future research, including longitudinal designs to establish causality, larger and more diverse samples across provinces, and incorporation of additional variables, such as leadership or economic policies. Further qualitative expansions through case studies could validate themes and explore human-centric supply chain dynamics in greater depth.

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Strategic competency development for Industry 5.0 leaders: perspectives from the manufacturing sector

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ABSTRACT

This paper aims to identify and define key leadership competencies required for Industry 5.0 in the manufacturing sector, emphasising the integration of advanced technologies with human-centric and sustainability values across different organisational levels.

A two-round Delphi study was conducted with 30 manufacturing experts from multiple priority sub-sectors in Indonesia. Quantitative consensus was assessed using median ≥ 4.0 and IQR ≤ 1.0, complemented by Kendall's W to measure agreement strength.

The study generated a comprehensive Industry 5.0 Leadership Competency Framework consisting of five core dimensions: technical mastery, strategic leadership, people management, business acumen, and sustainability, supported by 24 validated competencies prioritised across senior, middle, and entry-level leadership roles.

This study advances leadership theory by proposing a multilevel (macro-meso-micro) human-centric leadership model that integrates sustainability and ethical technological implementation, addressing a missing linkage in current Industry 5.0 literature.

The framework guides manufacturing organisations in designing tiered leadership development pathways, performance evaluation instruments, and succession strategies aligned with Industry 5.0 transformation and sustainable operational excellence.

KEY WORDS

Industry 5.0, manufacturing leadership, competency framework, Delphi study, sustainable transformation

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Introduction

Industry 5.0 represents a major step forward in the development of interventions compared to Industry 4.0, which focuses on the sustainability of economic progress alongside novelty, toughness, and humanistic solutions. Compared to Industry 4.0, which was mainly concerned with the digital evolution and automation, Industry 5.0 is a more proportional approach to human potential and smarter technologies (Ghobakhloo et al., 2023). The change would require a drastic modification in manufacturing processes, especially in how organisations are

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leading towards leadership development and competency development. According to Suciu et al. (2023), core competencies should be carefully considered in this transition to achieve sustainable and resilient development in the manufacturing conditions. In the digital age, the role of leadership competencies has become even more significant, especially in the context of the continuously growing complexity of available technologies, technological environments, and ecosystems, which require a high-level mix of technical, strategic, and people-oriented skills (Kwiotkowska et al., 2021).

Modern challenges in manufacturing leadership are connected to the need to unite technological progress with a focus on people and sustainability. Shet et al. (2021) listed 14 key managerial competencies for qualified leaders who demonstrate effective leadership skills in this dynamic environment. Kipper et al. (2021) identified competencies such as strategic vision, self-organisation, proactivity, and interdisciplinary thinking as essential leadership requirements in a digitalised manufacturing environment. The post-COVID-19 environment has exacerbated these difficulties, as much more attention has been paid to relationship development and employee wellbeing (Majczyk et al., 2022). Also, manufacturing leaders must address competency gaps in strategic perspective and digital transformation, and ensure operational excellence (Kwiotkowska et al., 2022).

Past studies have outlined competence requirements for manufacturing practices across different areas, but fail to integrate humanistic and sustainability issues, which are the focus of Industry 5.0. Gudanowska et al. (2018) suggested that competencies in the production industry are defined locally, whereas Grzybowska and Lupicka (2017) indicated the requirements of Industry 4.0 without envisioning the anthropomorphic gears of Industry 5.0. Likewise, Singh et al. (2014) focused on listing competencies that influence industrial competitiveness and omitted the sustainability aspects of manufacturing strategy that determine it. Although Schinner (2022) examined competency management in manufacturing and Dahl et al. (2023) examined future competency learning methods, the two papers do not include the integrative thinking needed to support a sense of participation in a human-AI setting. Wickramaratne et al. (2014) examined entrepreneurial competencies, but did not consider the ability to build resilience, a new requirement in the work environments of Industry 5.0.

The lack of a complex, definite competency model for Industry 5.0 manufacturing leadership is a major challenge for organisational development. It has been found that manufacturing leaders may lack the integrated abilities required for effective navigation in the world of technological development and humanised approaches (Ghobakhloo et al., 2023). The research by Kwiotkowska et al. (2022) found that more than 60 per cent of manufacturing industry companies reported a significant lack of competencies in strategic perspectives and digital transformation skills. This inconsistency is especially pronounced in sustainability leadership and stakeholder involvement, where traditional manufacturing leadership is not sufficient. Almost every seventh manufacturing organisation is facing ineffective leadership in digital transformation, and the main reason is insufficient competency development frameworks (Kwiotkowska et al., 2021).

The combination of technological progress and humanistic leadership tendencies offers special prospects of institutional reconstruction and new invention. A report shows that the new manufacturing leaders should attain skills beyond the technical experience and understanding, including emotional intelligence and advanced thinking (Bianco et al., 2023). Companies that use integrated leadership development models in their operations achieve higher performance and become more innovative. Current studies indicate that adaptive leadership characteristics are crucial for swift responses to technological change and market conditions (Kaur & Anand, 2022). This research gap underlines the requirements for a framework that combines technological expertise and humanistic proficiency, alongside sustainability principles that drive transformations beyond the Industry 4.0 era. Such a structure would accommodate the needs of the present and the demands of future manufacturing leadership under Industry 5.0, allowing organisations to achieve sustainable change without losing operational excellence.

1. Literature review

1.1. Evolution from Industry 4.0 to Industry 5.0

The adoption of Industry 5.0 brings a major change from Industry 4.0, focusing on human-centric practices. Industry 5.0 is a radical shift in the Industry

4.0 paradigm, which is largely focused on technology-based solutions towards a more balanced integration of human capability with high-tech technologies. Whereas Industry 4.0 was all about digitalisation, automation, and cyber-physical systems, Industry 5.0 centres on three major pillars: sustainability, resilience, and human-centricity (Ghobakhloo et al., 2023; Lagorio et al., 2022). This development is an admission that the use of technology is no longer a comprehensive solution to difficult industrial problems; hence, an additional element should be incorporated in the change, i.e., viewing human resources in terms of creativity, ethical practices, and respect for the environment, to effectively effect the change. Industry 5.0 is characterised by distinctive features of collaborative human-machine activities, regenerative production systems, circular-economy practises, and value-driven technological implementations that place particular stress on human wellbeing and the environment (Oeij et al., 2024; Poszytek et al., 2023; Giedraiti & Stašys, 2019). As a result, manufacturing grounds need to find a balance between high-tech and high-touch, or create an environment or a setting where technology does not substitute for human capabilities but rather supplements them (Pinto et al., 2024; Tschiedel et al., 2025; Sahban, 2019). There is also a need for new leadership practices that incorporate technical knowledge and awareness alongside emotional intelligence and moral decision-making (Kipper et al., 2021; Shet et al., 2021). Moreover, it is necessary to implement sustainability measures in their manufacturing, in addition to implementing performance measures, to stress the responsible use of resources and reduce environmental burdens (Suciu et al., 2023). These changes require rethinking competency frameworks alongside human-oriented, sustainable manufacturing conditions, as the future of the industry would presuppose in Industry 5.0.

The development of Industry 4.0 to 5.0, as presented in Fig. 1, shifts industrial systems to a human-centred, sustainable, and resilient model. Whereas Industry 4.0 was mainly concerned with the digitalisation and the efficiency of industries with the help of such inventions as the Internet-of-Things (IoT),

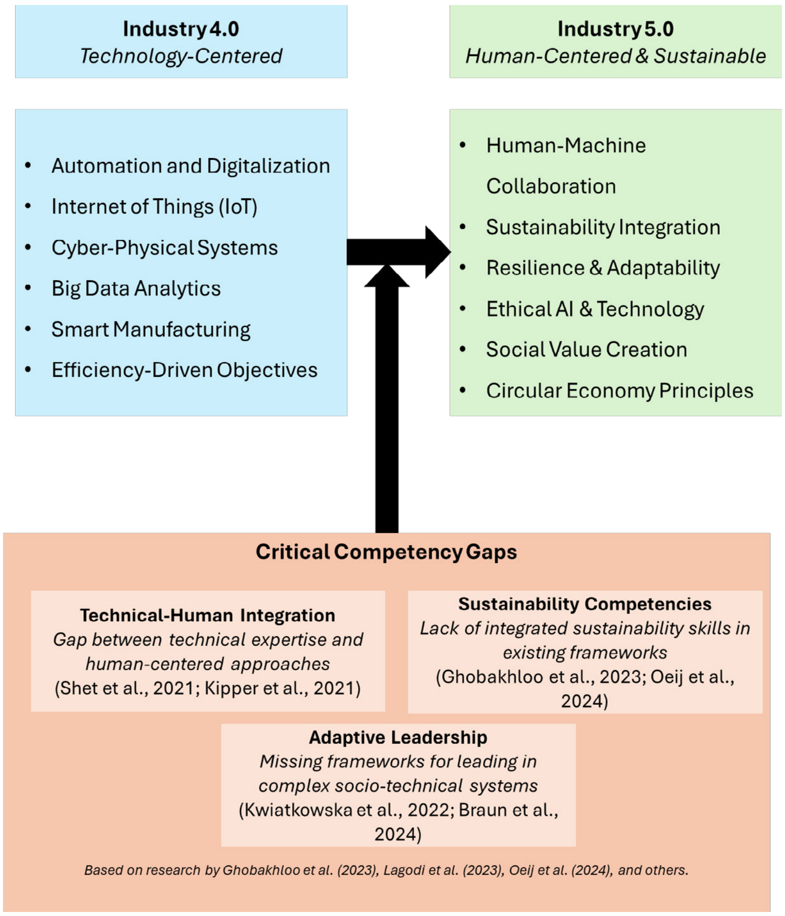

Fig. 1. Evolution from Industry 4.0 to Industry 5.0 and competency gaps

Cyber-Physical Systems, and Big Data Analytics, Industry 5.0 would continue these concerns, but with a new area of focus, which would be the collaboration between the human and the machine, integration with sustainability, and adaptation simplicity and robustness (Ghobakhloo et al., 2023; Oeij et al., 2024). Moreover, Fig. 1 shows the essential competency gap caused by this transition. To begin with, technical-human integration skills are needed to fill the gap between humanistic strategies and technical knowledge (Kipper et al., 2021; Shet et al., 2021). Second, sustainability competencies should be integrated into the line of operations to incorporate responsible and ethical production (Ghobakhloo et al., 2023; Oeij et al., 2024). Third, the skills of adaptive leadership become increasingly relevant while navigating through the social-technical interactions that complicate Industry 5.0 media (Braun & Clarke, 2006; Kwiatkowska et al., 2022). It is essential to address these competency gaps to take a step towards creating future manufacturing ecosystems where advanced technologies enable human creativity and foster environmental protection.

1.2. Gaps in existing competency frameworks

Though substantial progress has been made in determining the competencies needed for Industry 4.0, the move to Industry 5.0 identifies gaps beyond the scope of current frameworks. As Table 1 shows, most earlier frameworks have focused on digitalisation, automation, and technical expertise and have failed to incorporate a human angle, sustainability, and resilience (Ghobakhloo et al., 2023; Lagorio et al., 2022; Poszytek et al., 2023). The transition from Industry 4.0 to Industry 5.0 requires a reorientation of competency frameworks to incorporate human-machine collaboration, ethical decision-making, sustainability integration, and adaptability in complex socio-technical systems. Technical competencies identified for Industry 4.0 - such as operating emerging technologies and digital adaptability - lack the necessary connection to human skills, such as emotional intelligence, workplace wellbeing, and ethical technology use (Grzybowska & Łupicka, 2017; Oh et al., 2024; Singh et al., 2014).

Similarly, while the importance of soft skills and leadership has been acknowledged in earlier research, existing models often fall short in designing competencies for human-AI collaboration, systematic integration of sustainability principles, and development of circular economy capabilities (Pinto et al., 2024; Shet et al., 2021; Ward et al., 2025). Current training and development methodologies remain predominantly conventional, relying on formal learning approaches without sufficient emphasis on adaptive, personalised learning and continuous competency development pathways (Braun & Clarke, 2006; Kutty Mammi & Ithnin, 2012; Peláez-Sánchez et al., 2024). In addition, implementation and measurement strategies remain highly qualification-oriented, where dynamic evaluation systems and situational adjustments are much needed in an Industry 5.0 surrounding (Dahl et al., 2023; Kipper et al., 2021; Kwiotkowska et al., 2022). In a broader sense, numerous frameworks are confined to a particular part, lacking an integrated approach to managing socio-technical systems productively (Bianco et al., 2023; Schinner, 2022; Suciu et al., 2023). Moreover, organisational readiness strategies are usually related to reactive or one-dimensional interventions, rather than proactive, changeable transformation patterns corresponding to the competency maturity demands of Industry 5.0 (Gudanowska et al., 2018; Kaur & Anand, 2022; Majczyk et al., 2022).

On the whole, an integrated competency framework is greatly needed to close a significant gap between industrial demands and the disjointed current methods. This kind of framework would have to integrate technical, human-centric, sustainability, and strategic aspects into a single model that can be used to drive leadership and the workforce, in the future, in the age of Industry 5.0. Until these gaps are closed, manufacturing organisations face significant difficulties in continuing with innovation, operational excellence, and resilience in a world that is increasingly complex and dynamic.

2. Research methods

2.1. Research design

The research used a modified Delphi technique to build expert consensus regarding leadership competencies needed for Industry 5.0 in the Indonesian manufacturing sector. Delphi is particularly effective when the aim is to synthesise specialised knowledge in emerging topics with limited empirical grounding (Hasson et al., 2000). A total of 30 experts from diverse sub-sectors participated in two iterative rounds of rating and refinement. The authors' institution granted ethical approval, and informed consent

Tab. 1. Identified gaps in existing competency frameworks for Industry 5.0 transition

KNOWLEDGE DIMENSION	WHAT EXISTS	GAPS IDENTIFIED	KEY REFERENCES
Industry evolution from 4.0 to 5.0	Focus on digitalisation and automation	Lack of integration of human-centric approaches	Ghobakhloo et al. (2023)
	Competency frameworks for Industry 4.0	Unclear mapping of transition from 4.0 to 5.0	Lagorio et al. (2022)
	Emphasis on technology	Sustainability principles not fully embedded	Poszytek et al. (2023)
Technical competencies	Identification of specific technical skills	Integration with human skills	Grzybowska and Łupicka (2017)
	Expertise in operating technology	Human-machine collaboration	Singh et al. (2014)
	Technical adaptability	Ethical awareness in technology use	Oh et al. (2024)
Human-centric approaches	Importance of soft skills	Design of human-AI collaboration	Shet et al. (2021)
	Interpersonal competencies	Workplace wellbeing competencies	Pinto et al. (2024)
	Basic leadership skills	Ethical decision-making skills	Ward et al. (2025)
Sustainability and resilience	Some sustainability aspects identified	Systematic integration of sustainability in competencies	Tschiedel et al. (2025)
	Focus on resource efficiency	Environmental risk management	Oeij et al. (2024)
	Basic operational resilience	Circular economy competencies	Wickramaratne et al. (2014)
Development methodology	Conventional training models	Adaptive development methodology	Pelaez-Sanchez et al. (2024)
	Formal learning approaches	Personalised learning pathways	Kutty Mammi and Ithnin, 2012
	Competency-based systems	Integration of continuous learning	Braun and Clarke (2006)
Implementation and measurement	Descriptive competency frameworks	Measurable success metrics	Kipper et al. (2021)
	Qualification-based assessment	Dynamic evaluation systems	Kwiotkowska et al. (2022)
	Generic implementation models	Contextual adaptation mechanisms	Dahl et al. (2023)
Multidisciplinary perspective	Focus on single domains	Integrated multidisciplinary frameworks	Suciu et al. (2023)
	Sectoral and siloed approaches	Knowledge synthesis across domains	Schinner (2022)
	Limited cross-disciplinary integration	Socio-technical systems perspective	Bianco et al. (2023)
Organisational readiness strategy	General implementation guidelines	Organisational transformation strategies	Majczyk et al. (2022)
	Focus on individual competencies	Competency maturity models	Kaur and Anand (2022)
	Reactive approach	Proactive and adaptive approaches	Gudanowska et al. (2018)

was obtained from all participants with confidentiality safeguards in place.

Purposeful sampling was used as the data collection method to select participants who had the qualities described and relevant backgrounds to provide diverse and exhaustive views on the research question (Saunders, 2017). The 30 Indonesian manufacturing experts covered a variety of sub-sectors, allowing the study to gain a broad picture of competencies in the industry as opposed to a specific niche. Special consideration was given to the inclusion of experts from manufacturing industries, which are considered the cornerstone of the Indonesian manufacturing ecosystem, such as textile, automotive, electronics, food and beverage, and chemical industries. Details of the companies are given in Table 2.

Table 2 provides an overview of the companies represented in the study, highlighting the diversity of sectors, industrial focus, and production scales in the Indonesian context. The sample includes both private and public/government organisations, reflecting Indonesia's manufacturing landscape where state-

Tab. 2. Manufacturing company information in the Indonesian context

	FREQUENCY	PERCENTAGE
Sector		
Private	21	70.00
Public/government	9	30.00
Industrial type		
Heavy manufacturing	18	60.00
Consumer goods	12	40.00
Industrial sector		
Textiles and apparel	6	20.00
Food and beverage	5	16.67
Automotive and transportation	5	16.67
Electronics and components	4	13.33
Chemicals and pharmaceuticals	3	10.00
Metals and machinery	3	10.00
Furniture and wood products	2	6.67
Mining and processing	2	6.67
Production scale		
Large (>1000 employees)	12	40.00
Medium (500-1000 employees)	12	40.00
Small (<500 employees)	6	20.00
Geographic location		
Java	18	60.00
Sumatra	6	20.00
Sulawesi	3	10.00
Kalimantan	2	6.67
Eastern Indonesia	1	3.33

owned enterprises coexist with private companies. The represented sectors span heavy manufacturing and consumer goods, with particular emphasis on priority sectors identified in Indonesia's Making Indonesia 4.0 roadmap, including food and beverage, textiles, automotive, electronics, and chemicals. The range of company sizes - from large-scale operations with over 1,000 employees to smaller enterprises - ensures a comprehensive understanding of leadership competencies across varied manufacturing contexts within Indonesia's industrial ecosystem.

Table 3 summarises key demographic characteristics of the study's participants, including gender, age, educational background, years of experience, and job positions. Participants represent a balanced mix of genders and a broad age range, with most holding advanced degrees in fields such as engineering, business, and technical sciences. The range of experience levels and seniority - from plant managers to senior executives - provides well-rounded insights into the competencies needed for effective leadership in Industry 5.0 within the manufacturing sector.

2.2. Data collection

The Delphi study was conducted in two distinct rounds, each designed to systematically refine and validate leadership competencies required for Industry 5.0 in manufacturing contexts.

2.2.1. Round 1: competency identification and initial rating

The first round focused on identifying and generating a comprehensive list of potential leadership competencies. A questionnaire was developed based on a literature review and theoretical frameworks, including Industry 5.0 principles, Leadership Pipeline theory, and Situational Leadership theory. The questionnaire was structured into five thematic sections,

Tab. 3. Manufacturing company information in the Indonesian context

	FREQUENCY	PERCENTAGE
Gender		
Male	18	60
Female	12	40
Age range		
30-39 years	6	20
40-49 years	12	40
50-59 years	9	30
60+ years	3	10
Education level		
PhD	6	20
Master's	15	50
Bachelor's	9	30
Education background		
Engineering	12	40
Business/management	9	30
Technical sciences	6	20
Other	3	10
Years of manufacturing experience		
10-15	9	30
16-20	12	40
21-25	6	20
>25	3	10
Position		
Senior executive/director	6	20
Operations director	6	20
R&D/technical head	6	20
Quality/safety head	3	10
Government official	3	10
Association head	3	10
Plant manager	3	10

Tab. 4. Delphi questionnaire's thematic sections

SECTION	FOCUS AREAS
I. Respondent background	Professional experience Current roles and responsibilities Exposure to digital transformation and Industry 5.0
II. Understanding of Industry 5.0	Definition and conceptualisation of Industry 5.0 Differences between Industry 4.0 and 5.0 Perceived impact on the manufacturing sector
III. Leadership competencies for Industry 5.0	Identification of critical competencies Differences from previous industrial eras Practical application in daily operations Relevance across leadership levels (entry, middle, and senior)
IV. Challenges and opportunities	Barriers to competency development Organisational strategies for overcoming challenges Emerging opportunities from Industry 5.0 transformation
V. Future vision	Projected evolution of the manufacturing sector Workforce development preparation strategies Long-term competency needs

as shown in Table 4. Participants were asked to identify key competencies they believed essential for effective leadership in Industry 5.0 manufacturing environments and to provide rationales for their selections. Additionally, participants rated the importance of each competency on a 5-point Likert scale (1 = not important, 5 = extremely important) and specified the leadership level (entry, middle, and senior) at which each competency was most critical. The objective of this round was to canvass as many views as possible and advance to the process of consensus-building in the next round.

2.2.2. Round 2: consensus building and final validation

A summary of the results of the first round was anonymised and given to participants in the second round (aggregate ratings and results of qualitative analysis of themes). The prioritisation of the competencies was based on the mean importance ratings given by the participants, and to contextualise it, the individual participants' rationalisations were also provided. Then, participants were invited to see these outcomes and reconsider their ratings based on the group's response. For each competency, participants could retain or modify their previous ratings and were expected to provide a rationale if their ratings differed substantially from the median value. Also, the participants rated the suitable level of leadership for each competency and its applicability across various manufacturing situations. This feedback process enabled quantitative consensus and qualitative development of the findings (Table 4).

2.3. Data analysis

The data analysis strategy was designed to give a quantitative and qualitative understanding of the Delphi findings. Quantitative ratings were subjected to statistical analysis, whereas qualitative responses were analysed using the thematic method.

2.3.1. Quantitative analysis

The Likert scale ratings were statistically analysed to determine the importance of each identified competency. Measures of central tendency (mean and median), measures of dispersion (standard deviation and interquartile range), frequency distributions, and percentage agreement were calculated. Consensus was defined as median ≥ 4.0 (indicating high perceived importance) and IQR ≤ 1.0 (indicating high agreement), with IQR ≤ 0.5 reflecting strong consensus among participants. To evaluate the stability of responses across Delphi rounds, agreement levels between Round 1 and Round 2 were further assessed using Kendall's coefficient of concordance (W) and its significance values (Schmidt, 1997), enabling a more robust measure of inter-expert reliability.

2.3.2. Qualitative analysis

A thematic analysis of the qualitative data collected through open-ended replies was conducted, followed by a six-phase method suggested by Braun and Clarke (2006). Data familiarisation was the first step, which involved reading and re-reading all the responses and taking preliminary notes. Next was the first coding stage, which involved systematically identifying the pertinent features in the responses and coding them. The following step was to code these codes into possible themes in the data. After themes were identified, they were re-examined based on their internal consistency and coherence across the entire dataset. Then, themes were refined and clearly defined, and each theme was assigned a specific name. The report, which contained illustrative examples and provided links between the findings and the research questions, was prepared at the end of the analysis. Interrater reliability was used to enhance the analysis by having two analysts work independently and code a portion of the data. The kappa coefficient devised by Cohen was used to analyse the agreement between the coders, and values greater than 0.75 were considered excellent (Fleiss et al., 2003). Coding inconsistencies were determined and eliminated by agreement.

2.3.3. Integration and framework development

The last step of the analysis entailed synthesising the quantitative consensus ratings with the qualitative thematic outputs to develop a combined competency framework. The integration enabled a multidimensional perception of each competency, including its relative significance, the level of leadership at which it can be applied, its contextual uses, and the relationship with other competencies. This framework clustered the competencies in a rational and logical way depending on the statistical relations as well as the thematic prerequisites to produce an apparent, organised model that reflects not only the consensual priorities of the expert panel but also the context-based nuances identified through qualitative analysis.

3. Research results

The first round of the Delphi study yielded a comprehensive set of leadership competencies considered essential for Industry 5.0 in manufacturing contexts. Table 5 presents the initially identified competencies, their mean importance ratings, and standard deviations. The table also shows the leadership level at which experts believed each competency was most critical.

The qualitative analysis of Round 1 responses revealed several key themes regarding the nature and application of these competencies in manufacturing contexts. Participants emphasised the fundamental shift from technology-centred to human-centred approaches in Industry 5.0, identifying human-machine collaboration as the highest-rated competency (M = 4.82, SD = 0.38). One senior executive commented:

"The essence of Industry 5.0 lies in the harmonious collaboration between humans and technology. Leaders must orchestrate this interaction to maximise both technological capabilities and human creativity".

Sustainability leadership (M = 4.73, SD = 0.45) emerged as another critical competency, reflecting Industry 5.0's emphasis on environmental responsibility. Participants noted that this represented a significant departure from previous industrial paradigms, which focused primarily on efficiency and productivity without necessarily considering environmental impact (Table 6):

"Previous manufacturing approaches treated sustainability as an afterthought or compliance issue. In Industry 5.0, it must be embedded in every decision and process, requiring leaders who can balance economic, social, and environmental objectives".

The results summarised in Table 6 reflect the particular characteristics of the Indonesian manufacturing context. Two additional competencies - cross-cultural management and local resource optimisation - emerged as especially critical, receiving strong consensus ratings from the expert panel. These competencies were not originally emphasised in broader international frameworks but were seen as essential for addressing the cultural diversity and resource variability that characterise Indonesia's industrial landscape. Furthermore, competencies such as supply chain resilience and SME integration capability were highlighted as particularly relevant for Indonesia's manufacturing ecosystem, where supply chain

Tab. 5. Industry 5.0 leadership competencies: Round 1 results

COMPETENCY	MEAN RATING	SD	PRIMARY LEADERSHIP LEVEL
Human-machine collaboration	4.82	0.38	Middle
Digital transformation management	4.76	0.43	Senior
Sustainability leadership	4.73	0.45	Senior
Adaptive decision-making	4.70	0.47	All levels
Systems thinking	4.67	0.48	Middle/senior
Ethical technology deployment	4.63	0.49	Senior
Data-driven leadership	4.60	0.50	Middle/senior
Resilience building	4.57	0.50	All levels
Cross-functional integration	4.53	0.51	Middle
Human-centred design thinking	4.50	0.57	Middle
Technological foresight	4.47	0.57	Senior
Workforce upskilling management	4.43	0.63	Middle
Collaborative innovation	4.40	0.67	All levels
Complexity management	4.37	0.72	Senior
Agile change leadership	4.33	0.76	Middle/senior
Social value creation	4.30	0.79	Senior
Circular economy implementation	4.27	0.83	Senior
Multi-stakeholder engagement	4.23	0.86	Senior
Digital wellbeing facilitation	4.17	0.91	Middle
Cultural intelligence	4.13	0.94	All levels

Tab. 6. Industry 5.0 leadership competencies in Indonesian manufacturing: Round 2 results and consensus indicators

Competency	Round 1 Mean	Round 2 Mean	Change	IQR	Consensus Level*
Human-machine collaboration	4.82	4.9	0.08	0	Strong
Digital transformation management	4.76	4.87	0.11	0	Strong
Sustainability leadership	4.73	4.83	0.1	0	Strong
Adaptive decision-making	4.7	4.8	0.1	0.5	Strong
Cross-cultural management	4.65	4.77	0.12	0.5	Strong
Systems thinking	4.67	4.73	0.06	0.5	Strong
Local resource optimisation	4.61	4.73	0.12	0.5	Strong
Ethical technology deployment	4.63	4.7	0.07	0.5	Strong
Data-driven leadership	4.6	4.67	0.07	1	Moderate
Resilience building	4.57	4.67	0.1	1	Moderate
Human-centred design thinking	4.5	4.63	0.13	1	Moderate
Cross-functional integration	4.53	4.6	0.07	1	Moderate
Technological foresight	4.47	4.57	0.1	1	Moderate
Supply chain resilience	4.43	4.57	0.14	1	Moderate
Workforce upskilling management	4.43	4.53	0.1	1	Moderate
Collaborative innovation	4.4	4.53	0.13	1	Moderate
Agile change leadership	4.33	4.47	0.14	1	Moderate
Complexity management	4.37	4.43	0.06	1.5	Moderate
Social value creation	4.3	4.4	0.1	1.5	Moderate
SME integration capability	4.27	4.37	0.1	1.5	Moderate
Circular economy implementation	4.27	4.33	0.06	1.5	Moderate
Multi-stakeholder engagement	4.23	4.3	0.07	1.5	Moderate
Digital wellbeing facilitation	4.17	4.23	0.06	2	Weak
Cultural intelligence	4.13	4.2	0.07	2	Weak

*Consensus levels: strong (IQR ≤ 0.5), moderate (IQR 0.6-1.5), weak (IQR > 1.5)

vulnerabilities and the importance of small and medium-sized enterprises (SMEs) present unique leadership challenges. These findings underscore the need for localised adaptation of Industry 5.0 leadership frameworks to ensure contextual relevance and operational effectiveness within different national manufacturing environments.

4. Discussion of the results

The transition to Industry 5.0 requires leadership competencies that simultaneously address technological advancement, sustainability integration, and human-centric innovation. As demonstrated in the preceding analysis, Indonesian manufacturing confronts distinctive contextual challenges, including resource variability, workforce diversity, and uneven levels of digital maturity. Accordingly, a structured, multilevel competency framework is essential to support sustainable, resilient transformation across the sector. As one senior leader noted, "The future of Indonesian manufacturing is not just about machines - it is about how well we can orchestrate people, policies, and technologies into a sustainable system".

To strengthen conceptual coherence and enable a better grounding for multilevel analysis, the validated competencies were organised into five overarching dimensions, as summarised in Table 7.

To address this need, the proposed framework adopts a macro-meso-micro structure. At the macro level, the competencies of the leadership will align with the goals of manufacturing ecosystems of the nations, this would be policy alignment, national transformation, and sustainability integration. With the meso level, a concentration on organisational capabilities, that is, on human-technology integration, sustainability practices, and systems-driven innovation is made. Lastly, at the micro level, the framework defines the technical, adaptive and con-

Tab. 7. Mapping of validated competencies into five core dimensions

Dimension	Key validated competencies (examples)
Technical mastery	Human-machine collaboration; digital transformation management; technological foresight
Strategic leadership	Sustainability leadership; systems thinking; complexity management; circular economy implementation
People management	Cross-cultural management; collaborative innovation; cultural intelligence; workforce upskilling management
Business acumen	Data-driven leadership; supply chain resilience; local resource optimisation
Sustainability	Ethical technology deployment; social value creation; multi-stakeholder engagement; digital wellbeing facilitation

textual competencies necessary at various levels of leadership in the firms. The avalanche model of strategic cascade extends coherence in strategic ambitions all the way to individual behaviours and reduces the risk of fragmentation, as alerted by analysts who regard it as a possible hindrance to sustainable change (Ghobakhloo et al., 2023).

4.1. Meso-level: organisational competency clusters

At the organisational (meso) level, leadership development work must revolve around three related and independent groups of competencies: human-technology integration, sustainability, and systems and innovation. The Delphi participants repeatedly made it clear that Industry 5.0 leadership requires combined, multidimensional skills rather than a separate technical competency. As a plant manager aptly remarked, "We can no longer separate machine learning from people learning - they must grow together, sustainably and ethically". Echoing this sentiment, another participant further stressed, "Industry 5.0 requires us to think like ecosystem builders, not just factory managers". Yet another participant from the food and beverage sector noted, "Our leadership challenge is not just technical upgrades; it's building organisations that can think, adapt, and evolve with both people and technology in mind". These reflections highlight the urgency of developing leadership capabilities that transcend traditional boundaries between technological, human, and environmental domains.

Based on these reflections, specific competencies were methodically identified and graded using the two-round Delphi technique. The importance scores (e.g., 4.90 for human-machine collaboration) reflect the average scores from the expert panel evaluations across the rounds of data collection. These competencies are also categorised to have a systematic career growth within the workforce, including higher specialised roles, specialised roles, technician roles, and entry-level employees.

Within the human-technology integration cluster, there are very specialised leadership roles that deal with human-machine collaboration (mean rating of 4.90), which is the core capability within the human-centric technologies orchestration. Niche activities prioritise digital transformation management (4.87), training leaders to drive transitional changes in technical directions. For technician personnel, ethical technology deployment (4.70) is also essential, making these competencies vital for maintaining an ethical view of the innovation. In parallel, the human-centred design thinking (4.63) and digital wellbeing facilitation (4.23) work at the level of elementary employees to realise their leadership potential by integrating human values into daily relationships with technologies.

One similarity in the sustainability cluster concerns the parallel structure. It is also expected that highly specialised leaders will become proficient in sustainability leadership (4.83), through which organisations will integrate environmental and social stewardship into the strategic decision-making process. Specialised roles are aimed at local resource optimisation (4.73), which will encourage the efficient utilisation of resources depending on the various regional settings, applicable to Indonesia. The technician jobs are focused on supply chain resilience (4.57), guaranteeing operating stability, and ethical supply in the times of growing global turbulence. At the basic level, competencies such as social value creation (4.40) and circular economy implementation (4.33) enable the extension of sustainability throughout the workplace. As a Delphi participant commented, "Everyone, from directors to floor staff, must own a piece of the sustainability agenda".

The systems and innovation cluster similarly reflects a scaling complexity of leadership needs. Higher specialised roles require cross-cultural management (4.77), which is critical for managing Indonesia's integration into global supply networks. Specialised roles focus on developing systems thinking (4.73) to handle dynamic, interconnected production environments. Technician-level leaders are tasked with strengthening data-driven leadership (4.67), making operational decisions based on real-time insights. At the frontline, elementary employees are expected to contribute through competencies such as cross-functional integration (4.60), technological foresight (4.57), SME integration capability (4.37), multi-stakeholder engagement (4.30), and cultural intelligence (4.20), supporting agility and innovation at the system periphery. As a plant manager emphasised, "Innovation happens when insights flow freely across functions, hierarchies, and cultures - and that must start from the ground up".

Collectively, this organisational competency clustering, grounded in rigorous Delphi data, reflects a necessary evolution from rigid, siloed skill models towards dynamic, systemic, and sustainable leadership development pathways. It enables Indonesian manufacturing organisations to integrate human-machine collaboration with environmental imperatives and systemic innovation across all operational layers, creating a robust foundation for thriving in the increasingly complex and volatile ecosystems of Industry 5.0 (Bianco et al., 2023; Oeij et al., 2024). Through this approach, leadership becomes not just a set of technical capabilities, but an organisational fabric woven with ethics, adaptability, and systemic awareness.

4.2. Micro-level: Individual Leadership Competency Development

At the micro level, based on the organisational clusters introduced at the meso level, the development of leadership competencies needs to be differentiated by tiers of leadership responsibility. It is important to differentiate competencies for specific strategic, operational, and contextual roles required by leaders at various organisational levels and adopt a top-to-bottom approach, instead of a one-size-fits-all model. This was supported by all participants in the Delphi study, who indicated that the ability to be an effective leader in the Industry 5.0 context depends on competency specialisation across multiple hierarchical levels. As one senior operations director explained, "You cannot expect plant supervisors to think about global ESG policies daily, but you must empower them to make resource-optimised, adaptive decisions on the ground". Complementing this, an executive from the food and beverage industry noted, "Top executives must be visionary but grounded in the operational realities that middle and lower tiers experience daily". These insights highlight the necessity for a carefully tiered leadership development strategy that reflects both the strategic ambitions and the operational complexities of manufacturing organisations.

At the senior leadership level, the emphasis is on driving broad, transformational initiatives aligned with Industry 5.0 imperatives. The human-technology integration competency at this level is digital transformation management, enabling senior executives to lead enterprise-wide technological renewal. Their adaptive competency and sustainability leadership ensure that strategic initiatives are pursued with a balance between profitability and broader environmental and social responsibilities. Meanwhile, systems thinking emerges as the contextual competency, equipping senior leaders to manage complexity and to integrate disparate operational units under a coherent strategic framework (Braun & Clarke, 2006; Kwiotkowska et al., 2022). Senior leaders, thus, are positioned as architects of integrated, sustainable, and resilient organisational transformation.

Transitioning to middle management, the focus shifts towards operationalising strategic initiatives and managing the interface between technologies, people, and processes. Their technical competency in human-machine collaboration becomes essential for harmonising human and technological contributions to manufacturing performance. The adaptive competency of cross-functional integration supports middle managers in facilitating collaboration across organisational silos, ensuring agility and coherence across units. Simultaneously, cross-cultural management as a contextual competency prepares middle managers to navigate increasingly diverse teams and stakeholder networks (Pinto et al., 2024). In this way, middle managers act as critical conduits, translating strategic direction into actionable, operational results.

At the entry-level leadership tier, competencies are designed to foster agility, responsiveness, and localised innovation. The technical competency of data-driven leadership equips young leaders to leverage analytics and digital tools for real-time decision-making. Meanwhile, adaptive decision-making strengthens their ability to respond flexibly to fast-changing conditions. Supporting this, local resource optimisation as a contextual competency instils an early awareness of sustainability and efficiency at the operational level (Kaur & Anand, 2022). Entry-level

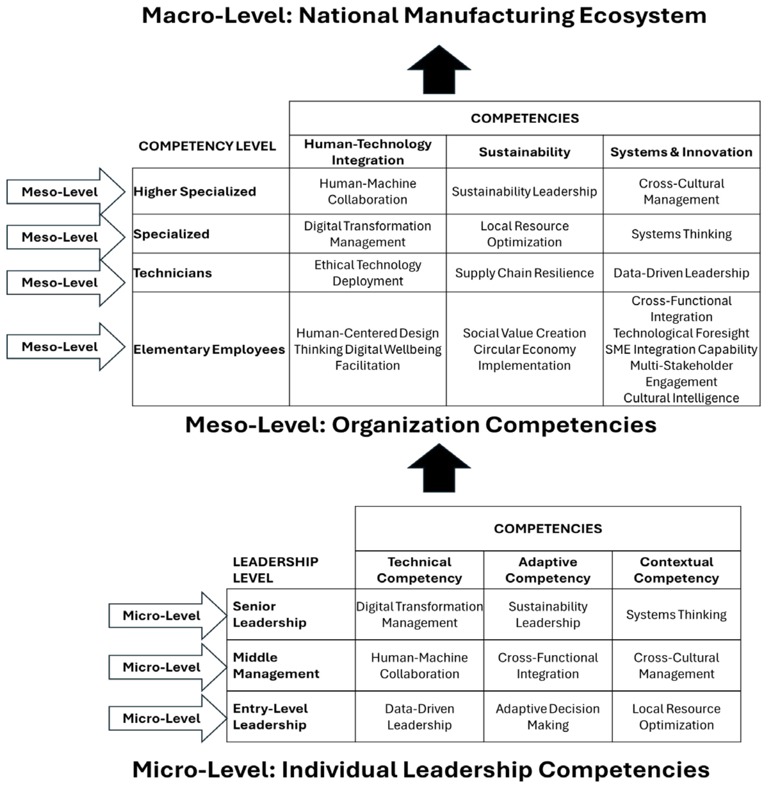

Fig. 2. Multilevel Leadership Competency Structuring Tool for Industry 5.0 Development (adapted from Tommasi et al., 2022)

leaders, therefore, play a vital role in embedding Industry 5.0 principles at the grassroots, sustaining innovation and adaptability from the bottom up.

These capabilities, taken in their combination, will indeed make sure that the leadership development pipelines are not merely resilient but dynamically constructed to the realities of Industry 5.0, which are complex. Techniques to promote systemic and consistent leadership development within organisations include sharing leadership potential throughout the hierarchical strata of any organisation, as well as integrating the principles of innovation, adaptability, and sustainability within the organisation at the very top and flowing down to its very foundation. The visual representation of this multi-tiered structuring strategy is illustrated in Fig. 2, which is the Multilevel Leadership Competency Structuring Tool for Industry 5.0 Development, suggested by Tommasi et al. (2022), and on which the offered leadership development technique is based.

4.3. Towards an integrated leadership development framework for Industry 5.0

Leadership development models will not only need to be refined to accommodate the move towards Industry 5.0, but also reimagined. Earlier frameworks, discussed by Ghobakhloo et al. (2023) and Moldovan (2019), were mostly focused on technological competence, i.e., digital fluency, mastery of automation, and systems control. Nevertheless, these technology-driven solutions can no longer be considered adequate in the modern world, where the manufacturing environment is influenced not only by technologically-driven innovation but also by ethical principles and sustainability demands. In the proposed study, these emerging dimensions are considered intentional and incorporated into a multilevel framework, which represents a paradigm shift towards upskilling models of Industry 4.0 that are largely linear, in contrast to the systemic, interconnected approach to Industry 5.0 transformation (Suciu et al., 2023; Tommasi et al., 2022).

One of the most important innovations of the offered framework is its responsiveness to the local context, which is among the most overlooked aspects of globalised leadership theories. Leadership competencies in the Indonesian manufacturing sector are characterised by diverse resources, vulnerable supply chains, and varied workforce capabilities, requiring skills that are not merely international but must be executed locally. Majczyk et al. (2022) argued that

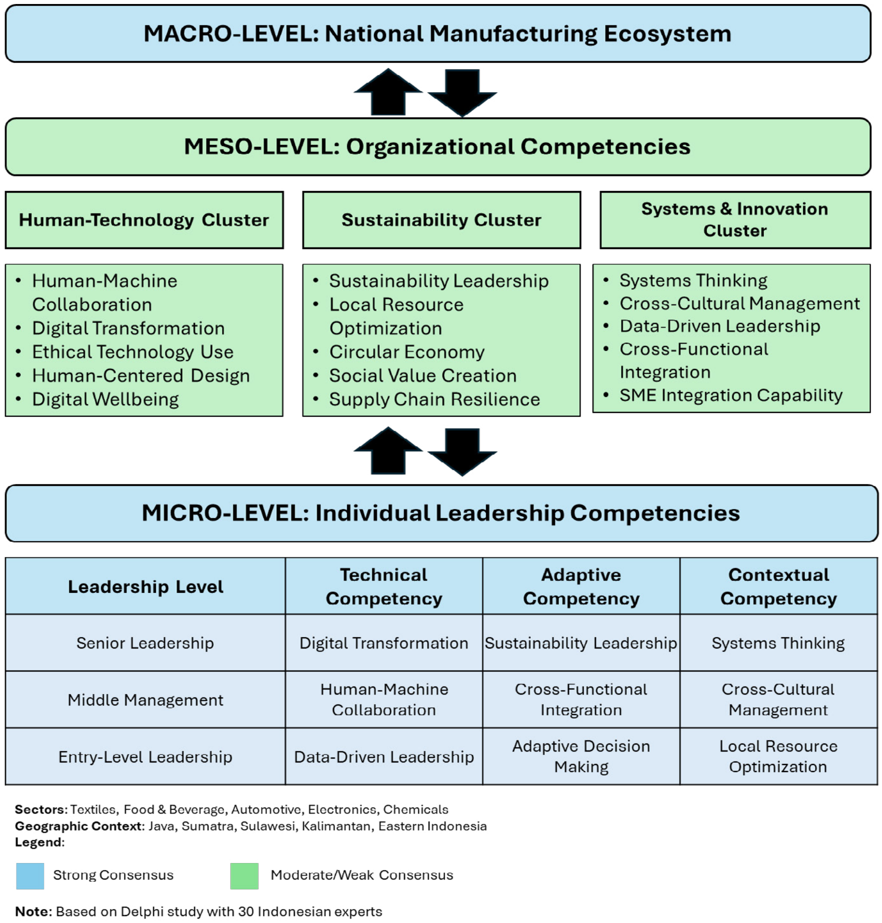

Fig. 3. Manufacturing Leadership Competency Framework for Industry 5.0 Transformation

leadership development should consider national priorities and realities, and this idea is supported by Gudanowska et al. (2018), who proposed the idea of proactive and adaptive leadership approaches to fit regional industrial ecosystems. Thus, local resource optimisation, SME integration capability, and multi-stakeholder engagement competencies are tailored as inherent parts of this framework to align with Indonesia's plans under the Making Indonesia 4.0 roadmap and Sustainable Development Goals in general. Through this, it supplements previous studies by providing a more area-specific model that can integrate global leadership theories with the local operational requirements.

Further, the leadership competencies must be structured at the macro, meso, and micro levels to increase strategic alignment and operational resilience. At the macro level, leaders should influence national manufacturing policy and sustainability agendas, and proactively engage in industry transformation efforts. Unless competencies are developed on the macro level, as Tommasi et al. (2022) believe, national strategies will be vulnerable to becoming disjointed and unbalanced. At the meso level, organisational leadership must learn to incorporate human-technology collaboration, ethical digitalisation, and systems innovation as operational practices, as Pinto et al. (2024) and Tschiedel et al. (2025) indicated as necessary. Micro development of leaders should be very specific at a certain level, providing adaptation, contextual, and technical skills adapted to the reality on the ground that governs the leaders at various levels. This tiered organisation must directly counteract the lack of such integration, which was lacking in previous competency models.

This tiered solution is needed to avoid the traps epitomised in previous leadership systems. Perini (2021) demonstrated a discrepancy among leadership levels: senior leaders change vision, whereas middle and frontline managers lack the skills to implement it, which can potentially be disaster-causing for changes. The proposed framework would achieve strategic alignment, operational unification, and the capability to handle results of systematic disruption by aligning leadership development across the macro, meso, and micro levels. Next, integrating sustainability, human-centred ideals, and an ethical vision will ensure that leadership growth does not become technocratic skill-drilling but rather a driving force of social change and care for the natural world (Pereira & Lacerda, 2021). To this end, the framework follows previous research in applying a humanistic and sustainability-centred paradigm at the heart of leadership competency development.

To graphically combine this concept design, Fig. 3 is a particularisation and extrapolation of the multi-level comprehension tool designed by Tommasi, Perini, and Sartori (2022). The figure describes lively dynamic encapsulation of macro (nationwide ecosystem alignment), meso (organisational competency clusters), and micro (personally leadership pathways) spheres with a final focus on the systemic nature of leadership development in the post-industrial technological age of Industry 5.0. In contrast to the more linear models, the proposed framework supports the development of competencies through the paradigm of continuous, iterative stratification of leadership skills on strategic and operational fronts, with the Indonesian manufacturing companies preparing to attain long-term competitiveness, human-centred innovativeness, and sustainability.

This figure represents the Manufacturing Leadership Competency Framework. The research development in this study focuses on responding to the systemic leadership problems arising in the Industry 5.0 context. Contrary to the more traditional linear leadership models, this framework is a dynamic, multilayered framework that engages a highly systematic connection of macro (national policy and ecosystem alignment), meso (organisational practice and capability building), and micro (individual leadership development) levels (Pinto et al., 2024; Tommasi et al., 2022). It represents the increasing school of thought provided by the approach that leadership strategies should not only be technologically competent but also people- and sustainability-focused and resilient to socio-technical complexity (Ghobakhloo et al., 2023; Pereira & Lacerda, 2021). The structure pays utmost attention to the strategic importance of leadership in influencing and keeping pace with the national industrial ambitions, as in the macro-level initiative titled Making Indonesia 4.0 (Majczyk et al., 2022). Competencies at this level primarily focus on integrating sustainability, advocating policy, cross-sectoral cooperation, and orchestrating an ecosystem to ensure that industrial renewal is not disjointed but rather tactically unified (Tschiedel et al., 2025). Next, the framework establishes such essential organisational competencies at the meso level as human-technology collaboration management, cross-functional integration, and ethical innovation leadership, just as it has been recommended recently to integrate the principles of Industry 5.0 directly into the practice of organisations (Bianco et al., 2023; Pinto et al., 2024). Such competencies enable manufacturing companies to adopt new technologies while remaining highly dedicated to human welfare, environmental stewardship, and sustainable manufacturing processes (Suciu et al., 2023).

At the micro level, the structure identifies the competencies that the individual leaders working in complex, dynamic manufacturing conditions require, including adaptive, technical, and contextual skills (Kwiotkowska et al., 2021; Schinner, 2022). Whether line management and governance, middle leaders, or senior leaders, each has the differentiated but interdependent competencies, including data-driven leadership, resilience building, and cultural intelligence, all of which have been identified as part of the skills needed to become a future-ready leader (Dahl et al., 2023; Wickramaratne et al., 2014). Such bottom-up empowerment strengthens top-down strategic imperatives and builds a feedback cycle, enhancing the organisational learning, flexibility, or innovation resilience at every level of hierarchy. Establishing these three levels in mutual engagement and development enables the Manufacturing Leadership Competency Framework to build a strong basis for transforming leaders who will be able to lead through the technological, environmental, and social changes that define Industry 5.0 (Ghobakhloo et al., 2023; Oeij et al., 2024). This way, it partially fills the gap which was created by the past leadership development models, giving an inclusive, capable, and context-sensitive framework that helps provide sustainable, inclusive, and human-centred development of the manufacturing industry in the Indonesian context.

Conclusions

The shift from Industry 4.0 to Industry 5.0 calls for an essential reconsideration of the term manufacturing leadership, which may entail a fundamental transition from strict technological capability building to a holistic form of leadership that balances human-driven innovation, a moral orientation, and environmentally minded development. The study was driven by the important research gap revealed by previous studies, in which leadership models were still overly focused on digitalisation and flawless operations and were concerned with human-machine partnership, emotional intelligence, strategic flexibility, and sustainability requirements. Although the requirements of Industry 4.0 possess significant technical skills, which were proposed by earlier research, they could not foresee the extraordinary socio-technical requirements that constitute the current Industry 5.0 landscape. The absence of an integrated, multilevel leadership competency framework - especially in emerging manufacturing contexts such as Indonesia - posed a serious challenge for sustainable and resilient industrial transformation.

Through a systematic and context-sensitive approach, this study developed the Manufacturing Leadership Competency Framework, addressing both the immediate competency gaps and the broader strategic needs of organisations operating in Industry 5.0 ecosystems. By adopting a multilevel structure - macro (national policy and ecosystem alignment), meso (organisational practice and systems integration), and micro (individual leadership development) - the framework reimagines leadership development as a dynamic, iterative, and contextually grounded process. It not only complements but extends previous research by embedding sustainability leadership, local resource optimisation, SME integration, and ethical human-technology collaboration at the core of leadership development pipelines. In doing so, this study offers a robust and actionable model that enables manufacturing organisations to cultivate leaders capable of driving innovation, maintaining operational excellence, promoting human-centric workplaces, and achieving resilience against future disruptions. The framework directly answers the research gap framed in the Introduction: providing a comprehensive, adaptive, and sustainable leadership development approach for Industry 5.0 transformation.

Theoretical implications

Theoretically, the study adds to the body of knowledge on leadership and competency development, as it offers a novel model of leadership and development with multilevel, systemic orientations, directly aligned with the Industry 5.0 framework. In contrast to earlier frameworks, where competency building was systematically flat or siloed, emphasising only the technical skills, the new model integrates the macro, meso, and micro approaches into a consistent direction. The identified studies have critical gaps because of the underrepresentation of human-centric and sustainability competencies (Ghobakhloo et al., 2023; Grzybowska & Lupicka, 2017). Moreover, including localised capabilities, including the capabilities of SME integration and local resource optimisation, within the competency map, the given research will highlight the significance of contextual and regional specificity, following the arguments advanced by Majczyk et al. (2022) and Gudanowska et al. (2018). This means that the framework contributes to the theoretical knowledge of leadership development as a repetitive, iterative, and multi-actor process that is important in the delivery of successful transitions into Industry 5.0 ecosystems.

This paper also helps address the increasing demand for leadership theories to meet the challenge of encompassing socio-environmental factors and the ethical requirements of leadership constructs within general leadership theories. This implies that, in future theoretical models, cross-level interactions must be considered, and that national policies, organisational systems, and individual behaviours must be identified as dynamically linked. These results provide a basis for further empirical studies that can be undertaken to determine the extent to which the multilevel leadership framework can be applied in different national backgrounds, industrial types, and levels of digital maturity.

Practical implications

In practice, the Manufacturing Leadership Competency Framework developed in this study offers a concrete guide for policymakers, organisational leaders, and training institutions seeking to prepare leaders for Industry 5.0 challenges. For policymakers, the findings underscore the necessity of designing national industrial strategies that are not merely aspirational but systematically translated into organisational competency-building initiatives. Embedding sustainability and human-centric leadership development into national programs such as "Making Indonesia 4.0" will be crucial for achieving systemic industrial transformation.

For manufacturing firms, the framework provides a structured roadmap for aligning leadership development programmes with the evolving demands of the Industry 5.0 environment. Organisations are encouraged to move away from fragmented, one-size-fits-all training approaches and instead develop tiered competency pathways that address strategic, operational, and individual-level leadership needs simultaneously. Human resources departments, corporate universities, and professional development providers can use the identified competencies to design more targeted learning interventions, mentorship programmes, and evaluation metrics. By doing so, firms will not only enhance their innovation and operational resilience but also ensure long-term sustainability and competitiveness in a rapidly changing global landscape.

Limitations and future research

While the Delphi approach enabled expert-driven validation, several limitations remain. First, the panel was primarily composed of Indonesian experts, which may limit cross-cultural generalisability. Second, the framework was validated through perception-based consensus rather than empirical implementation evidence. Future research should include pilot applications or case studies within diverse manufacturing environments to examine the operational effectiveness of the competency framework and mitigate potential cultural and contextual biases. Expanding the panel to include international experts would strengthen applicability across different Industry 5.0 maturity levels.

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Author Contributions

Donald Crestofel Lantu contributed to the conceptualization, methodology design, data analysis, and manuscript writing. Yuliani Dwi Lestari contributed to the literature review, data collection, and manuscript editing. apt. Aghnia Nadhira Aliya Putri contributed to the research design, data interpretation, and critical revision of the manuscript. All authors reviewed and approved the final version of the manuscript.

Ethics Declarations

This study was approved by the Research Ethics Committee of Institut Teknologi Bandung under Ethical Clearance Number KEP/II/2024/X/M96564377NJ-EESB. The committee confirmed that the research adheres to ethical standards and guidelines, ensuring its compliance with the required ethical considerations.

Consent to Publish

All participants who may be identifiable in this manuscript have reviewed the final version and provided written consent for publication.

Conflict Of Interest

The authors declare no conflict of interest.

Declaration of Conflicting Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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Building energy performance and housing market regimes: evidence from EU countries

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ABSTRACT

In assessing developments in the real estate market, the energy efficiency of buildings is increasingly considered important from an environmental and economic perspectives. However, empirical evidence on the relationship between energy performance indicators and house price dynamics at the macro level remains mixed, suggesting that this relationship may vary across countries and contexts. This article examines whether and how building energy performance indicators are related to house price dynamics across European Union countries, focusing on short- and long-term relationships and cross-country heterogeneity. The study is based on panel data for 2010-2023, using house price indices as the dependent variable and several energy efficiency indicators, including final energy consumption in buildings and the share of renewable energy sources. Various econometric methods were applied, including panel cointegration analysis (FMOLS and DOLS), dynamic panel models (Arellano-Bond GMM), Granger causality tests, impulse-response analysis, quantile regression, threshold models, and exploratory country clustering. The results show that energy efficiency indicators are not strongly associated with house prices at the aggregate EU level, and their short-term effects are generally weak. Instead, the findings reveal significant heterogeneity across countries and income regimes, suggesting that the capitalisation of energy efficiency in house prices is highly context-dependent. By combining econometric analysis with exploratory segmentation approaches, the study helps structure heterogeneous energy housing interactions into distinct market environments relevant for investment and policy analysis. These results highlight the limitations of uniform macro-level approaches and underline the importance of differentiated market analysis.

KEY WORDS
energy efficiency, housing prices, panel analysis, market heterogeneity, energy-housing linkages

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Introduction

Energy efficiency is one of the recent priorities for the sustainable development of the European Union (Okunevičiūtė Neverauskienė, 2025). Reducing energy consumption is directly linked to climate change mitigation, reduced fossil fuel imports, and stronger energy independence (Bakhsh et al., 2024). This issue particularly affects the construction and energy sectors, as they account for more than a third of total energy consumption in the EU (González-Torres et al., 2022). Therefore, the European Green Deal includes retrofitting of buildings as one of its key

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measures to mitigate climate change (Ma et al., 2021). Energy consumption is not only an environmental issue, but also an economic and social one, as it directly affects household spending, energy security, and the sustainability of investments (Chen et al., 2024).

Energy efficiency is promoted by measures such as large-scale building renovation, energy performance certificates, and financial incentives for consumers choosing efficient solutions (Anarene, 2024). In recent years, the European Union has been strengthening legislation in this area, obliging Member States to introduce energy performance certificates and to move towards the nearly zero-energy building standard (Zangheri et al., 2021). These regulatory changes are increasingly affecting market behaviour as information on energy performance becomes an integral part of housing market transactions rather than just a formal requirement. Such measures and legislative changes alter market standards as consumers no longer evaluate only location, size, or infrastructure, but also the energy value of housing (Olasolo-Alonso et al., 2023).

The energy efficiency issue is not only environmental (Chen et al., 2024). It is increasingly linked to the financial sector, as energy-efficient buildings are the standard and are considered a more attractive investment due to lower operating costs and greater liquidity (Okunevičiūtė Neverauskienė et al., 2025). Therefore, energy efficiency is often discussed as a potential factor influencing housing prices and investment dynamics, especially in markets with developed credit systems and higher income levels. However, the extent to which energy efficiency is capitalised in housing prices may vary depending on broader macroeconomic and institutional conditions. Consequently, energy efficiency is becoming a strategic financial factor, affecting the energy, economic, and social sectors and shaping new and progressive standards (Durmus Senyapar, 2024).

More researchers are studying the relationship among energy efficiency, housing prices, and investment dynamics in different countries. However, comprehensive empirical research is still lacking to substantiate this link (Kholodilin, 2024). Existing studies provide mixed results, particularly in cross-country analyses, where estimated effects often differ in size, significance and even direction. Such discrepancies suggest that average correlations may mask fundamental structural differences between markets, and that the relationship between energy efficiency and housing prices may depend on the broader economic and institutional context rather than follow a single uniform model.

This article aims to fill the existing gaps, including econometric models that analyse the lagged effects and assess the impact of energy efficiency indicators on real estate prices in the EU region (Baležentis et al., 2021). Rather than focusing solely on the average effect size, the article particularly centres on the stability and heterogeneity of the relationship between energy efficiency and housing price dynamics across countries. To support a more structured interpretation of these differences, the analysis incorporates cross-country segmentation as a complementary analytical perspective. Thus, it not only expands the academic discussion on the role of energy efficiency in the real estate market but also provides valuable insights for investors and policymakers making complex decisions. The novelty of the article lies in its systematic assessment of cross-country differences and the structural limitations of macro-level approaches, which helps to explain why empirical evidence in this area often remains inconclusive.

1. Literature review

Changes in the real estate market are a complex phenomenon influenced by many fragile, interrelated components (Montvydaitė, 2024). Traditionally, the real estate market is influenced by various macroeconomic factors, demographic changes, and other economic and social trends (Stan, 2022; Ginevičius et al., 2025). However, in recent years, a newly emerging effect has also been observed due to changing legislation and requirements, i.e., environmental protection and energy efficiency (Wu & Tham, 2023). As energy-related regulations become more binding, energy efficiency indicators are increasingly incorporated into housing market assessments, and public expectations and standards are growing; therefore, energy efficiency indicators are becoming a significant component of the real estate market (Mugarra et al., 2025).

Macroeconomics is among the most critical aspects when analysing the real estate market (Okunevičiūtė Neverauskienė, Linkevičius et al., 2025a, 2025b). Higher incomes and employment are usually positively correlated with growth in energy-efficient housing, as residents who earn more tend to invest in long-term value and lower operating costs (Lee, 2023). Urbanisation also contributes to this process, as growing cities and populations increase the demand for housing, and energy efficiency indicators are used as additional value points when looking for new housing (Ascione et al., 2024). Conversely, in regions with lower incomes, energy-efficiency methods can appear burdensome rather than beneficial, since renovation increases current costs and does not consider the future value of the housing (Özdemir & Koukoufikis, 2025). These differences suggest that the capitalisation of energy efficiency is highly context-dependent and unlikely to follow a uniform pattern across countries.

Real estate and financial markets are equally closely linked (Alqaralleh et al., 2023). Preferential interest rates, credit availability, and government subsidies determine the extent to which residents can become interested and afford to purchase energy-efficient housing (Carozzi et al., 2024). Sustainable financing options, such as green loans, further emphasise the relevance of this issue (Kwilinski et al., 2025). Thus, energy efficiency becomes an integral part of the real estate sector, and its integration into analyses enables the assessment and understanding of real estate price formation processes across different economic environments (Walacik & Chmielewska, 2024). Concurrently, these mechanisms imply that the observed impact of energy efficiency may depend on credit conditions and the institutional environment, rather than being universal.

The integration of energy efficiency into the housing assessment and investment decision-making processes is the most crucial development in recent years (Blomqvist et al., 2022). The energy efficiency certificate has become mandatory in Member States. It informs market participants about a building's energy consumption before they make any decision (Khazal & Sønstebø, 2023). Such information is not only a legal obligation, but also an element of market competition. Studies show that a high-energy class usually correlates with higher housing prices, and the sales period is significantly shorter than for other market objects (Taruttis & Weber, 2022). However, this evidence is largely based on micro-level or country-specific analysis and therefore has limited direct applicability to macro-level circumstances.

The emergence of energy efficiency criteria encourages the financial market to develop new products that link the real estate market to various sustainability aspects, such as green bonds, preferential renovation loans, and more favourable interest rates for energy-efficient buildings (Cara et al., 2025). The financial sector uses such products to signal that energy efficiency is not only an essential environmental requirement but also an economic advantage (Zhang et al., 2024).

It is worth noting that research encounters issues, especially at the methodological level, as differences in countries' economic levels, regulatory systems, and consumer behaviours can affect the impact of energy efficiency on housing prices (Sun et al., 2022). It is also sometimes challenging to distinguish how much of the increase in housing prices is due to energy efficiency and other factors, such as population growth, geographical location, or simply the quality of construction (Galster & Lee, 2021; Cordeiro et al., 2023). As a result, estimates based on aggregated data may mask substantial heterogeneity and lead to inconclusive or contradictory conclusions.

As mentioned earlier, the importance of energy efficiency for the real estate market is acknowledged. However, there are still significant gaps in empirical research, which are limited to specific regions and are difficult to generalise in the broader European Union context. Similarly, some studies assess the direct link between energy efficiency and housing prices without considering the potential lagged effects of multiple other relevant factors (Farhaoui & Slimani, 2022; Wilhelmsson, 2023). This situation highlights the need for analytical approaches that explicitly address cross-country heterogeneity, dynamic adjustment processes, and market regimes when examining energy efficiency and housing price dynamics.

2. Research methods

This study's methodology is based on panel data analysis, which enables the assessment of short- and long-term relationships between energy efficiency and housing price dynamics in European Union countries. The data sample covers 2010-2023, and countries are selected based on their level of economic and social development, allowing for the identification of potential heterogeneity in effects across different economic contexts. The study uses data from Eurostat and national statistical offices.

The dependent variable is the house price index, denoted by Y_it, where i is the country and t represents the period. The primary independent variable is energy efficiency, measured by final energy consumption in the buildings sector, the structure of energy performance certificates, and the share of renewable energy sources. Control variables include GDP per capita, unemployment rate, population density, interest rates, and average income.

First, stationarity tests are performed using the Im-Pesaran-Shin and Levin-Lin-Chu unit root tests. If the data are non-stationary, cointegration is assessed using Fisher-type panel cointegration tests based on the Engle-Granger framework. This step is necessary to ensure that the regression analysis is not misleading due to long-term non-stationary processes. Once cointegration is detected, the long-term relationship between the variables is assessed using the panel FMOLS (fully modified ordinary least squares) and DOLS (dynamic ordinary least squares) methods, which correct for endogeneity and autocorrelation problems. The form of the long-term model is written as follows (Formula 1):

$$Y_{it} = \alpha_i + \beta_1 EE_{it} + \beta_2 GDPpc_{it} + \beta_3 UNEMP_{it} + \\ + \beta_4 DENS_{it} + \beta_5 IR_{it} + \beta_6 INC_{it} + u_{it} \quad (1)$$

Where α_i denotes individual country effects, and u_{it} is the error term. This model enables the identification of the extent to which energy efficiency indicators are related to housing prices in the long run.

To analyse the short-term impact, a dynamic panel model with a lagged dependent variable is applied, which allows capturing the inertia of housing prices (Formula 2):

$$Y_{it} = \alpha_i + \rho Y_{i,t-1} + \beta_1 EE_{it} + \beta_2 GDPpc_{it} + \\ + \beta_3 UNEMP_{it} + \beta_4 DENS_{it} + \beta_5 IR_{it} + \\ + \beta_6 INC_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

The parameter ρ reflects the inertia in housing prices, and the model is estimated using the Arellano-Bond GMM estimator, which addresses endogeneity in dynamic panels.

To verify the direction of the relationships, Granger causality tests are additionally performed in a panel context, the logical form of which is as follows (Formulas 3 and 4):

$$Y_{it} = \sum_{k=1}^{p} a_k Y_{i,t-k} + \sum_{k=1}^{p} \gamma_k EE_{i,t-k} + \varepsilon_{it} \quad (3)$$

$$EE_{it} = \sum_{k=1}^{p} \phi_k EE_{i,t-k} + \sum_{k=1}^{p} \theta_k Y_{i,t-k} + \upsilon_{it} \quad (4)$$

These models allow for testing whether energy efficiency drives changes in housing prices, or vice versa - higher housing prices encourage greater investments in energy conservation.

Dynamic relationships are also investigated using local projection methods in a panel setting, which allow tracing impulse-response functions without imposing the full structure of a panel VAR. This approach is particularly suitable in heterogeneous panels and enables the assessment of how an energy consumption shock affects housing prices over multiple horizons.

To assess differences in impact between different market segments, quantile regression is applied in a panel context. It allows testing whether the effects of energy efficiency are uniform across the entire distribution of housing prices or are more substantial only in the cheaper or more expensive segments. The model is written as follows (Formula 5):

$$Q_\tau(Y_{it}|X_{it}) = \alpha_\tau + \beta_\tau EE_{it} + \gamma_\tau Z_{it} \quad (5)$$

Where Q_τ $(Y_{it}|X_{it})$ denotes the conditional quantile function at quantile τ, X_{it} is the primary variable, and Z_{it} are the controls.

In addition, to assess possible marginal effects, Hansen panel threshold models are used to test whether the impact of energy efficiency on housing prices changes when a country's GDP per capita or population density reaches a certain threshold.

Additional robustness tests are performed: the Breusch-Pagan heteroscedasticity test, the Wooldridge autocorrelation test, and a multicollinearity check using the VIF indicator. Finally, countries are grouped using a cluster analysis based on Euclidean distance to identify more homogeneous groups based on energy efficiency and housing market indicators. Finally, countries are grouped using cluster analysis based on Euclidean distance as an exploratory tool to structure cross-country heterogeneity in energy efficiency and housing market characteristics, rather than to infer causal relationships.

3. Research results

In 2011-2023, a clear trajectory of house price (HPI) growth was recorded after 2014 in all countries: it was the most pronounced in Poland and Germany, and the slowest in Italy. Temporary "pit-rebound" episodes in the early years, followed by accelerating growth later, indicate a strong trend and characteristic I(1) behaviour in the levels. These facts are essential for further tests and models: they explain why simple level comparisons are misleading, and panel tests and dynamic specifications are necessary (Fig. 1). Importantly, the acceleration after 2016 varies considerably across countries, reflecting the heterogeneous dynamic and distributional effects identified in later sections.

The dynamics of final energy consumption in households (by fuel) in most countries are moderately decreasing, but with short-term spikes (especially in Germany and Poland), which reflect both price/climate and policy effects. There is no precise movement with the HPI here, so it would be a mistake to conclude from flat correlations alone (Fig. 2). This weak visual association encourages the use of dynamic and nonlinear methods rather than static correlation-based inference.

The share of renewables is consistently growing in all countries, with the sharpest increases in Sweden and Spain. This structural trend is essential for interpretation: growing "green" energy can operate through price, income, or expectation channels, but does not necessarily explain changes in the housing price by itself if other macro factors change at the

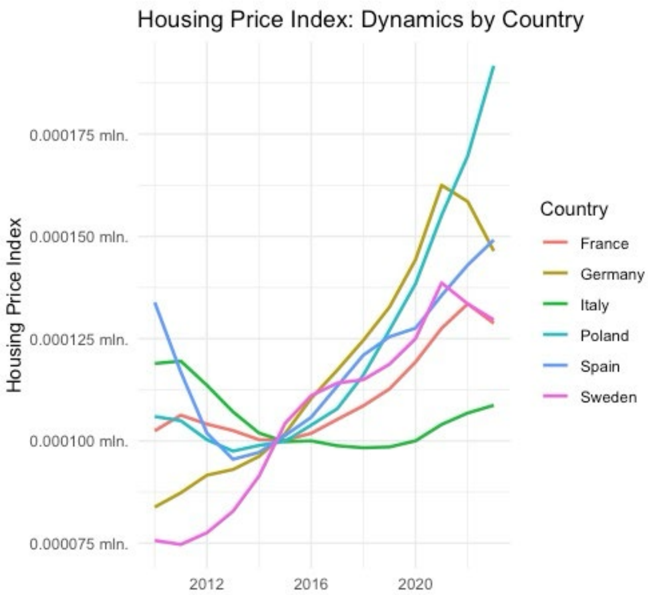

Fig. 1. Housing Price Index: dynamics by country

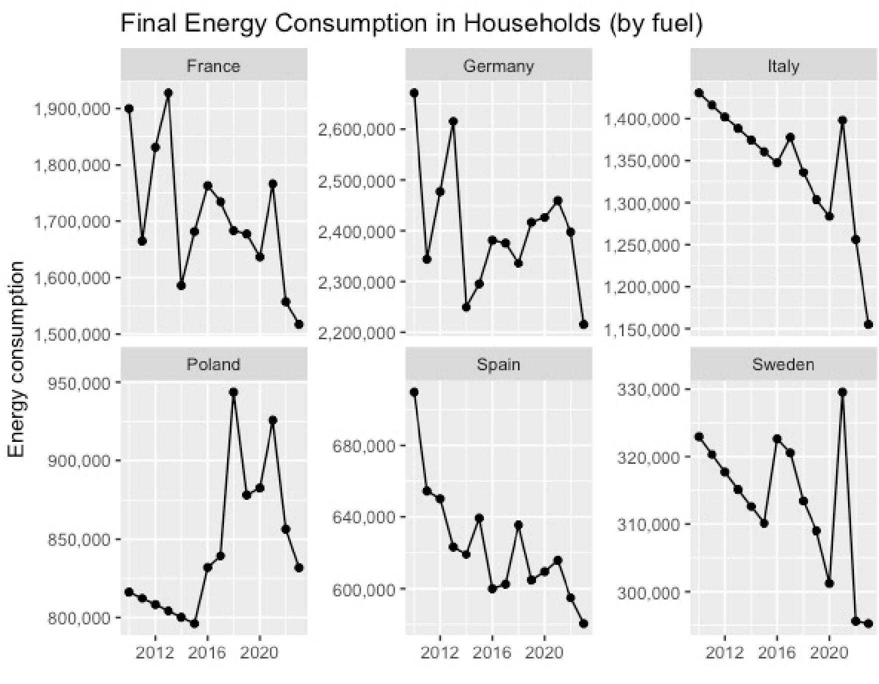

Fig. 2. Final energy consumption in households (by fuel)

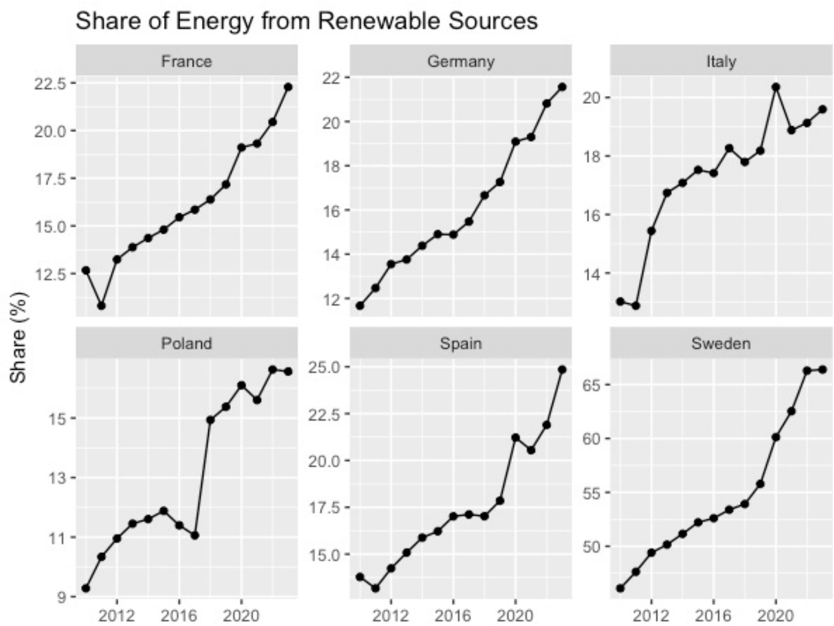

Fig. 3. Share of energy from renewable sources

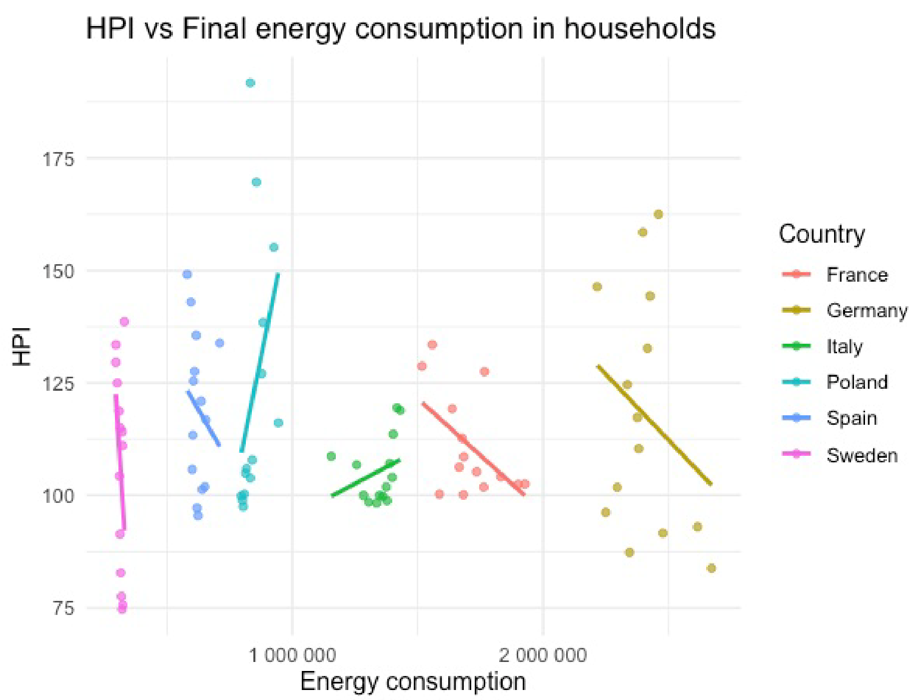

Fig. 4. HPI vs final energy consumption in households

same time (Fig. 3). Its steady trajectory suggests that any impact on housing prices is more likely indirect and subject to time lags.

The scatter plot with country OLS lines shows a heterogeneous HPI-energy relationship: negative in France and Germany, weakly positive in Poland and Spain, and close to zero in Sweden and Italy. The small slopes and large dispersion suggest that the energy variable will have little explanatory power in dynamic/fixed effects specifications (Fig. 4). This

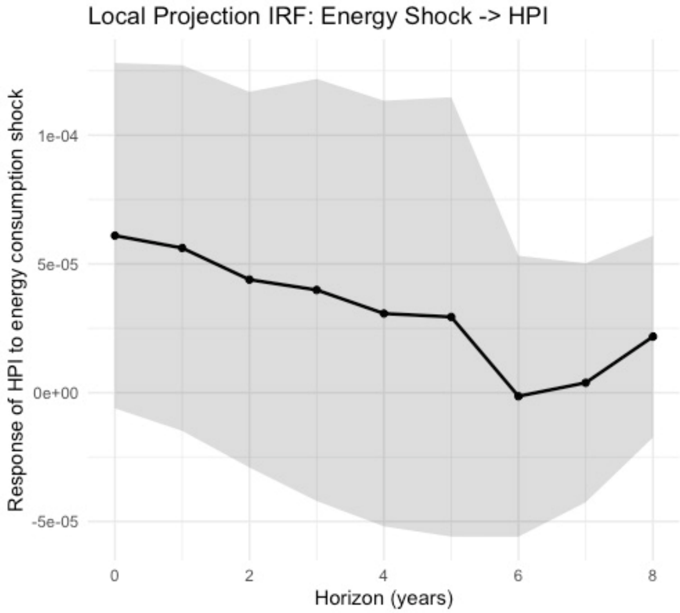

Fig. 5. Local projection IRF: energy shock -> HPI

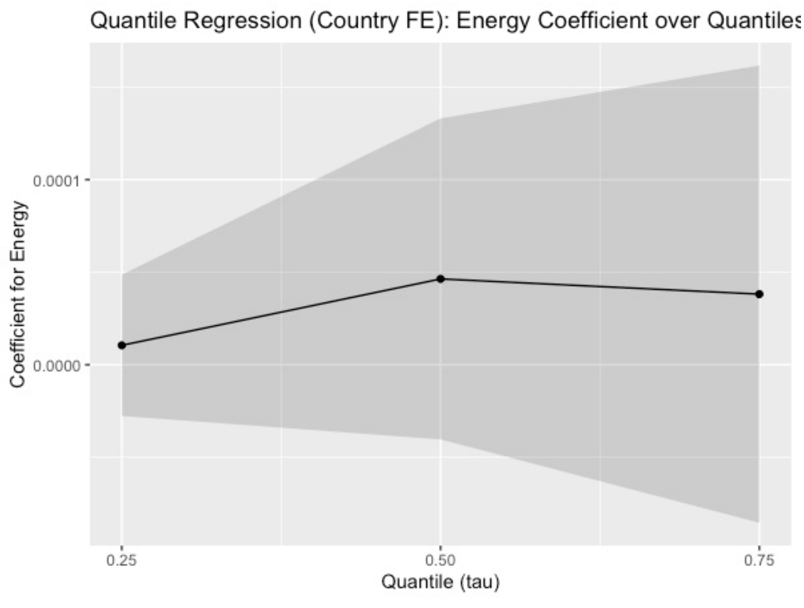

Fig. 6. Quantile regression (country FE): energy coefficient over quantiles

heterogeneity reinforces the need for country-level dynamics, fixed effects, and regime-dependent modelling.

Panel unit root tests (IPS/LLC) confirm that most series are non-stationary in levels (I(1)). The Fisher-type combined Engle-Granger cointegration test yields a marginal result (overall p-value ≈ 0.07), suggesting that a common long-run equilibrium relationship between housing prices and energy indicators is weak at the aggregate EU level. Consequently, long-run effects should be interpreted with caution, and analytical emphasis is placed on dynamic responses and cross-country heterogeneity rather than on a single shared trend.

The dynamic response estimated using Jordà's local projection method shows that a unit shock to household energy consumption generates minimal and statistically insignificant responses of the HPI over a 0-8-year horizon. The median impulse-response trajectory remains close to zero, and the 95

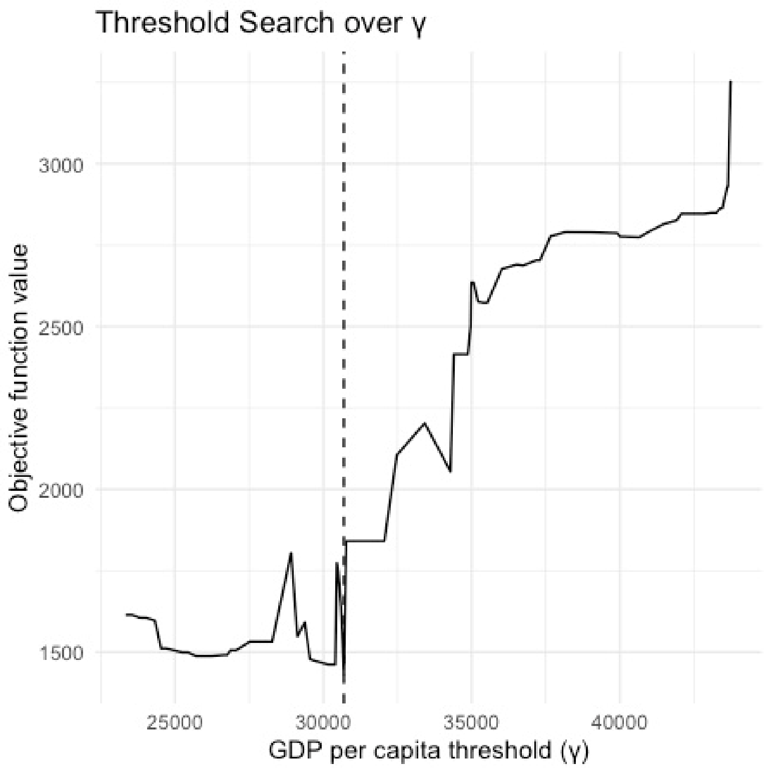

Fig. 7. Threshold search over gamma (objective function value)

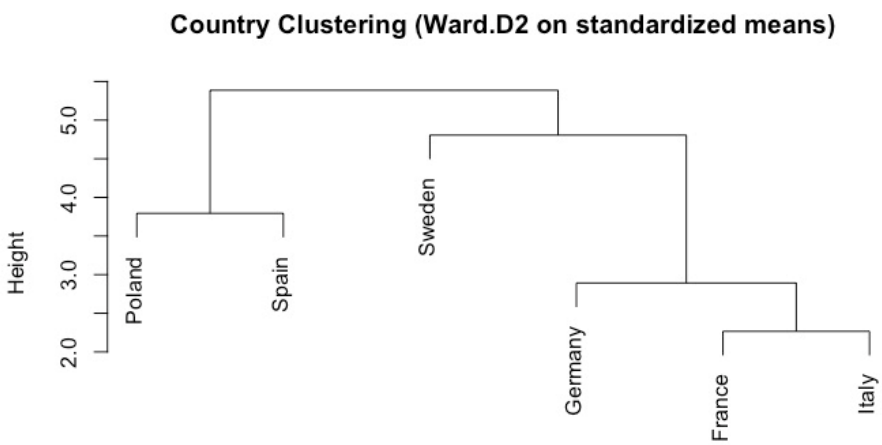

Fig. 8. Country clustering (Ward.D2 on standardised means)

% confidence bands consistently include zero, indicating that this channel-absent additional transmission mechanisms are secondary to broader macroeconomic (Fig. 5).

Quantile analysis with country fixed effects ($\tau = 0.25; 0.50; 0.75$) and cluster bootstrap by country shows only weak heterogeneity: the energy coefficient is highest at the median ($\tau = 0.50$), but the confidence intervals for all τ intervals overlap with zero. Thus, the effect of energy efficiency on housing prices does not differ significantly across lower and higher-priced market segments (Fig. 6).

The threshold analysis by GDP per capita allows the energy coefficient to vary below and above a data-selected threshold ŷ≈15890. The Wald test rejects the hypothesis of equal slopes in both regimes ($p < 0.01$). While this indicates income-dependent transmission mechanisms, the estimated coefficients remain economically small in both regimes, suggesting that energy effects on housing prices are context-specific rather than uniformly strong (Fig. 7).

Finally, hierarchical clustering using the Ward. D2 method and standardised variables identifies distinct country profiles. France clusters closely with Italy, Germany with Spain, while Poland and Sweden form separate branches. These groupings reflect differences in housing price dynamics and energy profiles, providing an additional structural perspective for interpreting cross-country heterogeneity (Fig. 8).

4. Discussion of the results

This study aimed to assess whether and how building energy efficiency indicators are related to housing price dynamics at the macro level in EU countries, distinguishing between short- and long-term relationships and assessing heterogeneity between countries and price distribution segments. Rather than focusing on determining a single average effect size, the discussion emphasises the stability and variability of the estimated relationships across different economic contexts.

First, the main context should be highlighted: after 2014, a clear HPI growth trajectory was recorded in all analysed countries (the fastest in Poland and Germany, and the slowest in Italy), which immediately signals a strong inertial nature of I(1) levels and prices. Later, it was also captured by dynamic models. Meanwhile, the trajectories of household final energy consumption in most countries are declining moderately, though with episodic spikes (especially in Germany and Poland), while the share of renewable resources is consistently growing. These visual observations alone show that comparing levels and simple correlations would be misleading, since individual links move under the influence of different structural factors, which encourages the use of panel and dynamic methods.

From a long-run perspective, unit root tests for the IPS/LLC panel confirmed the level non-stationarity of most series. At the same time, the Fisher-type combined Engle-Granger cointegration test yielded a marginal result (overall p-value ~0.07), which is closer to the 10 % threshold, but does not reach the 5 % level. This result is particularly important, as it indicates that the capitalisation of energy efficiency in housing prices cannot be assumed to follow a uniform long-run pattern at the EU level. Importantly, this suggests that any long-term relationship, where present, is conditional rather than universal.

The practical conclusion is that the evidence for a general sustainable long-run level relationship between the HPI and energy indicators is weak for the entire sample, so FMOLS/DOLS interpretations must be treated with caution. Even when estimated coefficients point in a direction consistent with rising energy costs, such patterns cannot be interpreted as a general macroeconomic rule (Bashmakov et al., 2024). In other words, certain macroeconomic factors, such as income, cost of credit, urbanisation, or the labour market, are likely to overshadow the impact of energy efficiency. As a result, models calibrated solely on levels may fail to capture regime shifts and heterogeneous adjustment paths (Blažun Vošner & Završnik, 2023). This weak evidence of cointegration is consistent with visual observations (scatterplots show different directions of country-level slopes and large variance) and reinforces the argument that searching for a single average elasticity across the EU is unlikely to be valuable.

The dynamic (Arellano-Bond GMM) specification with a lagged dependent variable logically captures the slow changes in house prices — a typically positively significant parameter of price inertia driven by transaction expectations and financing conditions. In this study, energy indicators have low predictive power for short-term changes in HPI, and their coefficients are economically insignificant. This finding reinforces the view that short-term housing price dynamics are primarily driven by macro-financial conditions rather than energy-related signals alone.

This finding is consistent with the observed fact that short-term changes in energy consumption are often driven by price shocks or temporary policy measures that, when controlling for general macro variables, do not translate into a systematic increase in house prices (Bednář et al., 2022; Ciccarelli & Marotta, 2024; Qi et al., 2025). In practice, this means that, in the short term, energy transformation signals in the market can be “drowned out” by the noise of the credit cycle, labour income, and demographic flows. Methodologically, the choice of AB-GMM is appropriate: it suppresses endogeneity across instruments, but marginal cointegration and heterogeneity still reduce the stability of the values of energy variables (Khatib, 2025).

Impulse-response analysis based on local projection methods shows that a single shock to household energy consumption yields minimal, statistically unreliable HPI responses over a 0-8-year horizon; the median trajectory is close to zero, and the 95 % intervals are wide and include zero. This finding is consistent with the scatterplots' heterogeneity and the small coefficients in the dynamic models. This result further supports the view that energy-related shocks, isolated from additional transmission channels, have limited overall pricing power. From an economic perspective, a change in energy consumption alone, without additional channels (e.g., changes in the EPC level strictly related to housing quality, targeted subsidies, or changes in credit conditions), is not sufficient to create a sustainable, noise-free effect on house prices. From a policy perspective, this statement comforts the debate on affordability: improvements in energy efficiency do not systematically lead to "renovation-driven inflation" at the aggregate market level. Capitalisation effects are not precluded at the micro level, but rather tend to dissipate in macro-level panels (Balsiūnaitė et al., 2025).

Quantile panel regression: searching for distributional heterogeneity. Quantile BE regression (τ = 0.25; 0.50; 0.75) with the cluster bootstrap method by country revealed only weak heterogeneity: the energy factor is highest at the median, but the confidence intervals of all quantiles coincide with zero. This indicates that distributional position alone does not substantially modify the energy-housing price relationship at the macro level.

This model shows that distributional differences do not substantially change the overall relationship between energy efficiency and housing prices. Consequently, at the macro level, the energy factor is not "particularly important" in the dynamics of either the cheaper or the more expensive housing segments: its "price" is capitalised heterogeneously and most likely more through a project/facility-based channel (Energy Performance Certificate level, building type, local micro-characteristics), which this panel does not reveal (Birch & Muniesa, 2020). A practical signal for policymakers: general, "one-size-fits-all" measures may be of limited effectiveness; instead, targeted interventions (e.g., by building age, urban density, and access to credit) should be applied where the probability of capitalisation is higher.

Regime (threshold) analysis by GDP per capita. The Hansen panel threshold model allows the coefficient to vary above and below a data-based threshold; the Wald test rejected the hypothesis of equal slope ($p < 0.01$), allowing the energy coefficient to differ across income levels. While income acts as a conditioning variable, the estimated coefficients remain economically small in both regimes, indicating that income moderates rather than amplifies energy-related price effects.

The interpretation is that in higher-income countries, energy efficiency is more easily recognised in the market and "priced in" (through discounting of operating costs, access to "green" loans, and expectations), while in lower-income countries, pure affordability and credit constraints become more critical in the short term, relegating the energy factor to the background (Landis et al., 2021). This conclusion is in good agreement with the findings of the IRF and dynamic models: the effect exists in some regimes, but at the macro level, it is not large.

Country clustering using the Ward.D2 method identifies natural groupings: France with Italy, Germany with Spain, and Poland and Sweden forming separate branches. These clusters reflect differences in housing price trajectories and energy profiles and provide a contextual framework for interpreting cross-country heterogeneity. Importantly, clustering is used here as a descriptive rather than causal tool, highlighting structurally distinct market environments. For instance, higher renewable energy penetration and urban density may enhance the visibility of energy-related signals in some markets, without necessarily producing a stronger aggregate price response if macro-financial conditions change simultaneously (Ang et al., 2022; Gayen et al., 2024; Zach et al., 2019).

Robustness checks and limitations. Diagnostics for heteroscedasticity, autocorrelation, and multicollinearity (Breusch-Pagan, Wooldridge, and VIF) reduce the risk that the result is "engineered" due to technical discrepancies, but two critical limitations remain. First, the macro indicators (final energy consumption, renewable energy share) are far from corresponding to micro-EPC levels and building quality; therefore, capitalisation may be distorted. Second, 2010-2023 includes multi-regime shocks (COVID-19 and 2021-2022 energy crisis) that are difficult to capture using average coefficients alone. These limitations support interpreting the findings as evidence of structural constraints rather than model misspecification. Further research directions include micro-level data (EPC, sales transaction prices), natural experiments (subsidy/standard changes), DiD models, and a more precise identification of credit supply and interest rate regimes.

Conclusions

At the macro-level EU panel, the energy consumption and "greenness" indicators of buildings are not strongly cointegrated with the house price index: the combined Engle-Granger test yields a marginal result ($p \approx 0.07$), so a single stable long-term relationship cannot be claimed across all countries. This finding shows that the long-term capitalisation of energy efficiency is structurally heterogeneous rather than uniform across the European Union. The evidence for long-term capitalisation remains weak and context-dependent.

The dynamic specifications reveal strong price inertia, and the short-term impact of energy variables is statistically and economically small; in the short term, house price trajectories are mainly determined by income dynamics, credit conditions, and demographic factors. The impulse-response functions show a near-zero response of the HPI to an energy consumption shock over the 0-8-year horizon, suggesting that the "pure" energy channel at the macro level is secondary, unless it operates jointly with financial, regulatory, or market-specific transmission mechanisms.

The quantile analysis does not reveal significantly different effects of energy factors in the cheaper and more expensive housing segments, as the confidence intervals of the coefficients overlap with zero across the quantiles. At the same time, threshold analysis shows that income level modifies the effect: the hypothesis of different slopes is rejected ($p < 0.01$), but the coefficients themselves remain small. Capitalisation is therefore more likely to occur in higher-income countries, whereas in lower-income contexts it is constrained by affordability and credit limitations.

These results emphasise that the observed effects are regime-dependent rather than universal. The structure of country clusters confirms that one-size-fits-all solutions are unlikely to be effective; instead, differentiated analytical and policy approaches tailored to specific credit, income, and urban contexts seem more appropriate.

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Building safe organisations: using machine learning to decode safety habits of blue-collar workers in the construction industry

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A B S T R A C T

This study aims to provide a framework for categorising safety behaviours of construction workers, recognising the importance of employee safety in the competitive business environment. Employee safety is crucial to overall efficiency, productivity, and well-being, and the study seeks to contribute to understanding and managing workplace safety in the construction industry.

This study utilises machine learning (ML) algorithms, like logistic regression, support vector machine, and decision trees, to develop a categorisation framework for the safety behaviours of construction workers. The framework is validated using frequent safety behaviours observed in a random sample of construction professionals.

The study finds that workplace safety behaviours (WSB) are primarily influenced by supervisor support, reckless habits, and safety motivation. Limiting workplace accidents, enforcing safety laws, properly documenting safety processes, and organising sessions to educate staff are identified as critical sub-factors. Advancements in technology have resulted in significant improvements across construction organisations in allied domains. Additional considerations include education, pre-empting the possibility of accidents in different workplace situations, and enforcing strong disciplinary measures.

The framework proposed can serve as a valuable tool for organisations to tailor safety interventions. By recognising the diverse influences on safety behaviours, companies can implement targeted measures to address specific root causes of unsafe practices. The practical implications of these findings for safety management in the construction industry are noteworthy.

K E Y W O R D S

occupational health, safety, workplace, machine learning (ML), construction industry

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Introduction

Occupational health and safety (OHS) is a critical concern in the construction industry due to its high-risk nature (Karthick et al., 2022). Unsafe behaviour is a prominent cause of accidents at construction sites, leading to severe consequences for workers (Moosa & Oriet, 2022). Different types of accidents are associated with different sets of unsafe behaviours. Despite existing OHS regulations, fatal accidents continue to occur, resulting in loss of lives and high costs for organisations. Fall from heights, electric shocks, heavy equipment accidents, and repetitive motion injuries

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are common dangers faced by construction workers (Liang et al., 2022). Safety behaviour can be classified into safety compliance, which is task-related, and safety participation, which is voluntary and initiated by employees (Guo et al., 2022). Addressing unsafe behaviours and promoting safety compliance and participation are crucial for improving OHS in the construction industry (Segbenya & Yeboah, 2022).

Participation in safety can be divided into proactive and affiliative behaviours. While proactive behaviours require taking the initiative to increase workplace safety, affiliative behaviours involve supporting and cooperative acts (Wu et al., 2022). Accident risk is increased by unsafe behaviour on construction sites, such as failing to adhere to safety regulations. Such accidents result in falls, electrical mishaps, and other dangerous scenarios (Ahamad et al., 2022; Turgay & Özyurt, 2025). The consequences of risky behaviour in the workplace can result in significant injuries, property loss, and even death (Mohajeri et al., 2022; Mohammadi et al., 2025). To limit the likelihood of accidents and the consequences of risky behaviour, construction organisations must develop a safety culture (Fang et al., 2023), provide training on safe work practices (Ahamed & Mariappan, 2023), and enforce safety rules (Oni et al., 2023). Some real-life incidents reported from construction sites affirm the influence of unsafe behaviour in causing accidents. Failure to use personal protective equipment (PPE), such as hard helmets, safety glasses, or gloves, can increase the risk of harm in the case of an accident. It is observed that failure to adhere to safety measures on construction sites can result in fatal accidents. Such behaviour includes failure to wear proper safety gear, such as a hard helmet, or using equipment, such as ladders, incorrectly. Such incidents have been reported in the past, with workers suffering from head injuries or falling from heights and losing their lives. Therefore, it is essential to prioritise safety protocols and ensure that workers are adequately trained to avoid such incidents.

Alcohol and drug misuse can cloud judgment and raise the possibility of accidents in the construction sector (Brumfield et al., 2023). Compared to other industries, construction workers are particularly vulnerable to fatal accidents (Kaymedical, 2023). Unattended power tools and other equipment can potentially cause accidents (He et al., 2023). Training, updated procedures, improved monitoring, and the development of a safety culture are required to prevent accidents (Arzahan et al., 2022). Companies in the construction industry can safeguard their employees by complying with regulations by bodies like the Occupational Safety and Health Administration (OSHA). Compliance is encouraged, and workplace safety is ensured by following safety procedures and rules (Viscusi & Cramer, 2023). Construction organisations can use the collected data to gauge the safety behaviour in the workplace to make data-driven decisions about how to prioritise. Considering the arguments, the following research questions (RQs) are proposed:

RQ1: What are the most common types of unsafe behaviours observed at construction sites?

RQ2: How do these unsafe behaviours contribute to accidents and incidents at construction sites?

RQ3: What Machine Learning (ML) algorithms are suitable for predicting safety compliance in the construction industry?

To cater to the highlighted RQs, the corresponding research objectives (ROs) are as follows:

RO1: To identify the most common types of unsafe behaviour that contribute to accidents at construction sites and their impact on worker safety.

RO2: To develop an ML model for predicting safety compliance in the construction industry.

The study is divided into the following sections. The Introduction in Section 1 is followed by a detailed literature review in Section 2. Section 3 presents the materials and methods used to accomplish the ROs. The results and discussions are presented in Sections 4 and 5, respectively. Section 6 discusses the study's practical implications for construction management. Finally, the paper concludes with Section 7.

1. Literature review

1.1. Safety behaviour indicators: input and output indicators

Compared with other industries, the construction sector faces challenges due to low labour productivity, inefficient production, and technological advancements (Woodhead et al., 2018). Research on automated labour monitoring and risk-avoidance strategies is still in its infancy. Globally, research efforts are concentrated on automated control of risky construction behaviours, mobility monitoring, and real-time risk identification (Kumar et al., 2020; Rao, 2022). Construction workers' behavioural patterns and safety inclinations have been predicted using ML algorithms. Real-time worker behaviour and dangerous events can be predicted using simulation models that have demonstrated encouraging results. ML models make more accurate predictions and help identify workers at risk of engaging in risky behaviours. The safety behaviour of construction employees can be measured using virtual reality (VR) techniques, which also help improve workplace safety (Gao, 2022).

The construction sector has used ML research to identify perceived risks with excellent accuracy. Automation techniques, such as supervised algorithms and wearable biosensors, offer more accurate and affordable worker behaviour and workplace safety monitoring than conventional techniques (Xu et al., 2021). It has proven successful to monitor employee risk perception using non-invasive techniques. ML tools are required to recognise typical physical and psychological reactions related to industrial accidents (Lee, 2021). Continuous data is provided by biosensors for tracking psychophysical motions. ML models, such as Leave-One-Subject-And-Context-Out Cross Validation (LOSCOCV), improve the precision of real-time bio signal monitoring and recording for worker safety (Lee et al., 2022).

Construction employees must adhere to safety regulations, and if they do not, accidents may not be covered by insurance. Worker safety can be efficiently monitored and managed in real-time by an automated system. When physical supervision was challenging during the COVID-19 pandemic, ML-based models enabled precise risk assessment. ML can use smart devices to address work-related problems, providing early warnings and enhancing safety. By anticipating and averting serious accidents in the construction sector, ML models have demonstrated effectiveness in Australia (Kamal, 2020; Duan, 2022; Alkaissy, 2023).

Computer-aided techniques have been widely useful for identifying, following, patterning and monitoring in the construction industry. A large number of research studies have been conducted to understand the prediction capacity of various ML algorithms. The results of growing experimental research on the use of ML algorithms in the construction industry have helped identify gaps and trends in preventing unsafe construction situations (Liu, 2019). Research experiments on safety management using programmed safety vests have proved useful to avoid accidents in the construction industry. The colour-coded vests and their movements were measured using image-processing devices, and deviations that may lead to accidents were identified. ML algorithms are used to assess and classify the nature of movements in the workplace environment (Seong, 2018).

Worker safety violations frequently result in accidents in the construction sector. It is difficult to manually supervise employees due to their erratic, unconscious movements (Han, 2012). Computer vision models and motion tracking algorithms are used in ML programs to provide accurate predictions and analyses of risky behaviour. Monitoring irregularities and taking preventive measures are made possible by real-time data gathering and analysis (Tang, 2021). Worker posture, the use of PPE, tool handling, and proximity to dangers can all be observed by multi-tasked recognition models. Wearable equipment and observed photographs help assess severity and improve worker safety (Yiu et al., 2022).

1.2. Smart construction industry and advanced digital technologies

The smart construction industry combines data analytics, real-time monitoring, and software visualisation. Captured visuals and images are compared with the recommended safety procedures to identify discrepancies in workers' real-time postures and movements. Deep learning (DL) techniques are used to predict construction safety monitoring (Zhang, 2022). Research is in progress to integrate the entire lifecycle of the construction industry with ML platforms. The stages of designing architecture, selection of materials, structural design, manufacturing in off-site locations, construction management, project progress control, etc., are all included in the automation process for easier monitoring and prediction of workers' safety. Technologies, such as smart vision-based sensors, data cleaning methods, data storage and analysis methods are used to improve the working environment in the construction industry (Baduge, 2022).

ML is essential for bridging the divide between technology and its applications and for the growth of the smart construction sector. The health and safety monitoring of construction workers can be improved through hybrid vision, real-time data collection, and the Internet of Things (IoT) devices (Fang, 2022). The future of the sector lies in sophisticated systems with broad sensor integration and error-free monitoring. The breakthroughs in physiological computing, artificial intelligence (AI), and ML provide precise, portable monitoring of workers' safety and behaviour (Khan et al., 2022; Khan, 2022). Digital twin (DT) and Industrial Internet of Things (IIoT) technologies provide real-time monitoring and measurement of workplace safety. Automated deep learning structures, such as stacked auto-encoders (SAEs), monitor unusual or unsafe labour movements to identify potential accidents. Bluetooth Low Energy (BLE), for example, is an intelligent service system that aids in construction (Zhan, 2022).

Construction robots are currently researched as a potential solution to the labour crisis and to increase efficiency in the construction sector. Research in China is concentrated on developing efficient construction robots, especially in response to the present pandemic, even though complete substitution is not yet realistic. Construction operations and safety regulations are transformed by automation and machine-human collaboration enabled by technologies like Industry 4.0 and ML (Javaid et al., 2022; Shayesteh, 2023). Body language analysis is one of the scientific methods used to comprehend, forecast, and prevent labour movements and accidents. The construction site can be made safer by using construction robots, ML, automatic warning systems, and safety training (Tavakoli et al., 2020; Ma, 2022; Ding, 2022). Techniques for human-robot collaboration are more affordable and secure than other solutions. Although AI is still used sparingly in managing complicated international building projects, the deployment of AI and ML in monitoring employee safety is becoming increasingly significant. The industry urgently needs the development and adoption of verified AI-based monitoring solutions (Saka, 2023).

2. Research methods

2.1. Data collection and questionnaire design

In this study, data were collected using a self-reported questionnaire developed using extant literature on assessing workplace safety conditions. The authors are indebted to the contributions of Yin et al. (2022), Xie et al. (2022), and Ghodrati et al. (2022), which were extensively employed for creating the questionnaire for this study. Additionally, this study was conducted in the Indian construction landscape; hence, multiple brainstorming sessions were held with management from the construction organisations, including the contractors, supervisors, and labourers working at the ground level. Multiple input safety indicators were either removed or modified to align with the Indian construction sector context. The questionnaire was circulated among several participants for pilot testing. It was observed that the wording of some indicators was complicated to understand. Therefore, the ambiguous indicators were rephrased to increase comprehensibility. One interesting observation was made by a participant in the pilot testing phase, suggesting that the questionnaire should be translated into the native language (Hindi) to make it more convenient for people who were not comfortable communicating or understanding English. The authors translated the questionnaire for the selected respondents, and finally, the data were collected.

The questionnaire was designed to collect information on numerous factors impacting workplace safety habits. Participants were asked for demographic information, including gender, age, job experience, and educational level. The questionnaire assessed the six major input indicators influencing the output indicator "safety behaviour" at construction sites: "management safety practices", "organisational support", "safety climate", "supervisor's support", "reckless habits", and "safety motivation". Each of these constructs was evaluated using a series of questions to which participants responded with either "yes" or "no". In the "Management safety procedures" section, for example, participants were asked to answer whether they agreed with statements such as "All project staff must receive safety training" and "Conduct frequent safety inspections". Similarly, the "Organisational support" section asked participants whether they supported the organisation. The final questionnaire is presented in the Appendix section. With a target population size of 80, a confidence level of 90 %, and a margin of error of ±5 %, a sample size of 63 was required. To secure sufficient, valid, and representative responses, the questionnaires were distributed online and offline to construction personnel, including managers, contractors, supervisors, and labourers, resulting in 125 respondents. After three rounds of administration, 65 responses were returned, yielding a response rate of 52 %. There were no missing responses in the collected data. The participants were appropriately instructed on the need for confidentiality and anonymity during this data collection. They were also told that the questions were subjective and that there was no right or wrong answer. The procedures described above were primarily intended to address common method variance that may have entered the study (Podsakoff et al., 2003).

2.2. Machine learning (ML) classifiers used in the study

In this study, multiple ML classifiers are applied to categorisation problems. Based on feature values, logistic regression (LR) calculates the chance that an observation belongs to a given class. Support vector machines (SVMs) choose the best border to separate classes in the feature space. Based on input features and their results, decision trees (DTs) build a model that resembles a tree. Each method has advantages and disadvantages. For example, LR is straightforward and effective but struggles with non-linear correlations. SVMs can accommodate non-linear boundaries but are expensive to compute. DTs can be interpreted; however, they are sensitive to slight data changes and prone to overfitting. It is possible to find the best classification result with the least amount of error by using many classifiers (Zabor et al., 2022; Ebrahimi et al., 2022; Liu & Huang, 2022; Park et al., 2022).

2.3. Optimal model

Model tuning is crucial for improving the performance of ML models on unseen data. Hyperparameter optimisation is used to find the best parameter values that minimise prediction error. Various hyperparameters, such as the regularisation strength in LR, kernel type and C parameter in SVMs, number of trees and maximum depth in random forest, and the smoothing parameter in Naive Bayes, can influence model performance. Adjusting these hyperparameters helps prevent overfitting and enhances the model's ability to generalise to new data. The study utilises a 10-fold cross-validation method, dividing the dataset into ten subsets. Each model is trained on nine subsets and validated on the remaining subset, repeating this process ten times. The average performance of the models across the ten validation sets is then calculated. Cross-validation helps select the best model and hyperparameters, while addressing overfitting. Evaluating the model across multiple validation sets ensures better performance on new, unseen data (Zabor et al., 2022).

3. Research results

3.1. Classification performance of different classifiers

ML classifiers are evaluated based on their ability to correctly classify objects and the errors they incur. The evaluation metrics are based on the number of correctly and incorrectly classified objects. When a model correctly predicts the positive class, it is referred to as a "true positive" (TP), while a correct negative prediction is a "true negative" (TN). An incorrect positive prediction is called a "false positive" (FP), and an incorrect negative prediction is called a "false negative" (FN).

Initial information about the performance of ML techniques can be obtained by observing the correctly and incorrectly classified instances. This information is gathered in a matrix that shows the model's correct and incorrect predictions, and how they relate to the true outcomes or labels. Table 1 shows the correctly and incorrectly classified instances by each classifier as indicated by the confusion matrix. In ML, the following metrics are commonly used to evaluate the classifier's performance.

3.1.1. Precision

Precision measures the proportion of TPs out of all positive predictions (TP + FP).

It indicates the classifier's ability to correctly identify positive instances without including FPs.

3.1.2. Recall or sensitivity

Recall, also known as sensitivity, measures the proportion of TPs out of all actual positive instances (TP + FN).

Tab. 1. Correct and incorrect classification by each classifier

	LR		SVM		DT	
	Correctly classified instances	Incorrectly classified instances	Correctly classified instances	Incorrectly classified instances	Correctly classified instances	Incorrectly classified instances
WSB1	60 (92.3%)	5 (7.7%)	59 (90.8%)	6 (9.2%)	60 (92.3%)	5 (7.7%)
WSB2	46 (70.8%)	19 (29.2%)	43 (66.2%)	22 (33.8%)	43 (66.2%)	22 (33.8%)
WSB3	42 (64.6%)	23 (35.4%)	44 (67.7%)	21 (32.3%)	37 (56.9%)	28 (43.1%)
WSB4	36 (55.4%)	29 (44.6%)	36 (55.4%)	29 (44.6%)	36 (55.4%)	29 (44.6%)
WSB5	41 (63.1%)	24 (36.9%)	47 (72.3%)	18 (27.7%)	38 (58.5%)	27 (41.5%)
WSB6	41 (63.1%)	24 (36.9%)	48 (73.8%)	19 (26.2%)	38 (58.5%)	27 (41.5%)

It indicates the classifier's ability to correctly identify all positive instances without missing any.

3.1.3. Specificity

Specificity measures the proportion of TNs out of all actual negative instances (TN + FP).

It indicates the classifier's ability to correctly identify all negative instances without including FPs.

3.1.4. ROC (Receiver Operating Characteristic) curve

The ROC curve is a graphical representation of a classifier's performance across various classification thresholds.

It plots the true positive rate (TPR) against the false positive rate (FPR) at different threshold values. A good classifier will have an ROC curve closer to the top-left corner, indicating high TPR and low FPR.

3.1.5. F-measure

The F-measure combines precision and recall, to provide a more balanced view of a classifier's performance.

It is the harmonic mean of precision and recall, given by the formula: 2 * (precision * recall) / (precision + recall). The F-measure considers both false positives and false negatives and provides a single score that reflects the classifier's performance.

Table 2 summarises the performance metrics of the classifiers for each of the six decision outcomes.

It is clear that LR outperforms SVMs and DTs in classification across all six decision outcomes. The performance of LR is equally appreciable for the recall characteristics for all the decision outcomes, except for WSB5 and WSB6, where random forest takes the lead. Specificity shows a mix of performance levels across all classifiers. As shown in Graph C, random forest is best for WSB3, WSB5, and WSB6,

Tab. 2. Performance characteristics of classifiers for the six decision outcomes

ROC characteristic				Precision			
	LR	SVM	DT		LR	SVM	DT
WSB1	97.3	83.6	83.5	WSB1	92.6	90.8	92.1
WSB2	72.5	63.5	54.3	WSB2	71.0	65.7	64.9
WSB3	76.1	66.8	54.1	WSB3	65.5	67.5	56.4
WSB4	59.1	49.1	41.0	WSB4	58.2	52.5	50.2
WSB5	67.2	61.9	48.6	WSB5	64.1	70.2	53.7
WSB6	67.2	61.5	48.0	WSB6	63.0	70.6	54.0
Measure				Recall			
	LR	SVM	DT		LR	SVM	DT
WSB1	92.4	90.8	92.2	WSB1	92.3	90.8	92.3
WSB2	70.9	65.9	63.8	WSB2	70.8	66.2	66.2
WSB3	64.7	67.5	56.5	WSB3	64.6	67.7	56.9
WSB4	56.1	53.3	51.4	WSB4	55.4	55.4	55.1
WSB5	63.5	70	55.6	WSB5	63.1	72.3	58.5
WSB6	63.5	69.4	55.6	WSB6	63.1	71.9	58.3
Specificity							
	LR	SVM	DT				
WSB1	75	72.7	80				
WSB2	61.5	56.5	60				
WSB3	58.8	65.4	52				
WSB4	41.9	35.3	30.8				
WSB5	40.9	58.3	23.1				
WSB6	41.0	58.0	22.7				

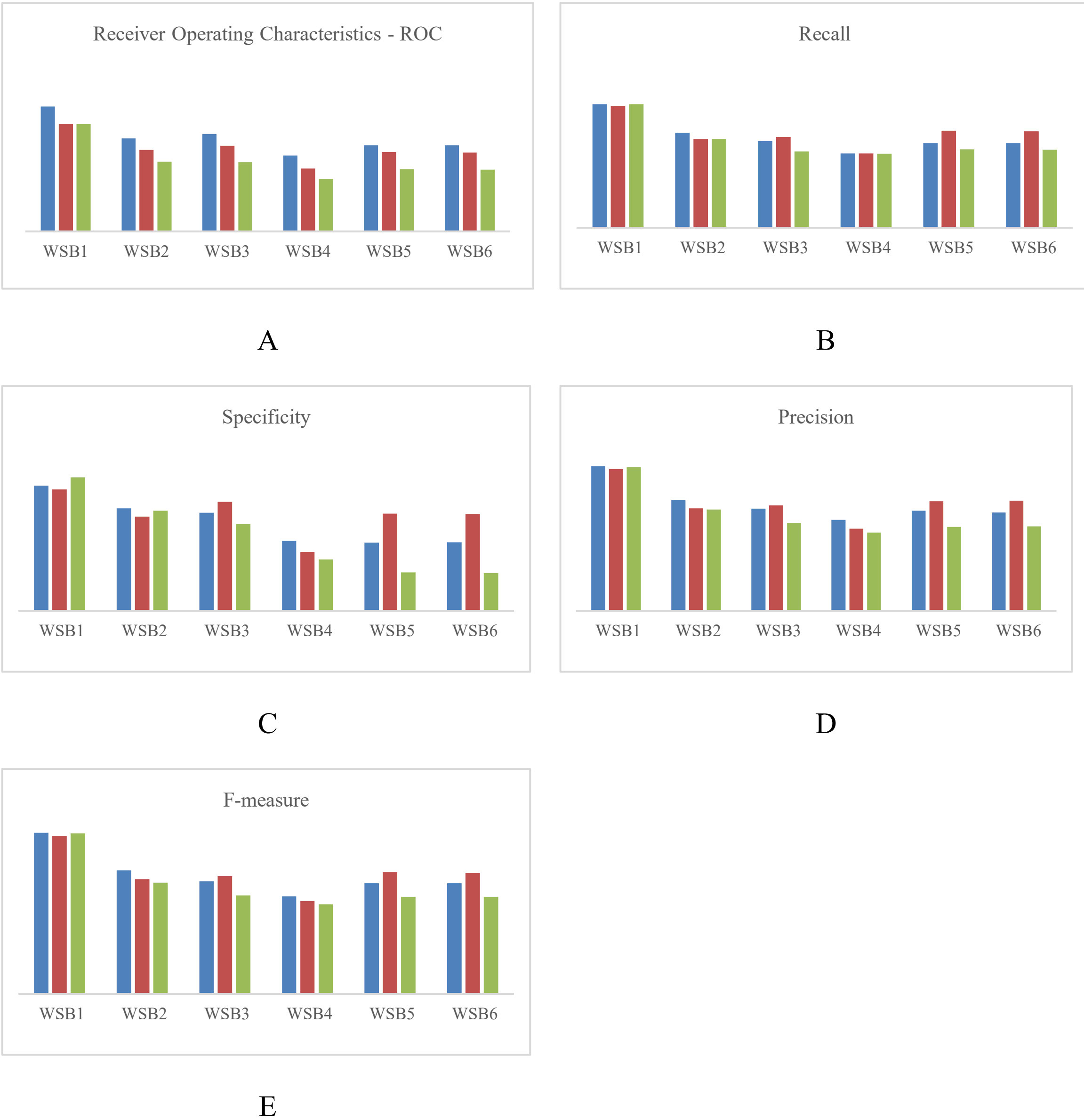

Fig. 1. Graphs representing the performance classifiers

whereas LR performs best for WSB2 and WSB4. The situation is rather like the precision characteristic, where LR and random forests are the closest competitors. DTs are found to be the worst performers across all the performance characteristics for all six decision outcomes. Fig. 1 shows the graphs for each performance characteristic for the six decision outcomes.

3.2. Feature selection

The best features for decision outcomes were chosen using a combination of performance indicators. The odds ratio and the ranker approach were used in logistic regression (LR) to determine the most significant features. Support vector machine (SVM) models were trained using the sequential minimal optimisation (SMO) algorithm, with the ranker approach used for feature selection. When choosing features for the J48 decision tree algorithm, the CfsSubsetEval search method considered each feature's capacity for prediction as well as its compatibility with other features. For automatic parameter selection, 10-fold cross-validation was used (Zabor et al., 2022). The set of important features for each of the six decision outcomes for the three classifiers is reflected.

Tab. 3. Best features selected for Workplace Safety Behaviour 1 (WSB1) by each classifier

WSB1	
Best feature set	
LR	It is critical to limit the likelihood of workplace accidents, my supervisor tries their best to enforce safety rules, experience, I have a healthy and nurturing relationship with my supervisor, colleagues appreciate efforts, safety rules protocols and processes are properly documented
SVM	It is critical to always maintain safety, supervisor uses innovative methods to encourage safety behaviours, keep workers informed of safety hazards, do not smoke, supervisor holds periodical meetings to sensitise employees to safety behaviours, management encourages employees to recommend safety tips
DT	Collaborative decision-making, it is critical to always maintain safety, my supervisor encourages us to participate in setting safety goal, it is critical to limit the likelihood of workplace accidents, my supervisor encourages us to participate in setting safety goal

Tab. 4. Best features selected for Workplace Safety Behaviour 2 (WSB2) by each classifier

WSB2	
Best feature set	
LR	Accidents and events are constantly recorded and reported, experience, supervisor holds periodical meetings to sensitise employees to safety behaviours, my supervisor tries best to enforce safety rules
SVM	Supervisor uses innovative methods to encourage safety behaviours, keep workers informed of safety hazards, gender, dedication to the projects aim
DT	Keep workers informed of safety hazards, strict disciplinary actions in the event of violation of rules, education, do not smoke

Tab. 5. Best features selected for Workplace Safety Behaviour 3 (WSB3) by each classifier

WSB3	
Best feature set	
LR	Experience, age, education, accidents and events are constantly recorded and reported, my supervisor tries best to enforce safety rules, smoking while at work
SVM	Gender, it is critical to always maintain safety, do not smoke, supervisor holds periodical meetings to sensitise employees to safety behaviours, handle all circumstances as though there is a chance of an accident
DT	Supervisor holds periodical meetings to sensitise employees to safety behaviours, my supervisor tries best to enforce safety rules, it is critical to always maintain safety

Tab. 6. Best features selected for Workplace Safety Behaviour 4 (WSB4) by each classifier

WSB4	
Best feature set	
LR	Keep workers informed of safety hazards, accidents and events are constantly recorded and reported, management organises meetings and get-togethers to build a cordial environment, smoking while at work, strict disciplinary actions in the event of violation of rule
SVM	Dedication to the projects aim, do not smoke, gender, supervisor uses innovative methods to encourage safety behaviours
DT	Supervisor holds periodical meetings to sensitise employees to safety behaviours, dedication to the projects aim, do not smoke, gender, supervisor uses innovative methods to encourage safety behaviours

Tab. 7. Best features selected for Workplace Safety Behaviour 5 (WSB5) by each classifier

WSB5	
Best feature set	
LR	Age, handle all circumstances as though there is a chance of an accident, accidents and events are constantly recorded and reported
SVM	Gender, dedication to the projects aim, supervisor holds periodical meetings to sensitise employees to safety behaviours, strict disciplinary actions in the event of violation of rule, smoking while at work, it is critical to limit the likelihood of workplace accidents, do not smoke
DT	Supervisor holds periodical meetings to sensitise employees to safety behaviours, do not smoke, education, it is critical to limit the likelihood of workplace accidents, strict disciplinary actions in the event of violation of rules

Tab. 8. Best features selected for Workplace Safety Behaviour 6 (WSB6) by each classifier

WSB6	
Best feature set	
LR	Age, handle all circumstances as though there is a chance of an accident, accidents and events are constantly recorded and reported, supervisor uses innovative methods to encourage safety behaviours, supervisor acknowledges my job requirements
SVM	Gender, strict disciplinary actions in the event of violation of rules, supervisor holds periodical meetings to sensitise employees to safety behaviours, it is critical to limit the likelihood of workplace accidents, smoking while at work, do not smoke
DT	Supervisor holds periodical meetings to sensitise employees to safety behaviours, do not smoke, education, it is critical to limit the likelihood of workplace accidents, strict disciplinary actions in the event of violation of rules

Table 3 highlights the best features for Workplace Safety Behaviour 1.

Table 4 highlights the best features for Workplace Safety Behaviour 2.

Table 5 highlights the best features for Workplace Safety Behaviour 3.

Table 6 highlights the best features for Workplace Safety Behaviour 4.

Table 7 highlights the best features for Workplace Safety Behaviour 5.

Table 8 highlights the best features for Workplace Safety Behaviour 6.

3.3. Comparison of different models

To get the most accurate classification performance, the study evaluates multiple ML approaches. To evaluate performance using measures such as accuracy, recall, F-measure, and the area under the ROC curve, statistical significance tests, such as paired sample t-tests, are used. The dataset, algorithm parameters, and chosen ML techniques (logistic, SVMs, and DTs) are set up for the experiment. To ensure statistically significant results, many runs with different random seeds or cross-validation folds are performed. Depending on the evaluation metric, paired t-tests or nonparametric tests are used to compare the results across techniques. Table 9 presents the results of the paired sample t-tests for testing the classification performance of each ML technique on evaluation metrics statistically.

Precision, recall, F-measure, and the area under the ROC curve have been used to test each classifier's performance. It can be observed that, for each decision outcome, almost all classifiers exhibit comparable performance. The output from Waikato Environment for Knowledge Analysis (WEKA) software (Frank et al., 2010) suggests that the values are not statistically significantly different from those of the LR regression. However, in several cases, such as in Tables A and C, DTs are observed to perform inferiorly to LR, and the inferiority is statistically significant. In Tables E and F, SVMs outperform LR with a statistically significant margin. Overall, the classification performance of all classifiers is very similar. In this situation, the decision on the best classifier for safety compliance classification lies entirely with the user, and any classifier can yield satisfactory performance. However, its simplicity, interpretability, and robustness to data noise make LR the most popular algorithm for classification tasks.

4. Discussions of the results

This study aims to investigate the major factors affecting workplace safety behaviour using ML techniques. WSB is influenced by various socio-technical variables. Socio-technical elements are workplace social and technological components that might influence an individual's safety behaviour, attitudes, and decision-making. It is noteworthy that the major determinants of all WSB categories predominantly lie in the "Supervisor's support", "Reckless habits", and "Safety motivation" categories. It can thus be concluded that, regardless of the presence of strict safety protocols and regulations at construction sites, keen supervision and support from the supervisors are essential to ensure workplace safety. Additionally, workers need to be constantly motivated to follow safety practices and stay vigilant of any deviation from safety protocols.

The decision to use the essential safety equipment to complete the task (WSB1) is observed to be critically influenced by the perceived criticality of limiting the likelihood of workplace accidents, as indicated by the factor "It is critical to limit the likelihood of workplace accidents". Those who understand the potential hazards of failure to use safety equipment are more likely to use the essential equipment to protect them-

Tab. 9. Comparison of classification performance using paired sample t-test

WSB1				WSB2			
	LR	SVM	DT		LR	SVM	DT
Precision	0.98	0.97	0.94	**Precision**	0.76	0.73	0.7
Recall	0.97	0.98	0.96	**Recall**	0.72	0.78	0.85
f-measure	0.97	0.97	0.95	**f-measure**	0.71	0.73	0.76
ROC	0.99	0.9	0.78*	**ROC**	0.73	0.63	0.59
WSB3				**WSB4**			
	LR	SVM	DT		LR	SVM	DT
Precision	0.76	0.72	0.55*	**Precision**	0.71	0.65	0.63
Recall	0.67	0.75	0.68	**Recall**	0.65	0.75	0.78
f-measure	0.69	0.72	0.59	**f-measure**	0.66	0.69	0.69
ROC	0.73	0.67	0.51*	**ROC**	0.59	0.52	0.51
WSB5				**WSB6**			
	LR	SVM	DT		LR	SVM	DT
Precision	0.8	0.77	0.72	**Precision**	0.8	0.77	0.72
Recall	0.73	0.88v	0.83	**Recall**	0.72	0.88v	0.83
f-measure	0.75	0.81	0.76	**f-measure**	0.75	0.81	0.76
ROC	0.72	0.64	0.55	**ROC**	0.72	0.64	0.55

selves from injury. This finding is consistent with observations on the risk factors of occupational accidents in the construction sector, where inadequacies in workplace safety procedures and untrained workers incapable or unwilling to use safety equipment were cited as the major reasons for the occurrence of accidents (Nayak et al., 2022). "My supervisor tries best to enforce safety rules", asserts that the supervisor's involvement in enforcing safety guidelines is equally critical in ensuring WSB1. An employee's conduct may be influenced if the supervisor has a reputation for valuing safety and supporting the use of safety equipment. Workers may be more motivated to use safety equipment if they believe their supervisor is concerned about safety and encourages its use. Experience can also influence an employee's decision to use safety equipment. If a person has been injured on the job or knows someone who has, they are more inclined to wear safety equipment in the future. They are more aware of the hazards because they have direct knowledge of the potential implications of failure to use safety equipment. The strength of an employee's connection with their supervisor can also impact safety behaviour, as pointed by the indicator "I have a healthy and nurturing relationship with my supervisor", and is ranked higher among the factors influencing WSB1. Employees who have a pleasant and supportive connection with their boss are more likely to follow safety standards and use safety equipment. This is because they believe their supervisor supports and values them, which might improve their drive to participate in safe conduct. Similar observations were made in the study involving the examination of employee perceptions of supervisor behavioural integrity, where it was reported that mediation between top-management safety climate and safety behaviours through safety motivation was stronger for employees who reported high supervisor behavioural integrity for safety. In this regard, the findings of the existing study align with Peker et al. (2022).

Appreciation from co-workers can also motivate for safe conduct, as indicated by the statement "Colleagues appreciate efforts". Employees who believe their co-workers appreciate safety efforts and encourage the use of safety equipment are more likely to engage in safe behaviour. They believe that colleagues notice and reward their safety efforts, which may improve their drive to continue behaving safely. Lastly, good documentation of safety regulations, protocols, and processes may have a big impact on workers' safety conduct, as indicated by the statement, "Safety rules, protocols, and processes are properly documented". Employees are more likely to behave safely if they have clear, accessible information about the importance of safety and the proper use of safety equipment ("It is critical to maintain safety at all times"), which makes them aware of potential hazards. Workers are more aware of the hazards if they are regularly informed about potential safety issues. Such incrementally improved knowledge can encourage workers to adopt safety equipment, such as PPE, to keep themselves safe. Workers, for example, are more likely to use protective gloves, goggles, or masks if they are warned about hazardous chemical exposure. The above finding is reinforced by the observation made in a study conducted to investigate the psychological causes for workplace accidents, where the cognitive factors were shown to propel unsafe behaviour of construction workers. The study recommends that management address stress and safety issues by organising stress management seminars, regular safety inspections, performance appreciation and recognition, and effective communication (Liang et al., 2022).

Smoking in the workplace may be hazardous, especially in industries that use flammable or combustible products, such as the construction industry. Workers are less likely to participate in conduct that increases the risk of a workplace accident if smoking is prohibited. Furthermore, separating smoking locations from dangerous products reduces the likelihood that employees will contaminate their PPE or cause a fire hazard. Workers are involved in detecting and addressing workplace safety hazards through "collaborative decision-making". Workers are more invested in the outcome and feel more accountable for their own safety when they participate in decision-making. They may be more motivated to use safety equipment if they have a sense of ownership over the process and consequences. Employees are more likely to take responsibility for their personal safety and feel involved in the process when they are encouraged to participate in defining safety goals. They may discover areas for improvement and implement adjustments that better represent workers' needs and viewpoints by incorporating them in the process. Workers may be more motivated to use safety equipment and other safety measures if they believe their feedback has been considered.

Adherence to safety protocols in every situation (WSB2) is found to be significantly influenced by factors such as indicated in statements "Accidents and events are constantly recorded and reported", "Experience", "Supervisor holds periodical meetings to sensitise employees to safety behaviours", and "My supervisor tries best to enforce safety rules". "Accidents and events are constantly recorded and reported", implying that there is a well-established system for recording and evaluating workplace mishaps. This provides better knowledge of different accidents that occur, as well as the identification of trends and areas for improvement. Keeping a record of accidents and incidents also communicates that safety is a seriously taken concern. Workers with more work experience may be more aware of potential risks and more likely to follow established safety procedures, which can positively influence adherence to safety measures, as indicated by the role of the factor "Experience" in determining WSB2. Nevertheless, expertise alone is insufficient to ensure adherence to safety measures; continual training and reinforcement of safety practices are also required. "Supervisor arranges periodical sessions to sensitise staff to safety behaviours" indicates a proactive approach to workplace safety, with monthly meetings to discuss and promote safe behaviours. This can help foster a safe culture and inspire employees to take responsibility for their own and their co-workers' safety. The statement, "My supervisor tries best to enforce safety rules", shows that the supervisor is dedicated to ensuring that safety measures are followed and that employees understand their significance. Such measures can increase responsibility and guarantee that everyone in the workplace is following the required procedures to keep the workplace safe. In construction projects, it is crucial to observe safety regulations and have effective communication. Workers' adherence to safety procedures can be positively influenced by a commitment to the project's objectives, ensuring that accidents and injuries do not impede progress. Education can be used for people to better comprehend the need for safety procedures and the potential repercussions of non-compliance. People who are well-informed are more likely to adhere to safety regulations and recognise their significance. Additionally, such steps as quitting smoking can influence how safety rules are followed. Smoking impairs lung health and may cause an individual to take more risks or disregard safety precautions. Non-smokers might be more devoted to adhering to safety precautions, more focused, and more alert. To develop a culture of safety and reduce hazards, building sites can encourage clear communication, education, and healthy practices.

Several factors are instrumental in ensuring the safety behaviours at construction sites, namely those indicated in statements "When doing the work, adhere to all safety precautions (WSB3)" and "Promote the safety programme enthusiastically (WSB4)".

Experience, for instance, is one of the primary indicators used to establish WSB3 and WSB4. Veterans and highly experienced construction personnel are likely to have encountered a wide range of hazards and accidents and have developed their own safety practices and protocols to mitigate those risks; hence, they are more likely to adhere to safety rules and follow safety practices. This is supported in the article published by Areia et al. (2022). Age is another factor that can significantly influence workers' adherence to safety protocols. Older individuals may be more risk-averse than the younger generation, and thus, they are more inclined to follow workplace safety practices. Workers' level of experience and age affect their dedication to safety procedures. Accident reporting and recording raise workers' awareness of potential risks and encourage safer behaviour. Workers should be made aware of the repercussions of breaking safety regulations to encourage accountability and attentiveness. Strict disciplinary measures, such as warnings and dismissal, can guarantee compliance with safety procedures. Innovative techniques, such as virtual reality simulations, improve the efficacy of safety training. According to Dahl et al. (2020), formal health and safety training in Norway has a beneficial effect on effective occupational safety and health management systems.

The last two safety behaviours, namely "Make further efforts to promote workplace safety (WSB5)" and "When co-workers are in perilous situations, assist them (WSB6)", have some common determinants. Older employees may have more experience, be more risk-averse, and be more inclined to promote workplace safety and assist co-workers in danger. Younger workers may be more prone to risk-taking and may require better training and direction to understand the necessity of safety. The mentality of approaching all situations as though there is a potential for an accident can increase safety and make personnel more aware of possible risks. Employees who are always concerned with safety are more likely to take measures and assist their co-workers in risky circumstances. It is vital to reduce the possibility of workplace accidents, emphasise the significance of safety, and encourage employees to take measures and assist co-workers in risky situations. A better understanding of employee job requirements among supervisors and managers can guarantee that safety precautions are taken to safeguard workers from potential risks. This can enhance safety and inspire employees to assist their co-workers in hazardous situations. Severe disciplinary procedures for breaking safety rules can force workers to take safety seriously and assist their co-workers in risky circumstances. Severe disciplinary measures can deter and motivate employees to be more cautious. Several studies emphasised that promoting workplace safety and responding effectively to workplace accidents are important aspects of maintaining a safe work environment. Some key findings of these studies align with the findings of the current study, including immediate action in the event of an accident or injury, proper protocols to report the incidents to management or regulatory agencies, and provide emotional support and access to resources for those involved (Zhang et al., 2020; Jung et al., 2020; Sattari et al., 2021).

Conclusions

This study highlights the importance of different drivers underlying various safety behaviours to develop targeted measures for cultivating safe workplace behaviours. ML techniques are valuable tools for exploring complex patterns among safety behavioural data. This research aimed to provide a categorisation framework for construction workers' safety behaviours using ML techniques, such as LR, SVMs, and DT, involving three critical steps: data collection and preprocessing, modelling and algorithm implementation, and optimal model acquisition. For this study, a random and representative sample of India-based construction personnel was used to validate the classification framework. The results demonstrate that WSB is primarily influenced by the supervisor's support, reckless habits at workplace including smoking and drinking, and safety motivation, and critical subfactors within each of the main category influencing WSB include "It is critical to limit the likelihood of workplace accidents", "My supervisor tries best to enforce safety rules", "Experience", "I have a healthy and nurturing relation with my supervisor", "Colleagues appreciate efforts", "Safety rules, protocols, and processes are properly documented", "It is critical to maintain safety at all times", "Supervisor uses innovative methods to encourage safety behaviours", "Keep workers informed of safety hazards", "Do not smoke", "Supervisor holds periodical meetings to sensitise employees to safety behaviours", "Management encourages employees to recommend safety tips", "Accidents and events are constantly recorded and reported", "Supervisor holds periodical meetings to sensitise employees to safety behaviours", "My supervisor tries best to enforce safety rules", "Keep workers informed of safety hazards", "Dedication to the projects aim", "Strict disciplinary actions in the event of violation of rules", "Education", "Do not smoke", "Experience", "Accidents and events are constantly recorded and reported", "Handle all circumstances as though there is a chance of an accident", "Strict disciplinary actions in the event of violation of rule", "Smoking while at work", and "Supervisor acknowledges my job requirements".

Although the study accomplished its objectives, a few limitations must be addressed in future research. Even though the ML approach has been created to overcome the small sample size issue, and some studies have employed smaller sample sizes, additional data is needed for future studies. Second, because the study employed an Indian sample, more research is needed to evaluate whether the findings can be applied to other countries/regions. Finally, the study did not identify all the elements that influence safety behaviours, and their interrelationships are unclear. Consequently, an additional in-depth study is needed in this respect. Fourth, the suggested categorisation system is general, and many construction sites are included.

Managerial implications

Based on the research findings, some important implications for industry practitioners can be used to ensure workplace safety. Some of the notable implications are mentioned below:

- It is paramount that management ensures the safety rules and protocols are properly documented and always accessible to workers. This will help increase workers' awareness of potential hazards and encourage them to comply with safety requirements. A safety manual, for instance, can be very effective and used during working hours. Additionally, a well-documented system for recording and evaluating workplace accidents and incidents should be developed, as it can potentially provide valuable insights into risk types present at a construction site.
- If workers are involved in collaborative decision-making of identifying and addressing safety hazards, they will feel more invested in the process, are more likely to take personal responsibility for their own safety and be motivated to use safety equipment.
- Construction management should train every employee, including senior management, supervisors, contractors, workers, and field workers, to enforce safety guidelines. Workers who share a good working relationship with their supervisors are more likely to follow safety standards and use safety equipment. High-quality training should be provided by specialised and skilled trainers with state-of-the-art technology. It is critical to introduce technology-driven safety methods in the construction sector, which is arguably the most hesitant sector to adopt new technologies.
- Workers with a consistent good record of adherence to safety rules and regulations should be awarded and recognised periodically. This helps establish trust and confidence in management as employees feel that their efforts are valued, hence, they stay motivated to remain compliant.
- Organising periodic meetings and sessions to sensitise employees towards safety behaviours can foster a safety culture, where all employees feel accountable for their own and their colleagues' safety.
- Encouraging employees to refrain from smoking or drinking during working hours can help them stay attentive, remain focused, and committed to safety protocols, reducing the risks of accidents and unwanted delays.
- Managers should ensure that their teams have a mix of experienced and younger personnel to increase safety on building sites. The former have their own safety procedures and protocols, which they may share with the younger generation. Experienced people are also more likely to observe safety guidelines, making them valuable assets to any building job.
- Workers should be informed about the consequences of violating safety rules, such as verbal or written warnings, suspension, or termination. This promotes vigilance, accountability, and hazard reduction. Consistent enforcement by management encourages compliance and sets safety as a top priority, fostering a safety culture where workers prioritise their own and co-workers' safety. To enhance safety training, virtual reality simulations can provide immersive experiences that simulate construction situations and teach workers about dangers and safety procedures. Interactive workshops, role-playing activities, and gamification tactics are also effective methods to engage employees and reinforce safety regulations.

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APPENDIX

Gender: Male (1), Female (2)
Age: <20 (1), 20-30 (2), 31-40 (3), 41-50 (4), >50 (5)
Experience: <3 (1), 3-10 (2), 11-15 (3), 16-20 (4), >20 (5)
Educational level: Below primary (1), Primary (2), Secondary (3), Certificate/Diploma (4), College or higher (5)

Input Indicators

a. Management safety practices (answer by 1 (Yes) or 2 (No))
- All project personnel must get safety training.
- Conduct frequent safety inspections.
- Responds quickly to safety concerns.
- Keep workers informed of safety hazards.
- Helps maintain a clean work area.
- Set safety performance targets.
- Immediate accident reporting is required.
- When meeting with contractors, prioritise safety.
- Prompt feedback on job performance.
- Dedication to the project's aim.
- Timely correction of any safety issues to prevent accidents.
- Handle all circumstances as though there is a chance of an accident.

b. Organisational support (answer by 1 (Yes) or 2 (No))
- Decision-making process satisfaction.
- Collaborative decision-making.
- Leadership assistance is provided.
- Colleagues are willing to assist teammates.
- Colleagues appreciate efforts.
- Colleagues recognise potential.
- Management organises meetings and get-togethers to build a cordial environment.

c. Safety Climate (answer by 1 (Yes) or 2 (No))
- The performance expectations are quite clear.
- Safety rules, protocols, and processes are properly documented.
- Strict disciplinary actions in the event of violation of rules.
- Accidents and events are constantly recorded and reported.
- Management encourages employees to recommend safety tips.
- The project manager monitors the safety of the employees.
- The whole project team is dedicated to safety.

d. Supervisor's support (answer by 1 (Yes) or 2 (No))
- Supervisor uses innovative methods to encourage safety behaviours.
- Supervisor holds periodical meetings to sensitise employees to safety measures.
- Good safety conduct is rewarded.
- My supervisor encourages us to participate in setting safety goals.
- My supervisor tries their best to enforce safety rules.
- My supervisor recognises my achievement.
- Supervisor acknowledges my job requirements.
- Supervisor understands and identifies bottlenecks.
- I have a healthy and nurturing relationship with my supervisor.

e. **Reckless habits (answer by 1 (Yes) or 2 (No))**

- Smoking while at work.
- Do not smoke.
- Drinking while at work.
- Do not drink.

f. **Safety Motivation (answer by 1 (Yes) or 2 (No))**

- Workplace health and safety are critical.
- Maintaining or improving my personal safety is advantageous to me.
- It is critical to maintain safety at all times.
- It is critical to limit the likelihood of workplace accidents and mishaps.

Output Indicators

g. **Safety behaviour (answer by 1 (Yes) or 2 (No))**

- Use the essential safety equipment to complete the task.
- Adherence to safety protocols in every situation.
- When doing the work, adhere to all safety precautions.
- Promote the safety programme enthusiastically.
- Make further efforts to promote workplace safety.
- When co-workers are in perilous situations.

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Evolving AI models: adoption patterns of transformers and diffusers

Paweł Cabała

ABSTRACT
This study investigates the development, adoption, and implications of artificial intelligence (AI) models by analysing a comprehensive dataset of over 316,000 models hosted on the Hugging Face platform. Focusing on two dominant model architectures - transformers and diffusion models - it examines their distribution across tasks, user engagement patterns, and practical applications in domains such as natural language processing, computer vision, audio processing, and generative media. The research highlights the growing prominence of generative AI, the role of open-source platforms in shaping model accessibility, and the divergence in use trends between foundational and emerging AI tools. Drawing on correlations between downloads, likes, citations, and model size, the paper discusses how each library's community-driven dynamics shape their respective strengths. Finally, the paper discusses implications for business strategy and adoption, encompassing practical considerations like infrastructure requirements and ethical challenges, and underscores the potential for these evolving model ecosystems to drive innovative, human-centric AI solutions across diverse sectors.

KEY WORDS
artificial intelligence (AI), transformer models, diffusion models, Hugging Face, open source software, model adoption, technological diffusion, natural language processing (NLP), computer vision (CV), innovation strategy

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Introduction

Generative artificial intelligence (AI) represents a paradigm shift, fundamentally altering how organisations and individuals approach innovation, creativity, and productivity. Transcending their origins in purely analytical tasks, contemporary AI models function as catalysts for novelty, generating original ideas, challenging established paradigms, and informing complex decision-making processes. Across diverse sectors - ranging from industry and education to healthcare and marketing - generative models, particularly large language models (LLMs)

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and chatbots, are reshaping business operations by automating routine tasks and enabling highly personalised user experiences. Concurrently, the proliferation of these technologies necessitates critical examination of human-AI collaboration, fostering new perspectives on design thinking and innovation strategy (Sedkaoui & Benaichouba, 2024). Transformer and diffusion models are among the most impactful innovations. Transformers have revolutionised language understanding and text generation capabilities (Gupta, 2023), whereas diffusion models have introduced new frontiers in image and content synthesis, underscoring AI's expanding repertoire across both analytical and creative domains (Ahirwar, 2023).

Against this technological backdrop, the present study investigates the development patterns and distribution dynamics of AI models, with a specific focus on transformer and diffusion architectures hosted on the Hugging Face (HF) platform. As a central and rapidly expanding hub for sharing AI models, datasets, and interactive spaces (Osborne et al., 2024), Hugging Face plays a crucial role in democratising access to cutting-edge AI technologies for diverse fields, including behavioural science (Hussain et al., 2024). Recent empirical studies have begun to analyse the complex dynamics of this ecosystem, examining challenges and benefits of model reuse (Taraghi et al., 2024), validating claims about platform use patterns (Jones et al., 2024), and mapping the structure of development activity and collaboration (Osborne et al., 2024). Situated within this growing body of research, the author's primary objective is to delineate use trends across key AI domains specifically for transformer and diffusion models, analyse associated user engagement metrics, and evaluate the broader implications for innovation, collaborative practices, and the ethical deployment of generative AI technologies hosted on this influential platform.

To achieve this objective, three central research questions guide this investigation. First, the study identifies the predominant model architectures - transformer and diffusion - and examines their distribution across disciplines such as NLP, CV, and audio processing. Second, it analyses how user engagement indicators (e.g., downloads, likes, citations) diverge between these architectural classes and assesses the implications of these differences for practical adoption. Third, it explores overarching patterns in generative AI deployment, with an emphasis on characterising innovation trajectories, discerning user preferences and evolving paradigms of creativity, human-AI interaction, and platform-mediated dissemination.

This research assumes transformer and diffusion models are key AI drivers whose Hugging Face visibility reflects broader trends. Engagement metrics (e.g., downloads, likes) are treated as imperfect proxies for utility and reception. Acknowledging platform limitations, we use HF data to analyse usage patterns and diffusion, assuming these dynamics partially reveal wider ethical, social, and strategic aspects of generative AI.

1. Literature review

1.1. Transformer models

Transformer models represent a significant inflection point in artificial intelligence, having fundamentally altered the processing of sequential data (Patwardhan et al., 2023). Introduced by Vaswani et al. (2017), the transformer architecture departed from traditional recurrent and convolutional neural networks by relying exclusively on attention mechanisms. The cornerstone of the transformer model is the self-attention mechanism, which dynamically assigns importance weights to different elements within an input sequence relative to each other. This capability allows the model to capture long-range dependencies more effectively than earlier recurrent architectures, where information transmission often degraded over extended sequence lengths (Islam et al., 2024). Standard transformer architectures typically comprise encoder and decoder stacks, each incorporating multi-head attention layers, position-wise feed-forward networks, residual connections, and layer normalisation (Vaswani et al., 2017). Architectural variations have emerged, tailored to specific task types: encoder-only models like BERT excel at tasks requiring deep bidirectional context understanding (e.g., sentiment analysis, named entity recognition), while decoder-only models such as the GPT series are optimised for autoregressive text generation (e.g., language modelling and creative writing). Architectures combining both encoder and decoder components - for instance, BART and T5 - demonstrate particular effectiveness in sequence-to-sequence transformations (Radford et al., 2019; Lewis et al., 2020; Raffel et al., 2022; Rothman, 2022).

Beyond their origins in NLP, transformers exhibit remarkable versatility across diverse scientific and industrial fields. In computer vision, transformer models have achieved competitive, and often superior, performance compared to convolutional neural networks on large-scale image classification, segmentation, and object detection benchmarks. Transformers also underpin advancements in speech and audio processing, including automatic speech recognition and speaker identification systems (Islam et al., 2024). Furthermore, their capacity to model complex dependencies has led to applications in medicine, aiding the analysis of intricate medical imaging data for disease diagnosis and prognosis, and even in neuroscience and psychiatry for decoding neural signals and modelling cognitive processes (Cong et al., 2024). As research continues to expand its capabilities and efficiency, transformer architectures are poised to remain a central pillar of modern artificial intelligence (Patwardhan et al., 2023).

1.2. Diffusion models

Diffusion models represent a distinct and powerful class of generative methods that learn to synthesise new data by reversing a predefined noise-injection process (Yang et al., 2024). Conceptually, this involves a forward process that gradually adds noise (typically Gaussian) to the original data over a sequence of steps until it approximates pure noise. Subsequently, a learned reverse process iteratively denoises the corrupted data, starting from noise, to generate a realistic sample from the target distribution. Foundational work in score-based generative modelling, which involves learning the gradient of the log-density of the data distribution (the score function), provided key theoretical underpinnings for these approaches (Song & Ermon, 2019).

A significant milestone was the development of Denoising Diffusion Probabilistic Models (DDPMs), which reformulated the objective and demonstrated high-fidelity image generation by training a model to predict the noise added at each step of the forward process (Ho et al., 2020; Gallon et al., 2024). DDPMs and subsequent refinements have established diffusion models as state-of-the-art in various generative tasks. Further innovations, such as Latent Diffusion Models (LDMs), perform the diffusion and denoising operations within a lower-dimensional latent space, significantly reducing computational demands while largely preserving high-quality output synthesis (Po et al., 2024; Rombach et al., 2022).

Diffusion models have achieved exceptional performance across a diverse array of applications, particularly in visual computing. They excel at high-resolution image and video generation, complex image editing, inpainting, super-resolution, and notably, text-to-image synthesis, which has garnered significant popular and research interest (Po et al., 2024; Yang et al., 2024). Their generative capabilities extend beyond 2D images to tasks including 3D shape generation, audio synthesis, and motion generation (Po et al., 2024; Yang et al., 2024). Moreover, researchers are actively exploring the application of diffusion models to challenging interdisciplinary problems, such as molecular generation for drug discovery and material design, highlighting their potential as a versatile and broadly applicable generative AI paradigm (Yang et al., 2024).

1.3. Hugging Face platform

The Hugging Face (HF) platform has emerged as a crucial ecosystem facilitating the development, sharing, and deployment of contemporary AI models, encompassing hundreds of thousands of model, dataset, and interactive space repositories (Osborne et al., 2024). Its open-source libraries significantly lower the barrier to entry, democratising access to advanced AI for researchers and practitioners across various disciplines, including the social and behavioural sciences (Hussain et al., 2024).

The transformers library, in particular, provides standardised interfaces for a vast collection of prominent transformer architectures (e.g., BERT, GPT, and T5), supporting a wide array of NLP, vision, and speech tasks. Empirical evidence confirms the significant preference for this library in the reuse and adaptation (fine-tuning) of pre-trained models (PTMs) within the HF community (Jones et al., 2024). Similarly, the diffusers library provides a modular framework for diffusion models, simplifying experimentation with generative tasks like text-to-image synthesis through pre-configured pipelines, interchangeable noise schedulers, and access to numerous checkpoints.

The platform enables straightforward inference via the HF Hub and provides efficient fine-tuning tools, promoting widespread model accessibility. Beyond basic model use, Hugging Face offers robust support for transfer learning, optimisation, and deployment, allowing models to be adapted and utilised efficiently (https://huggingface.co/docs). This accessibility demonstrably accelerates innovation across numerous fields (Hussain et al., 2024).

However, quantitative analyses reveal highly skewed, Pareto-like distributions for nearly all activity metrics, including downloads, likes, and contributions, indicating that a small fraction of models and users account for the vast majority of engagement. Collaboration patterns also show a core-periphery structure, with most developers working in isolation but a densely connected core driving significant activity (Osborne et al., 2024). While the platform fosters community support, users face challenges related to model understanding, implementation, and documentation quality (Taraghi et al., 2024). Notably, documentation quality (e.g., via model cards) strongly correlates with model popularity (Jones et al., 2024), yet documentation practices remain inconsistent across the Hub (Taraghi et al., 2024). Furthermore, the platform experiences rapid model turnover, higher than traditional software registries (Jones et al., 2024), and lacks licensing information for a majority of hosted artefacts (Osborne et al., 2024).

Despite these complexities - including skewed engagement metrics, collaboration patterns, and documentation challenges - the sheer scale and central role of Hugging Face in the open AI landscape make it an invaluable data source for analysing contemporary AI model trends, adoption patterns, and community dynamics (Jones et al., 2024; Osborne et al., 2024). Understanding the distribution and engagement surrounding key architectures, such as transformers and diffusers, in this specific, influential context provides crucial insights into the trajectory of modern AI development and deployment.

2. Research methods

Data were retrieved between 15 January and 15 March 2025 using Python-based tools to combine API queries with targeted web scraping. The Hugging Face Hub library facilitated direct interactions with official endpoints, while Requests and BeautifulSoup handled custom HTML parsing. dateutil supported date transformations and concurrent.futures enabled asynchronous data retrieval. Collected records were stored and organised in pandas data structures for subsequent filtering and analysis.

In cases where publicly documented API calls were insufficient - particularly for restricted or gated models - the research team employed carefully configured web scraping. This dual strategy balanced efficiency (through official endpoints) with data completeness (through supplementary parsing). Error-handling mechanisms included retry loops, pagination checks, and backoff strategies to avoid rate-limit issues, ensuring a robust extraction pipeline. Duplicate entries were addressed by merging

Tab. 1. Data collection stages, tools, and key results

Stage	Tools	Results
1. Organisational data (API queries)	• Hugging Face API • concurrent.futures for parallel requests • retry mechanisms and logging	• queried 207,831 organisational accounts • gathered stats on models, datasets, spaces, creation dates, modifications • identified 6 main organisation types (companies, non-profits, communities, universities, classrooms, government) plus 31,414 unclassified • noted top companies by team size
2. User profiles (web scraping)	• Requests & BeautifulSoup for HTML parsing • dateutil for date handling • follower count extraction from user pages	• mapped 56,019 individual users • captured follower counts, organisational affiliations, and membership • detected popular creators
3. Model & user discovery (pipeline tags)	• multiple sorting/filter approaches • automated merging of pipeline tags • incremental extension of a "master" dataset	• broadened coverage of model IDs, including newly identified ones • ensured minimal duplication by merging metadata for overlapping entries • established foundations for collecting model-level details (library, tasks, licensing, usage stats)
4. Model metadata (API + targeted scraping)	• pandas transformations (drop duplicates, filter outliers) • merging pipeline tags • task-based grouping	• filtered out models with nonpositive storage sizes or missing fields, reducing total from 762,971 to 674,800 • focused on 316,418 models using essential libraries (transformers, diffusers) • yielded final dataset of 263,850 users (organisations + individuals)

metadata tags, and restricted models were flagged separately.

The retrieval pipeline unfolded in four distinct phases, summarised in Table 1. Each phase contributed specific data points (organisational details, user profiles, model identifiers, and metadata) that were ultimately merged into a comprehensive master dataset.

Following data retrieval and filtering, the final dataset captures a broad cross-section of users and models on Hugging Face. Initially, 762,971 models were identified; however, rigorous cleaning and the exclusion of incomplete or invalid entries narrowed this total to 674,800. A subsequent focus on recognised tasks (e.g., text-generation and object-detection) and two key libraries (transformers and diffusers) further reduced the number of models to 316,418. At the user level, 263,850 unique accounts emerged in the dataset, comprising organisational and individual profiles.

Within organisations, companies constituted the largest group-76,210 in total - accounting for 52,384 hosted models and attracting 458,233 followers. Many organisations hosted no models at all, but a small subset maintained large repositories. For instance, Mars Republic stood out with 2,549 members, while DeepSeek commanded the highest follower count at 45,440. Other notable companies included Cognizant, Amazon, Google, IBM, NVIDIA, Intel, Dell Technologies, Cisco, and HUAWEI Noah's Ark Lab, reflecting substantial corporate interest and capacity in AI development.

Individual users varied significantly in both popularity and productivity. While most contributed only a handful of models, a small but prolific group -such as the user "team mradermacher" (mradermacher) with 31,728 repositories - produced a disproportionate share of the platform's outputs. Prominent community figures included Tom Jobbins (TheBloke), followed by Lvmin Zhang (lllyasviel), Merve Noyan (merve), and AK (akhaliq), each drawing thousands of followers. This combination of diverse institutional participation and high-output individual contributors underscores the platform's openness and the collaborative dynamics driving model creation and sharing.

3. Research results

3.1. Overall model distribution

Table 2 presents a high-level overview of the distribution of AI models across major categories - multimodal, computer vision (CV), natural language processing (NLP), audio, tabular, reinforcement learning (RL), and other - categorised by their underlying library (transformers or diffusers).

Aggregating the data reveals a total of 316,418 models within the scope of this analysis, with transformer-based models constituting the vast majority (280,034 models, or approx. 88.5 %), while diffuser-based models represent a smaller but significant segment (36,384 models, approx. 11.5 %). The NLP category exhibits the highest concentration of transformer models (229,875 out of 229,883 total NLP models), reflecting this architecture's established dominance and efficacy in language-centric tasks such as text classification, question answering, and generation. Conversely, diffusers are predominantly utilised within the computer vision domain, where they constitute a substantial proportion (36,342 out of 51,605 CV models, approx. 70.4 %), primarily employed for generative processes, such as text-to-image synthesis and image-to-image translation.

Smaller yet noteworthy domains, such as audio and multimodal, display a more nuanced architectural division. While transformers overwhelmingly dominate the audio category numerically (26,849 vs

Tab. 2. Task-level breakdown of transformers and diffusers on Hugging Face

Category	Transformers	Diffusers	Total
Multimodal	7 129	8	7 137
Computer vision (CV)	15 263	36 342	51 605
Natural language processing (NLP)	229 875	8	229 883
Audio	26 849	20	26 869
Tabular	115	1	116
Reinforcement learning (RL)	787	2	789
Other	16	3	19
Total	280 034	36 384	316 418

Source: author's elaboration on the basis of data retrieved from Hugging Face (March 2025).

20 diffusers), the presence of diffusers, albeit small, points towards emerging applications in generative audio synthesis and augmentation. Similarly, the multimodal category, comprising over 7,000 models, is largely driven by transformers; however, the inclusion of diffusers suggests expanding use cases in complex scenarios, integrating diverse data types like text, images, and potentially video. Collectively, the distribution outlined in Table 2 underscores a key trend in contemporary AI development: established analytical and sequential tasks rely heavily on transformer architectures, whereas the burgeoning field of generative AI, particularly in visual domains, spurs the adoption and development of diffuser models.

3.2. Comparative model metrics

This section analyses the characteristics of models across different libraries and task categories by examining summary statistics for model size, citations, downloads, and likes, as presented in Table 3. These metrics reveal distinct profiles reflecting varying development priorities, user engagement patterns, and application focuses within the Hugging Face ecosystem.

Comparing the two primary libraries, transformer models are characterised by a substantially larger average size (avg. 15.05 GB) and extremely high size variability (std 200.25 GB), likely reflecting the prevalence of large foundational models alongside smaller, specialised ones. They garner significantly higher average downloads (avg. 83k) but show lower average community appreciation via likes (avg. 2.43) compared to diffusers. Diffuser models, conversely, are smaller on average (avg. 6.58 GB) with less, though still considerable, size variability (std 106.03 GB). They exhibit much lower average downloads (avg. 22k) but receive markedly higher average likes (avg. 5.57), suggesting a strong resonance with users, perhaps focused on generative novelty, despite lower overall download volume and very low average citations (avg. 0.06). This contrast highlights a potential divergence between broad utility (transformers) and focused community enthusiasm for specific capabilities (diffusers).

Examining the major task categories reveals further nuances. Natural language processing (NLP) models mirror the overall transformer profile with large average size (avg. 16.01 GB) and immense size variability (std 219.10 GB), moderate average downloads (avg. 65k), and relatively low average likes (avg. 2.47). Computer vision (CV) models are smaller on average (avg. 6.55 GB) but attract higher average downloads (avg. 90k) and notably more likes (avg. 4.49) than NLP models, despite having the lowest average citation count among major tasks (avg. 0.10). Audio models stand out for achieving the highest average downloads (avg. 160k), coupled with extreme download variability (std 15089k), yet they receive the lowest average likes (avg. 1.17) and relatively few citations (avg. 0.14).

Specialised and emerging domains present distinct statistical profiles. Multimodal models, despite lower average downloads (avg. 29k), boast the highest average citation count (avg. 0.75) and like count (avg. 7.21), alongside a large average size (avg. 17.61 GB), suggesting strong academic interest and community appreciation for models that bridge different data types. Tabular models demonstrate an exceptional profile: minimal average size (avg. 0.56 GB) but

Tab. 3. Summary of model statistics across libraries and tasks

Category		Size (GB)		Citations		Downloads (000s)		Likes	
avg.		std	avg.	std	avg.	std	avg.	std	
Library	transformers	15.05	200.25	0.29	0.92	83	6968	2.43	46.61
	diffusers	6.58	106.03	0.06	0.35	22	731	5.57	93.85
Tasks	Multimodal	17.61	70.70	0.75	2.83	29	420	7.21	70.55
	CV	6.55	90.55	0.10	0.41	90	5139	4.49	80.4
	NLP	16.01	219.10	0.30	0.86	65	5225	2.47	47.87
	Audio	11.66	73.79	0.14	0.37	160	15089	1.17	34.86
	Tabular	0.56	1.90	0.28	0.61	1570	10425	5.29	18.15
	RL	2.05	9.99	0.05	0.23	2	20	2.44	30.33
	Other	5.29	8.65	0.62	0.50	958	3720	11	19.73
All models		14.07	191.81	0.26	0.88	76	6560	2.80	54.18

Source: author's elaboration on the basis of data retrieved from Hugging Face (March 2025).

extraordinarily high average downloads (avg. 1570k) with significant variability (std 10425k), indicating immense popularity for specific, likely efficient, tabular data solutions. Reinforcement learning (RL) appears as a niche field, characterised by a small average size (avg. 2.05 GB), very low average downloads (avg. 2k), and the lowest average citations (avg. 0.05). The "Other" category, though small, shows surprisingly high engagement across downloads (avg. 958k), citations (avg. 0.62), and likes (avg. 11.00), potentially representing highly impactful or novel models outside standard classifications. Overall, these diverse statistical footprints underscore the varied nature of development focus, user needs, and community engagement across different AI application domains on the platform.

3.3. Top models by engagement

Among the most downloaded transformer models on Hugging Face, the leader is ast-finetuned-audioset (10-10-0.4593 version), developed by the Massachusetts Institute of Technology (MIT) and released in November 2022, with over 2.1 billion downloads. It is followed by bert-base-uncased, released by Google in March 2022, which has surpassed 2 billion downloads. Other highly downloaded models include wav2vec2-large-xlsr-53-english by Jonatas Grosman and clip-vit-large-patch14 by OpenAI, both released in March 2022, with over 1 billion and 860 million downloads, respectively. The list also features gpt2 by OpenAI community, resnet-50 by Microsoft, and xlm-roberta-large by FacebookAI, all of which were introduced in March 2022 (Fig. 1).

This ranking reflects the cumulative adoption of key transformer models since their respective release dates. While many of the top models were introduced in early 2022 - such as those from Google, OpenAI, Microsoft, and FacebookAI - their high download counts may reflect longer availability rather than current usage trends. Overall, these patterns highlight the long-term utility of foundational models and the rapid uptake of high-impact architectures, especially those supporting speech, vision, and language understanding.

For diffusers, the most downloaded models highlight the rapid growth of generative image modelling in recent years. Leading the group is stable-diffusion-xl-base-1.0, released by Stability AI in July 2023, with over 81 million downloads. It is followed by AnimateDiff-Lightning, developed by ByteDance and introduced in March 2024, reflecting the increasing interest in generative video tasks such as text-to-video synthesis. Other popular models from Stability AI include stable-diffusion-2-1 (released in December 2022) and sdxl-img2img-1.0 (July 2023), both of which focus on text-to-image and image-to-image generation, respectively.

When analysing user appreciation through likes (Fig. 2), a different picture emerges. Leading the ranking is DeepSeek-R1, introduced on Hugging Face on 20 January 2025, with over 11,000 likes. Developed by the Chinese company DeepSeek, the model has quickly gained popularity by matching the performance of models like ChatGPT and Gemini while remaining significantly more affordable. As an open-source model under the MIT license, it is available for commercial use and can be run locally, mak-

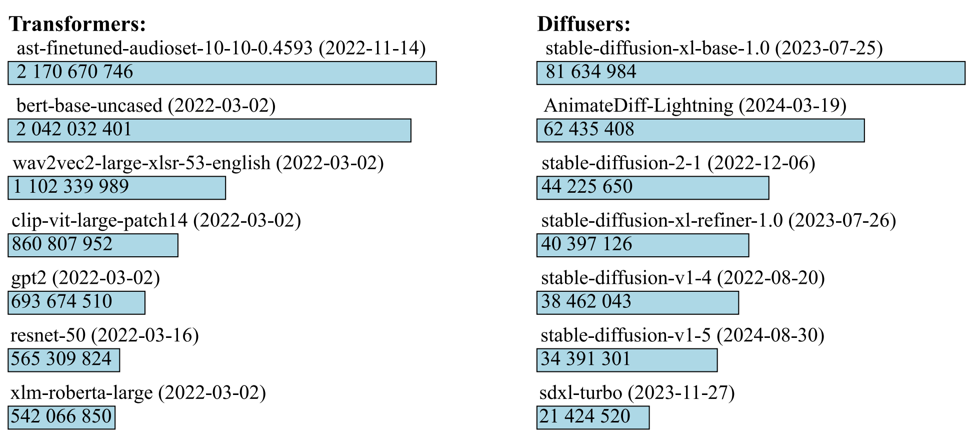

Fig. 1. Top models by downloads

Source: author's elaboration on the basis of data retrieved from Hugging Face (March 2025).

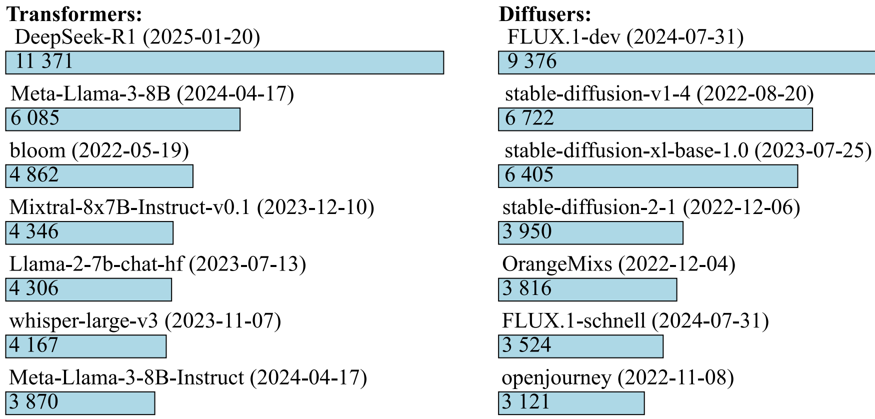

Fig. 2. Top models by likes
Source: author's elaboration on the basis of data retrieved from Hugging Face (March 2025).

ing it highly accessible (Lauridsen, 2025). Following DeepSeek-R are models such as Meta-Llama-3-8B and Meta-Llama-3-70B, both released in April 2024 by Meta Llama, and Mixtral-8x7B-Instruct-v0.1 by the French startup Mistral AI, launched in December 2023. These models, although not always the most downloaded, have earned significant user approval due to their technical sophistication and relevance to cutting-edge research. Their success highlights a clear trend: Hugging Face users gravitate toward models that represent the latest advancements in AI. Notably, OpenAI's whisper-large-v3, a speech recognition model released in November 2023, also ranks highly, reinforcing the preference for state-of-the-art performance across different application domains.

For diffusers, the model FLUX.1-dev by Black Forest Labs, created in July 2024, holds the top spot in likes, demonstrating significant community appreciation despite not being the most downloaded. Also highly rated are OrangeMixs by WarriorMama777 (released in December 2022) and openjourney by PromptHero (from November 2022), both of which are known for artistic and stylised image generation. These models serve more creative or experimental use cases and appear to resonate with users who value innovation, fine-tuned aesthetics, and novel diffusion capabilities. Other top liked models, such as FLUX.1-schnell (July 2024) and the stable-diffusion series, illustrate how the community appreciates both the refinement of established families and the introduction of newer, high-impact variations.

In summary, while download counts often reflect broad utility and cumulative adoption, particularly for foundational models, like counts appear more indicative of perceived innovation, state-of-the-art relevance, or unique capabilities. This distinction highlights both the enduring value of established models and the community's enthusiasm for novel architectures.

3.4. Correlation patterns across metrics

To deepen the understanding of user engagement and adoption dynamics, the author analysed Pearson correlation coefficients between key model-level metrics - downloads, likes, citations, and size - for transformer and diffuser libraries. These correlations help reveal whether popularity, scholarly recognition, or technical attributes tend to move together or reflect distinct use cases and community behaviours. The results, visualised in Fig. 3, uncover markedly different patterns for the two architectures.

For transformers, correlations across metrics are generally weak. The strongest relationship is observed between downloads and likes ($r = 0.16$), while downloads show virtually no correlation with citations ($r = 0.01$). Model size remains largely uncorrelated with other variables. This pattern suggests that adoption within the transformer ecosystem is broad and multifaceted, likely influenced by a wide variety of academic, industrial, and niche applications rather than simple engagement signals.

By contrast, diffusers exhibit notably stronger correlations - most prominently between downloads and likes ($r = 0.59$) - implying that widely used models in this category are also more likely to be positively received by the community. A moderate correlation also emerges between downloads and citations ($r = 0.14$), indicating some alignment between practical use and academic attention. As with transformers, model size remains a weak predictor. The tighter

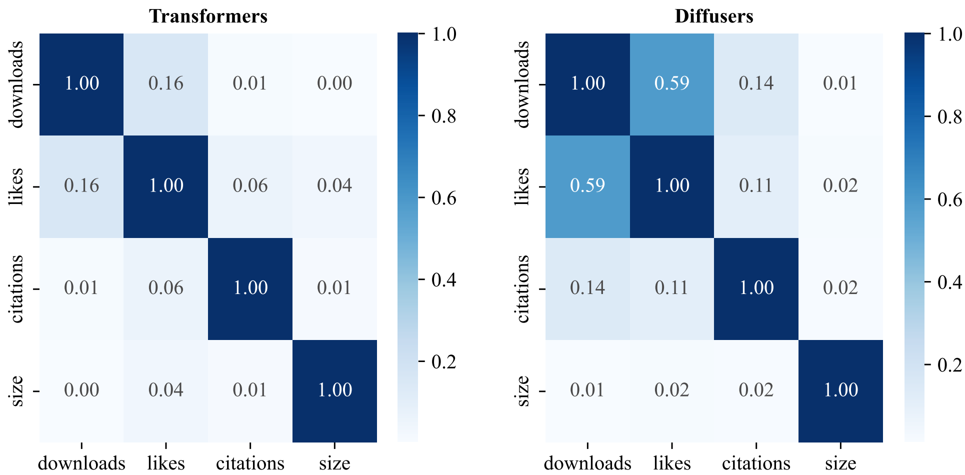

Fig. 3. Pearson correlation coefficients of model metrics for transformers and diffusers
Source: author's elaboration on the basis of data retrieved from Hugging Face (March 2025).

clustering of engagement metrics for diffusers may reflect a more focused and collaborative community, especially around fast-evolving generative capabilities where novelty and utility often go hand in hand.

4. Discussion of the results

4.1. Strategic implications for business adoption

The empirical findings on the distribution and engagement patterns of transformer and diffuser models on the Hugging Face (HF) platform carry direct implications for business adoption and strategic planning. The widespread prevalence of transformer architectures - particularly in NLP and established computer vision (CV) tasks - reflects their maturity and deep integration into applications that enhance operational efficiency and customer interaction. Advanced text-generation models (e.g., GPT-based architectures) are transforming areas such as marketing content creation, customer service automation (via conversational assistants), and internal knowledge management, offering cost savings alongside greater responsiveness and personalisation. Likewise, the high volume and download counts of foundational CV models underscore their practical value in domains such as automated visual inspection, media analysis, and security systems.

At the same time, the rapid growth and strong community engagement surrounding diffuser models signal their emergence as powerful engines of innovation, especially in creative industries. As demonstrated by their dominance in text-to-image tasks and their high average like counts, Diffusers excel in contexts where stylistic novelty and artistic experimentation are essential - such as design, advertising, entertainment, and media. Unlike traditional discriminative models, their ability to synthesise entirely new visual content or transform existing assets opens up new avenues for rapid prototyping (e.g., in fashion or product design), personalised content generation, and scalable aesthetic exploration.

Beyond platform-specific observations, the rise of generative AI is reshaping traditionally human-centred creative fields. In areas like luxury design, for instance, AI-generated outputs can now effectively convey brand identity and evoke targeted emotional responses (Pantano, Serravalle & Priporas, 2024). This evolution highlights AI's potential not only to automate but to genuinely augment human creativity - particularly within collaborative frameworks. However, this potential must be balanced with concerns around aesthetic homogenisation and the marginalisation of human artistry, calling for thoughtful, context-sensitive integration strategies.

The strong community enthusiasm for diffusers - despite their lower overall download volumes compared to transformers - suggests a highly engaged user base driving innovation in generative applications. This dynamic may serve as an early signal of emerging market opportunities, particularly in sectors seeking differentiation through bespoke content creation or AI-augmented creative workflows. Nonetheless, businesses should remain aware of the highly skewed adoption landscape on platforms like HF, where a small number of models accounts for a disproportionate share of engagement (Osborne et al., 2024). As such, initial adoption may concentrate around a handful of well-supported, widely validated models before broadening to more diverse use cases.

4.2. Challenges of enterprise-scale integration

Successfully integrating large-scale AI models, such as advanced transformers or diffusers, into enterprise environments requires careful consideration of several practical challenges. Scalability, encompassing computational resources and infrastructure costs, remains a primary concern. The significant size of many state-of-the-art models places substantial demands on cloud computing resources or on-premise hardware, potentially leading to high operational expenditures and latency issues. This finding aligns with challenges reported within the HF community regarding memory and performance limitations (Taraghi et al., 2024). Organisations must strategically balance model performance with infrastructure costs, often employing techniques, such as model distillation, quantisation, or efficient serving strategies, each involving trade-offs among accuracy, complexity, and maintainability.

Data governance, security, and regulatory compliance represent another critical dimension, particularly in sensitive sectors like healthcare, finance, and public services. Handling proprietary or personal data requires stringent privacy protocols (e.g., GDPR and HIPAA), robust audit trails, and secure deployment mechanisms. While open-source models offer advantages in transparency and the potential for local deployment to enhance data privacy (Hussain et al., 2024), significant gaps exist regarding licensing clarity for a large proportion of models hosted on platforms like HF (Osborne et al., 2024), creating potential legal risks for commercial use. Furthermore, the increasing focus on model security, evidenced by trends such as the adoption of formats like safetensors (Jones et al., 2024), highlights the need for vigilance against vulnerabilities. Failure to implement rigorous data controls and address licensing and security concerns can lead to severe reputational damage, legal liabilities, and erosion of stakeholder trust.

Finally, organisational readiness is paramount. Deploying and managing sophisticated AI models demands specialised expertise spanning data science and domain-specific knowledge. While platforms like Hugging Face provide user-friendly toolkits that lower entry barriers (Hussain et al., 2024), effective enterprise integration requires more than basic technical literacy. Users frequently encounter challenges in understanding model specifics, use nuances, and training pipelines (Taraghi et al., 2024), which underscores the critical importance of high-quality documentation - a factor strongly correlated with model popularity and adoption (Jones et al., 2024) - yet often found lacking or inconsistent (Taraghi et al., 2024). Organisations must invest in targeted talent development, either by hiring specialists or by upskilling existing teams in areas such as AI pipeline management, model lifecycle monitoring, ethical AI practices, and performance tuning. Fostering cross-functional teams that bridge technical depth with business acumen is crucial to unlocking the strategic value of these advanced AI tools.

4.3. Community engagement and development patterns

The vibrant user community surrounding platforms such as Hugging Face fosters a dynamic environment of rapid innovation and community-driven model improvement. As observed by Taraghi et al. (2024), the community provides significant benefits through shared expertise, collaborative problem-solving, and the contribution of new model checkpoints, fine-tuning scripts, and application examples. This collective, open approach can accelerate model refinement and performance gains for both transformer and diffuser architectures, allowing businesses to potentially benefit from cutting-edge AI developments without bearing the full cost of proprietary R&D, particularly when leveraging adaptable open-source models (Hussain et al., 2024). However, this collaborative picture is nuanced by findings suggesting a core-periphery structure in development activity, with influence concentrated among a few prolific developers and large organisations (Osborne et al., 2024), serving as a reminder that the open AI ecosystem is not immune to the dynamics seen in traditional open-source software.

The ongoing evolution of generative AI, driven in part by diffusers, is poised to reshape business models, particularly in the creative and digital sectors. As these models become more accessible and efficient, opportunities arise for novel generative services - from automated content creation and personalised advertising to virtual prototyping and environment design. This trend, coupled with lower entry barriers facilitated by platforms like HF, may fuel a "creator economy" dynamic, enabling smaller entities to compete by leveraging powerful generative tools. Furthermore, the high turnover rate observed in models on HF (Jones et al., 2024) suggests a rapidly evolving landscape, in which adaptability and continuous learning are key strategic imperatives for businesses seeking to maintain a competitive edge.

Looking ahead, the convergence of analytical capabilities (often associated with transformers) and generative prowess (increasingly linked to diffusers) likely points towards the development of powerful hybrid architectures. Such models could offer deep domain-specific understanding and fluid, multimodal generation capabilities, further transforming strategic planning, product innovation, and human-AI collaboration across diverse industries. Harnessing the potential of this evolving ecosystem requires not only technical proficiency but also strategic foresight regarding community trends, ethical considerations, and the shifting competitive landscape.

Conclusions

This study sought to illuminate the contemporary landscape of artificial intelligence development and adoption by quantitatively analysing the distribution, use patterns, and community engagement surrounding two pivotal architectures, transformers and diffusers, within the influential Hugging Face (HF) ecosystem. By examining a large-scale dataset derived from the platform, the research aimed to provide empirical insights into current trends, practical implications, and the evolving dynamics shaping the open AI movement.

Addressing the first research question concerning model distribution, the analysis confirms the marked dominance of transformer architectures, particularly within established domains, such as natural language processing (NLP) and audio processing. This underscores their enduring efficacy for tasks involving sequential data and complex language understanding. Conversely, diffusion models demonstrate significant and rapidly growing traction in computer vision (CV), especially for generative tasks such as text-to-image synthesis. This bifurcation highlights a key trend: while transformers remain foundational for many analytical AI applications, diffusers are spearheading advancements in creative content generation, particularly in the visual domain.

Regarding user engagement patterns (the second research question), the findings reveal distinct characteristics for each architecture. Transformer models collectively achieve higher aggregate download volumes, likely reflecting their broad applicability and deep integration into existing research and enterprise workflows. However, diffuser models exhibit stronger correlations between engagement metrics (likes, downloads, and citations), suggesting a potentially more cohesive and actively engaged community where perceived innovation, popularity, and academic relevance are more closely intertwined. The enthusiastic reception of diffusers for novel content creation points towards a dynamic user base focused on exploring capabilities beyond traditional AI tasks.

Examining broader trends and the alignment between model development and evolving work paradigms (the third research question), the data signal accelerating innovation trajectories, especially in creative industries, driven by the proliferation of powerful generative models. Emerging user preferences lean towards multimodal capabilities and accessible, customisable solutions, fostered by a vibrant community-driven ecosystem on platforms like HF that encourages rapid model refinement. The findings depict a shifting landscape where advanced generative architectures are increasingly integrated into design workflows, collaborative platforms, and diverse application frameworks. This emergent synergy between human expertise and AI-driven automation, as evidenced on HF, suggests a future where generative capabilities significantly augment professional roles and catalyse novel commercial opportunities and artistic domains.

This investigation offers valuable empirical insights into the proliferation and adoption dynamics of key AI architectures on the Hugging Face platform, highlighting the differential impact of transformers and diffusers on research agendas and commercial strategies. Nevertheless, the findings should be interpreted cautiously, acknowledging several limitations. The study's exclusive reliance on HF data means it may not fully capture developments within proprietary systems or other open-source communities. Furthermore, inherent platform factors, such as algorithmic visibility bias and potential metadata inconsistencies, could influence engagement metrics, requiring care when equating metrics like downloads directly with real-world utility or impact. Future research incorporating cross-platform analyses, longitudinal studies, and external performance validation is essential for a more comprehensive understanding of the AI landscape.

As generative models become increasingly embedded within organisational and societal functions, the imperative for responsible development and deployment intensifies. Addressing critical concerns related to bias, privacy, fairness, and labour market impacts requires robust ethical frameworks and proactive governance, alongside compliance with evolving regulatory requirements. Successfully navigating these complex challenges necessitates sustained interdisciplinary collaboration, bridging technical, managerial, ethical, and legal expertise. Ultimately, as Sedkaoui and Benaichouba (2024) suggest, realising the transformative potential of AI hinges not solely on technological advancement, but on collective, concerted efforts by all stakeholders - researchers, developers, policymakers, and the public - to foster inclusive, sustainable, and genuinely beneficial innovation for both industry and society at large.

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Building business models of high-growth enterprises based on AI systems

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ABSTRACT

To date, the use of artificial intelligence (AI) to shape the business models of high-growth enterprises (HGEs) remains an unexplored research topic. The article aims to examine the use of artificial intelligence to build business models for high-growth enterprises, considering the heterogeneity of these entities. The empirical research aimed to answer the following questions: (1) Does the use of artificial intelligence to build individual components of the business model depend on the size of the HGE? 2. Does the use of artificial intelligence to build individual components of the business model depend on the age of the HGE?

The study was conducted in the second half of 2024 on a sample of 200 Polish high-growth enterprises that declared using AI in their business activities. Data were collected through a survey questionnaire. The survey questions were derived from the assumptions of building a business model based on three value components: value proposition, value creation and delivery, and value capture. The chi-square test, the Kruskal-Wallis test, and measures of dependence for immeasurable features were used to address the research questions.

It has been shown that statistically significant relationships exist only between individual value components and the size of the enterprise when these components are perceived as the average of the values of the variables that comprise them. It has also been shown that the values of these components are differentiated by enterprise size.

The novelty of the article is the research on the use of AI to build business models for high-growth enterprises, accounting for their heterogeneity.

The article is addressed to scientific researchers and business practitioners, particularly those dealing with issues related to building business models and using AI to create value.

KEY WORDS

business model, value, artificial intelligence, high-growth enterprises

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Introduction

Artificial intelligence (AI) is increasingly influencing various aspects of economic life. Its growing importance in business activity is observed. According to Eurostat data, in 2024, 13.5 % of enterprises in the European Union used artificial intelligence, an increase of 5.5 percentage points from the previous year (Eurostat, 2025). Growing interest in this topic is also indicated in scientific publications that describe various aspects of AI in enterprise operations. In the Scopus database, the number of articles, book chapters and conference materials in the area of Business, Manage-

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ment, and Accounting increased from almost 1.5 thousand publications in 2020 to over 6 thousand in 2024.

The literature (Lee et al., 2019; Åström et al., 2022) indicates that the fundamental cause of the AI phenomenon in business activities is the ability to imitate cognitive processes, draw conclusions from large data sets, and predict unexpected events. This ability enables the automation of identifying and solving complex problems, thereby improving the operational efficiency of enterprises. The reasons for using AI systems in the economic sphere can also be taken from the generalised definition of this issue by Kaplan and Haenlein (2019), which indicates the AI's ability to correctly interpret external data, learn from it, and use this knowledge through flexible adaptation to achieve specific goals and tasks. In this context, Kristoffersen et al. (2020) and Sjödin et al. (2023) pointed out the potential benefits of using AI in industrial solutions, which include improved resource efficiency, increased productivity potential, enhanced diagnostics, and automated resource management.

AI can be used in many ways in business processes. Therefore, from a cognitive and utilitarian viewpoint, it may be interesting to analyse the use of AI in high-growth enterprises (HGEs). The literature (Otola et al., 2020) emphasised that HGEs respond quickly to market changes and adapt to requirements. Moreover, these entities are characterised by an above-average impact on the economy (Coad et al., 2022). Empirical studies conducted in this area (Nightingale & Coad, 2014; Pereira & Temouri, 2018) have shown that a small number of HGEs creates a disproportionately large number of jobs. According to the interpretation adopted by the Organisation for Economic Co-operation and Development (OECD, 2010), HGEs are characterised by an increase in sales revenues or an increase in employment on average by over 20 % annually over a period of at least three years. These premises encourage the analysis of the AI use by HGEs.

The above considerations suggested the article's purpose: to examine the AI use for building HGE business models, accounting for their heterogeneity. This article presents a literature review, discusses the theoretical foundations of the research, and identifies a research gap in the use of AI to build business model components, considering their diversity in entity size and market experience. The section on research methods describes the research sample, the survey questionnaire, and the statistical analysis tools employed. The research results present the outcomes of the chi-square test and the Kruskal-Wallis test for the variables comprising the value proposition, value creation and delivery, and value capture components, considering grouping variables such as company size and age. The discussion compares the obtained results with previous research studies on building business models based on artificial intelligence. The article's conclusions justify the answers to the research questions.

1. Literature review

HGE-related issues interest entrepreneurship researchers and business journalists. For example, current scientific publications in this area have focused on aspects such as the impact of foreign investment on productivity (Sokhanvar, 2025), the role of business clusters and intellectual capital in achieving the HGE status (Temouri, 2025), the HGE adaptation to the conditions caused by the COVID-19 pandemic (Otola et. al., 2023), the role of intellectual capital in the growth of benefit corporations (Del Baldo, 2023), or the assessment of the competitiveness of high-growth enterprises (Zhang, 2023).

The diversity of research on HGEs stems from their important role in both macroeconomic and microeconomic contexts. However, the literature has not extensively explored the impact of AI on HGEs. Teruel et al. (2024) examined the relationship between digitalisation and firm growth. They also analysed the digital technology investment activities of HGEs compared to non-HGEs. The authors found that firms investing in digitalisation are more likely to show rapid growth in employment, sales, and labour productivity. However, there is a need for interconnection between less and more advanced technologies, and different types of digital technologies are not uniformly associated with firm growth. They also noted that in the so-called "superstar firms", traditional business models have been displaced by the use of new digital technologies.

It should be emphasised that the topic of using AI to shape the HGE business model, specifically the creation of individual value categories within this model, is a research issue that has not yet been explored. Moreover, in in-depth scientific explorations, it is reasonable to consider HGE heterogeneity, as these entities are not uniform in size, occur in different industries, or have different ages. It is therefore reasonable to conduct research on the use of artificial intelligence in high-growth enterprises, given their diversity in terms of entity size or market experience.

In scientific discourse on the essence of the business model, researchers have repeatedly referred to the value concept. According to the classical approaches defining the concept of a business model, it can be indicated that: it is the basic logic that organisations follow when creating value (Linder, Cantrell, 2000), it reflects the management of transactions aimed at creating value by using business opportunities (Amitt, Zott, 2001), it describes the creation and acquisition of value (Chesbrough, 2007), and it is a way for an organisation to create, deliver and capture value (Osterwalder, Pigneur, 2010). It should be noted that the approaches to the business model issue are similar, but the value category itself is not homogeneous.

According to Richardson (2008), a widely accepted view in the literature, the basic components of a value-focused business model are value proposition (VP), value creation and delivery (VCD), and value capture (VC). The value proposition (VP) concerns products and services offered to customers. It comprises identifying products and services that generate value for specific customer groups, indicating the target group, or defining methods of acquiring customers. Creating and delivering value (VCD) refers to all activities related to production, providing services, sales, or transferring the offer to customers. For this purpose, an appropriate combination of tangible and intangible resources is necessary to generate value and then transfer it using customer communication and distribution channels. Value capture (VC) is a feedback loop related to the value transfer to customers by the company. In this case, value returns to the company in the form of sales revenues, or it is generated through an appropriate cost structure. Value capture (VC) occurs when the customer accepts the value proposition (VP).

The use of AI systems creates the prospect of shaping enterprise business models and thus influencing the proposition, creation and delivery, and value capture. As AI technology develops, it is becoming increasingly important to understand how AI tools can be used to create and capture value (Berg, 2023). In this context, Sjödin et al. (2021) indicated that the use of AI can enable the creation of value closer to the customer needs by enabling more precise identification of business processes that require improvement. In addition, the use of AI capabilities aims to improve production processes or monitor the flow of products during their delivery to the recipient. Such efforts should positively impact revenue sources from areas served by AI. However, an important issue in this respect is the potentially high costs of maintaining the necessary infrastructure.

Åström et al. (2022) noted that AI-enabled value creation can be divided into two main categories. The first category is activities aimed at increasing efficiency and reducing costs by improving and enhancing existing operations. For example, AI can reduce the repetition of work tasks, resulting in cost savings. The second category is the development of solutions that generate increased revenues by supplementing decision-making processes and making more accurate decisions under conditions of uncertainty. Companies usually emphasise the use of AI to provide conveniences for customers, or to explore and analyse data to predict work efficiency and the profitability of transactions and sales (Mishra, Tripathi, 2021).

It is also indicated that companies trying to implement AI do not generate the expected value due to the incompatibility of AI systems with existing systems (Tse et al., 2020). Sjödin et al. (2021) emphasised that many companies struggle to successfully implement AI systems into their business models. To fully utilise the possibilities of artificial intelligence, new procedures, skills, or operational processes are necessary to ensure AI implementation, its integration with activities in the field of value creation, delivery, and capture.

Haftor et al. (2024) observed two competing entities and noted that only one recognised the effect of creating and capturing value through AI use. The way of using AI plays a fundamental role in this case, particularly the elements of the business model that are activated thanks to AI and to what extent. However, the multifaceted results of research on the way of using AI to create and capture value should be emphasised. For example, Enholm et al. (2022) distinguished internal and external functions of AI. Internal functions include improving internal business processes. In this case, the customer does not have direct contact with the applied AI solution. External functions include the use of AI in products and services, which is associated with the use of AI to contact customers. On the other hand, Shollo et al. (2022) identified mechanisms (ways) of creating value based on machine learning (ML): providing organisational knowledge, supporting decision-making, and using process automation. The considerations indicate the diverse impact of AI on individual value categories. The multi-aspect nature of this issue encourages the deepening of knowledge about the use of AI in building business models.

Empirical research on the use of AI to build HGE business models has focused on answering the following research questions: RQ1. Does the use of artificial intelligence to build individual components of the business model depend on the size of the HGE? RQ2. Does the use of artificial intelligence to build individual components of the business model depend on the age of the HGE?

2. Research methods

The empirical verification used primary data obtained through a survey questionnaire that contained statements related to individual components of the HGE business model. The selected research sample was purposive. It was selected based on the criterion consistent with the OECD (2010) assumptions that HGEs are characterised by an increase in sales revenues or employment by at least 20 % per year on average over three years. The study was conducted in the second half of 2024 on a sample of 200 Polish HGEs that declared the use of AI in their business activities.

The survey questions were formulated using assumptions of building a business model based on three value components: value proposition (VP), value creation and delivery (VCD), and value capture (VC). Each component was assigned statements that characterise it, accounting for AI aspects. The answers were placed on a five-point Likert scale, where 1 means "strongly disagree" and 5 means "strongly agree".

The value proposition highlights: "We acquire customers thanks to the efficiency and functionality of technology that imitates human intelligence" (VP1), "We acquire customers because we use useful technology that imitates human intelligence" (VP2), "We acquire customers because we use reliable and predictable technology that imitates human intelligence" (VP3), and "Our customers prefer contacts based on technology that imitates human intelligence" (VP4).

For value creation and delivery the following were identified: "We create an offer for customers based on the functionality and efficiency of technology that imitates human intelligence" (VCD1), "We create an offer for customers based on the usefulness and usability of technology that imitates human intelligence" (VCD2), "We create an offer for customers based on the reliability and predictability of technology that imitates human intelligence" (VCD3), and "We prefer contacts between employees based on technology that imitates human intelligence" (VCD4).

Value capture was characterised based on the following statements: "Generation of revenues for a sold offer is based on the functionality and efficiency of technology imitating human intelligence" (VC1), "Generation of revenues for a sold offer is based on the usefulness and usability of technology imitating human intelligence" (VC2), "Generation of revenues for a sold offer is based on the reliability and predictability of technology imitating human intelligence" (VC3), and "Contacts with customers based on technology imitating human intelligence are more beneficial for us in generating revenues for a sold offer" (VC4).

Enterprises were further divided by:

1. Size: small, medium, large,
2. Age in years: 1-20, 21-40, 41-60.

To answer the research questions, the chi-square test, Kruskal-Wallis test and measures of dependence for unmeasured characteristics were used, whereby:

- The existence of statistically significant relationships between the size of HGE and the individual variables forming the constructs of value proposition, value creation and delivery and value capture was examined.
- The existence of statistically significant relationships between the age of the HGE and the individual variables forming the constructs - value proposition, value creation and delivery and value capture - was examined.
- The existence of statistically significant relationships between the size of the HGE and the constructs of value proposition, value creation and delivery and value capture, expressed in terms of the average value of the variables forming the construct, was examined.
- The existence of statistically significant relationships between the age of the HGE and the constructs of value proposition, value creation and delivery and value capture, expressed in terms of the average value of the variables forming the given construct, was examined.

To analyse the relationship between the size (age) of the HGE and the constructs of value proposition (VP), value creation and delivery (VCD) and value capture (VC), the values of the indicated constructs for the studied companies were put into two categories: below average and above average of the given construct for all companies.

3. Research results

To assess the reliability and validity of the applied measurement scales, an analysis of internal consistency and construct reliability was conducted. Cronbach's α was used to evaluate the consistency of items within each scale, indicating the extent to which the items measure the same latent construct. Additionally, Composite Reliability (CR) was calculated to assess the reliability of the overall latent construct, and Average Variance Extracted (AVE) served as a measure of convergent validity, indicating the proportion of item variance explained by the latent factor. To evaluate discriminant validity, the Fornell-Larcker criterion was applied by comparing the square root of AVE for each construct with its correlations with other constructs. This approach ensures that each construct is both reliable and distinct from the other variables under study. The results are presented in Table 1.

The analysis of reliability and validity for the three examined constructs - value proposition, value creation and delivery, and value capture - demonstrated high quality of the applied measurement scales. For the value proposition construct, the values of all indicators point to high internal consistency, solid reliability of the latent factor, and good convergent validity, indicating the construct's ability to explain most of the variance in its items. The value creation and delivery construct achieved similarly high results, confirming its stability, consistency, and convergent validity. In the case of the value capture construct, the high values of the estimated indicators indicate good internal consistency, high latent reliability, and an adequate ability of the construct to explain the variance of its items. All three constructs meet the standards for reliability and convergent validity, confirming that the applied scales are reliable and appropriately measure their latent constructs.

The analysis according to the Fornell-Larcker criterion showed that all three constructs - value proposition, value creation and delivery, and value capture - exhibit discriminant validity. This means that each construct represents a distinct aspect of the examined business concept and is clearly distinguishable from the other latent constructs. In practice, the

Tab. 1. Reliability and convergent validity assessment

Constructs Items	Cronbach's alpha	CR	AVE
Value proposition	0.840	0.893	0.677
Value creation and delivery	0.846	0.896	0.684
Value capture	0.817	0.880	0.647

Tab. 2. Chi-square test results (observed level of significance of the test)

Variable	Size of HGE	Age of HGE
VP1	p=0.17554	p=0.780562
VP2	p=0.253959	p=0.561761
VP3	p=0.58872	p=0.138981
VP4	p=0.015732*	p=0.15109
VCD1	p=0.072578	p=0.331531
VCD2	p=0.100039	p=0.60588
VCD3	p=0.184718	p=0.853636
VCD4	p=0.211808	p=0.927195
VC1	p=0.203894	p=0.651938
VC2	p=0.029978*	p=0.2116
VC3	p=0.05858	p=0.853356
VC4	p=0.072319	p=0.079712
VP	p=0.004077*	p=0.458885
VCD	p=0.007241*	p=0.435966
VC	p=0.008252*	p=0.032066*

*Stochastically dependent variables at the p<0.05 level

Tab. 3. Results of the Kruskal-Wallis test for the variables forming the component value proposition with company size as the grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VP1	Small enterprise	36	111.2917	4.515823	0.1046
	Medium enterprise	67	107.0821		
	Large enterprise	97	91.9485		
VP2	Small enterprise	36	117.4583	5.040549	0.0804
	Medium enterprise	67	102.3209		
	Large enterprise	97	92.9485		
VP3	Small enterprise	36	108.9583	1.951125	0.3770
	Medium enterprise	67	103.8358		
	Large enterprise	97	95.0567		
VP4	Small enterprise	36	115.7361	8.062811	0.0178*
	Medium enterprise	67	108.7090		
	Large enterprise	97	89.1753		

*Stochastically dependent variables at the p<0.05 level

Tab. 4. Results of the Kruskal-Wallis test for the variables constituting the component value creation and delivery, with the size of the enterprise as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VCD1	Small enterprise	36	100.9722	7.016216	0.0300*
	Medium enterprise	67	114.3881		
	Large enterprise	97	90.7320		
VCD2	Small enterprise	36	108.9861	7.185737	0.0275*
	Medium enterprise	67	111.8284		
	Large enterprise	97	89.5258		
VCD3	Small enterprise	36	110.4722	4.017922	0.1341
	Medium enterprise	67	106.8731		
	Large enterprise	97	92.3969		
VCD4	Small enterprise	36	116.2778	5.054541	0.0799
	Medium enterprise	67	103.7388		
	Large enterprise	97	92.4072		

*Stochastically dependent variables at the p<0.05 level

square root of AVE for each construct was higher than its correlations with the other constructs, confirming that the items assigned to a given construct truly measure a unique dimension of the phenomenon, rather than shared variance with other factors. These results indicate that the applied scales are both reliable and valid with respect to construct distinctiveness, providing a solid basis for further analysis of the relationships among variables in the theoretical model. Table 2 shows the results of the chi-square test.

A chi-square test of independence indicated that statistically significant relationships were observed only for specific variables and constructs in relation to company characteristics. Specifically, significant associations were found between the variable "Our customers prefer contacts based on technology that mimics human intelligence" and company size, and between the variable "Revenue generation for the offer sold is based on the usefulness and usability of technology mimicking human intelligence" and company size. In addition, the constructs "value proposition", "value creation and delivery", and "value capture" each demonstrated significant relationships with enterprise size, while "value capture" also showed a significant association with enterprise age.

These findings suggest that company size and age play a role in shaping perceptions and implementations related to technology-based offerings and their associated business model constructs.

Thus, it is possible to point to a statistically significant relationship between the size of the enterprise and the use of artificial intelligence to build individual components of the business model. Unfortunately, no statistically significant relationship is observed between the size of the enterprise and the individual variables forming the constructs that constitute the value components of business models. In the case of the age of the enterprise, it can be argued that it does not affect the use of artificial intelligence to build individual components of the business model. A statistically significant relationship exists only between the enterprise's age and value capture.

The results of the chi-square test were confirmed by the Kruskal-Wallis test, which was used to compare companies by identified value components in groups of companies categorised by size (Tables 3-6) and age (Tables 7-10).

Unfortunately, the Kruskal-Wallis test indicates that the size of the enterprise does not differentiate the results regarding the acquisition of customers by enterprises thanks to the efficiency and functionality of technology imitating human intelligence, the acquisition of customers thanks to the use of useful technology imitating human intelligence, the acquisition of customers thanks to the use of reliable and predictable technology imitating human intelligence. However, the size of the enterprise differentiates the preference of customers for contacts based on technology imitating human intelligence.

Tab. 5. Results of the Kruskal-Wallis test for variables constituting the component value capture with the size of the enterprise as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VC1	Small enterprise	36	110.3333	4.485199	0.1062
	Medium enterprise	67	107.7015		
	Large enterprise	97	91.8763		
VC2	Small enterprise	36	113.1111	12.60808	0.0018*
	Medium enterprise	67	114.6791		
	Large enterprise	97	86.0258		
VC3	Small enterprise	36	111.3056	3.347756	0.1875
	Medium enterprise	67	105.0746		
	Large enterprise	97	93.3299		
VC4	Small enterprise	36	118.1250	8.963406	0.0113*
	Medium enterprise	67	107.8881		
	Large enterprise	97	88.8557		

*Stochastically dependent variables at the p<0.05 level

Tab. 6. Results of the Kruskal-Wallis test for individual value components with company size as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VP	Small enterprise	36	113.1111	9.806638	0.0074*
	Medium enterprise	67	110.2090		
	Large enterprise	97	89.1134		
VCD	Small enterprise	36	111.8889	9.546606	0.0085*
	Medium enterprise	67	110.6866		
	Large enterprise	97	89.2371		
VC	Small enterprise	36	118.6667	10.94952	0.0042*
	Medium enterprise	67	107.2239		
	Large enterprise	97	89.1134		

*Stochastically dependent variables at the p<0.05 level

Customers prefer contacts based on technology that imitates human intelligence.

The Kruskal-Wallis test did not show that the size of the enterprise differentiates the results regarding the creation of an offer for customers based on the reliability and predictability of technology imitating human intelligence, and the preference for contacts between employees based on technology imitating human intelligence. Differentiation depending on the size of enterprises is observed in the case of the creation of an offer for customers based on the functionality and efficiency of technology imitating human intelligence, and the creation of an offer for customers based on the usefulness and usability of technology imitating human intelligence.

In the case of variables constituting component value capture, the Kruskal-Wallis test indicated that generating revenues for a sold offer based on the usefulness and usability of technology imitating human intelligence and customer contacts based on technology imitating human intelligence being more beneficial in generating revenues for a sold offer are differentiated by enterprise size in at least two groups of enterprises. The remaining variables concerning generating revenues for a sold offer based on the functionality and efficiency of technology imitating human intelligence and generating revenues for a sold offer based on the reliability and predictability of technology imitating human intelligence are not differentiated by enterprise size.

Tab. 7. Results of the Kruskal-Wallis test for variables constituting the component value proposition with the company age as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VP1	1-20	112	99.6071	0. 293379	0.8636
	21-40	70	103.0857		
	41-60	18	96.0000		
VP2	1-20	112	96.5223	1.29468	0.5234
	21-40	70	106.1286		
	41-60	18	103.3611		
VP3	1-20	112	96.9018	2.175683	0.3369
	21-40	70	108.3286		
	41-60	18	92.4444		
VP4	1-20	112	97.5714	0. 7730795	0.6794
	21-40	70	105.0714		
	41-60	18	100.9444		

*Stochastically dependent variables at the p<0.05 level

Tab. 8. Results of the Kruskal-Wallis test for variables constituting the component value creation and delivery, with the company age as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VCD1	1-20	112	98.7098	1.441546	0.4864
	21-40	70	99.4714		
	41-60	18	115.6389		
VCD2	1-20	112	99.5670	0.06977	0.9657
	21-40	70	101.6500		
	41-60	18	101.8333		
VCD3	1-20	112	98.7143	0.6556149	0.7205
	21-40	70	100.8571		
	41-60	18	110.2222		
VCD4	1-20	112	101.6875	1.645898	0.4391
	21-40	70	95.2214		
	41-60	18	113.6389		

*Stochastically dependent variables at the p<0.05 level

By viewing the individual value components in business models as one average value of the variables constituting a given component, the Kruskal-Wallis test showed that for all components - value proposition (VP), value creation and delivery (VCD), and value capture (VC) - differences can be observed at least between two groups of companies.

Unfortunately, the Kruskal-Wallis test indicates that the age of the enterprise does not differentiate the results regarding the acquisition of customers by enterprises thanks to the efficiency and functionality of technology imitating human intelligence, the acquisition of customers thanks to the use of useful technology imitating human intelligence, the acquisition of customers thanks to the use of reliable and predictable technology imitating human intelligence, the preference of customers for contacts based on technology imitating human intelligence.

The Kruskal-Wallis test also did not show that the age of the enterprise differentiates the results regarding the creation of an offer for customers by enterprises based on the functionality and efficiency of technology imitating human intelligence, the creation of an offer for customers based on the usefulness and usability of technology imitating human intelligence, the creation of an offer for customers based on the reliability and predictability of technology imitating human intelligence, and the preference for contacts between employees based on technology imitating human intelligence.

For the variables that make up the component value capture, the Kruskal-Wallis test indicated that only customer contacts based on technology imitating human intelligence, which are more beneficial in generating revenues for the offer sold, are differentiated by the age of the enterprise in at least two groups of enterprises. The remaining variables concerning generating revenues for the offer sold based on the functionality and efficiency of technology imitating human intelligence, generating revenues for the offer sold based on the usefulness and usability of technology imitating human intelligence, and generating revenues for the offer sold based on the reliability and predictability of technology imitating human intelligence are not differentiated by the age of the enterprise.

Considering the individual value components in business models as one average value of variables that make up a given component, the Kruskal-Wallis test showed that only for the value capture (VC) component, differences can be observed at least between two groups of companies categorised by age. For the remaining components: value proposition (VP) and value creation and delivery (VCD), no differences are observed due to the age of the companies.

The study was supplemented with an analysis of dependencies based on measures estimated for qualitative variables (Table 11).

All estimated measures of the strength of relationships between the distinguished variables have values below 0.350, which indicates that no strong relationships are observed between the variables. Values equal to or above 0.3 were adopted by the measures for the relationship between:

Tab. 9. Results of the Kruskal-Wallis test for variables forming component value capture with company age as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VC1	1-20	112	102.3750	3.115941	0.2106
	21-40	70	93.0000		
	41-60	18	118.0000		
VC2	1-20	112	100.8125	3.245249	0.1974
	21-40	70	94.6571		
	41-60	18	121.2778		
VC3	1-20	112	103.6116	0.929957	0.6281
	21-40	70	97.7214		
	41-60	18	91.9444		
VC4	1-20	112	102.1563	6.016319	0.0494*
	21-40	70	91.1214		
	41-60	18	126.6667		

*Stochastically dependent variables at the p<0.05 level

Tab. 10. Results of the Kruskal-Wallis test for individual value components with company age as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VP	1-20	112	96.6429	1.550121	0.4607
	21-40	70	104.8571		
	41-60	18	107.5556		
VCD	1-20	112	101.1071	1.652081	0.4378
	21-40	70	96.2857		
	41-60	18	113.1111		
VC	1-20	112	104.2500	6.845499	0.0326*
	21-40	70	89.4286		
	41-60	18	120.2222		

*Stochastically dependent variables at the p<0.05 level

Tab. 11. Measures of the strength of the relationship between the size and age of the enterprise and other variables

Variable	Size of the company				Age of the company			
	T Czuprow	V Cramer	Φ Yule	Pearson C corrected	T Czuprow	V Cramer	Φ Yule	Pearson C corrected
VP1	0.085	0.090	0.240	0.272	0.055	0.058	0.155	0.179
VP2	0.080	0.084	0.225	0.257	0.065	0.069	0.184	0.212
VP3	0.064	0.068	0.181	0.208	0.088	0.093	0.248	0.281
VP4	0.109	0.115	0.307	0.343	0.087	0.092	0.245	0.278
VCD1	0.095	0.100	0.268	0.303	0.076	0.080	0.214	0.244
VCD2	0.091	0.097	0.258	0.293	0.063	0.067	0.178	0.205
VCD3	0.084	0.089	0.238	0.270	0.050	0.053	0.142	0.164
VCD4	0.082	0.087	0.233	0.265	0.044	0.047	0.125	0.145
VC1	0.083	0.088	0.234	0.266	0.094	0.099	0.265	0.300
VC2	0.103	0.109	0.292	0.327	0.061	0.065	0.173	0.199
VC3	0.097	0.103	0.274	0.309	0.082	0.087	0.233	0.265
VC4	0.095	0.100	0.268	0.303	0.050	0.053	0.142	0.165
VP	0.166	0.235	0.235	0.300	0.062	0.088	0.088	0.115
VCD	0.157	0.222	0.222	0.284	0.064	0.091	0.091	0.119
VC	0.155	0.219	0.219	0.281	0.131	0.185	0.185	0.239

1. Enterprise size and:

- customer preference for contacts based on technology, imitating human intelligence;
- creating an offer for customers based on the functionality and efficiency of technology imitating human intelligence;
- generating revenues for the sold offer based on the usefulness and usability of technology imitating human intelligence;
- generating revenues for the sold offer based on the reliability and predictability of technology imitating human intelligence;
- contacts with customers based on technology imitating human intelligence, which are more beneficial for the enterprise in generating revenues for the sold offer;
- value proposition component.

2. Enterprise age and generating revenues for the sold offer based on the functionality and efficiency of technology imitating human intelligence.

Measures equal to or above 0.3 were observed for specific relationships, including enterprise size and several variables related to customer preferences, offer creation, revenue generation based on the functionality, usability, reliability, and predictability of technology mimicking human intelligence, as well as the value proposition component. Additionally, enterprise age showed a measure above 0.3 for revenue generation based on the functionality and efficiency of the technology. Therefore, these relationships can be interpreted as moderate, suggesting that while some associations exist between enterprise characteristics and the examined variables, their strength is generally average rather than strong.

4. Discussion of the results

The empirical studies enabled the analysis of AI use in building business models, accounting for the heterogeneity of these entities. They align with current scientific issues in the field of AI's impact on enterprise achievements. AI and advanced technologies are increasingly recognised as drivers of enterprise productivity, enabling the transformation of almost all operations within and outside companies (Wahab, Radmehr, 2024). Da Silva Marioni et al. (2024) examined whether enterprise involvement in AI innovations translates into higher productivity than similar enterprises that do not undertake AI innovations. The results of these studies confirmed that AI can play a key role in increasing enterprise productivity, even in the early stages of the technology life cycle. Ali et al. (2024) emphasised the importance of AI in creating strategic capabilities and technical innovations that provide enterprises with a competitive advantage. In their study, Ante and Saggu (2025) focused on stocks and indices that provide investors with the opportunity to engage in and profit from AI technology. They found that companies with higher AI engagement showed more significant positive abnormal returns in the stock market. This study points to different opportunities for implementing, scaling, and monetising AI solutions, depending on the resources at their disposal, strategic goals, and the way they compete, which vary by company size.

Based on the results, a statistical relationship exists between the construction of a value proposition in an AI-based business model and company size. It was demonstrated that company size differentiates results regarding customer preference for contact based on technology that mimics human intelligence in at least two groups of companies. However, in the construction of a proposition based on artificial intelligence, no statistically significant relationship with the company's age was demonstrated.

Analogous conclusions can be drawn regarding AI-based value creation and delivery. A statistically significant relationship was also observed between this component of the business model and company size. It was identified that the offer created for customers is supported by technology imitating artificial intelligence due to its features, such as functionality, efficiency, usefulness, and usability, in at least two groups of companies distinguished by their size. In this case, the studied value-creation and delivery aspect did not demonstrate a statistically significant relationship with the company's age.

When considering the value returned to the enterprise supported by AI, there is a statistically significant relationship between this component of the business model and enterprise size. It has been observed that in at least two groups of enterprises, distinguished by size, the generation of revenue from the sold offer is based on the usefulness and usability of technology imitating human intelligence, and is also more beneficial due to contacts with customers based on AI technology. Referring to the age of the enterprise, value capture using AI is statistically significant in at least two distinguished groups in the aspect of using technology imitating artificial intelligence for customer contact.

Research findings indicate the importance of enterprise size in implementing modern technological solutions. Well-established approaches confirming these conclusions can be found in scientific publications. Prisco et al. (2022) found that small- and medium-sized enterprises are more effective at using blockchain technology than large companies. Ifinedo (2011) looked for reasons why small and medium-sized enterprises on the Canadian market are reluctant to accept Internet and e-business technologies in their operations. Bordonaba-Juste et al. (2012) found that medium and large companies use e-business more intensively, and small enterprises use IT outsourcing as a key factor in using e-business. On the other hand, Na et al. (2023) noted that various studies have shown that the size of the enterprise plays a key role in the development and acceptance of new technology. At the same time, these authors emphasised the two-faceted nature of this issue. On the one hand, large entities have greater financial capabilities and greater resources to implement modern technological solutions, but on the other hand, small and medium-sized enterprises have greater flexibility and adaptability. Considering the factors that determine AI investments, studies have shown that larger companies and those with greater cash reserves are more likely to invest in AI (Babina et al., 2024). In addition, large latecomer companies achieve the greatest benefits in terms of productivity and innovation from implementing AI methods (Kopka, Fornahl, 2024). The results of Yang et al.'s (2024) research show that larger companies with greater resources can implement AI more effectively, while smaller companies encounter greater difficulties in this process. Similar conclusions were drawn by Kinkel et al. (2022), who indicated that larger companies have greater opportunities to implement AI thanks to their organisational resources. In addition, larger companies with more structured processes can implement AI technologies more effectively (Rožman et al., 2024). This research may therefore constitute a premise for differentiating the use of AI to build individual components of the business model by the size of the company.

Conclusions

The article analyses the relationship between variables that create individual components of value for business models: value proposition, value creation and delivery, value capture, and enterprise size and age. The obtained results allow for an affirmative answer to the first research question: Does the use of artificial intelligence to build individual components of the business model depend on the size of HGE? The results of the chi-square and Kruskal-Wallis tests confirm statistically significant relationships between individual value components and the size of the enterprise when these components are perceived as the average of the values of the variables that create them. It has also been shown that the values of these components are differentiated by the size of the enterprise. However, the conducted analyses do not allow for an affirmative answer to the second research question: Does the use of artificial intelligence to build individual components of the business model depend on the age of HGE? The results of the chi-square test confirm the existence of a statistically significant relationship only between the age of the enterprise and the value capture component. Similarly, the results of the Kruskal-Wallis test do not confirm that individual variables and components are differentiated by the age of the enterprise, with the exception of variables concerning contacts with customers based on technology imitating human intelligence, which are more beneficial in generating revenues for the sold offer, and the value capture component. A limitation of the research is that it conducted analyses among high-growth enterprises without considering their business profiles. Allocation to specific industries would allow for the identification of similarities and differences in the use of artificial intelligence in building their business models. Future research could therefore include a sector classification of HGEs.

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Empirical insights into supply chain management integration with product lifecycle management: benefits and challenges

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ABSTRACT
Integration of product lifecycle management systems with supply chain management processes has proven challenging for companies that attempt it, with limited empirical research available on this topic. Consequently, this study aimed to explore whether implementing product lifecycle management systems can enhance supply chain management within an organisation. To obtain relevant data, this study employed a single qualitative case study design, using in-depth semi-structured interviews and on-site observations conducted at ABC TECH to examine how Sovelia PLM supports supply chain processes. The data was collected from a company in Northern Europe that uses Sovelia lifecycle management software. Findings showed that this software generally aids in enhancing supply chain process integration, traceability, and structure. However, it is design-centric, which makes it more difficult to adequately address the supply chain management department's operational requirements. These insights may enhance the decision-making processes and guide actionable strategies for seamless integration. The findings call for a more holistic product lifecycle management system that encapsulates both design and supply chain functionalities, thereby ensuring cohesive operations and improved communication within the company's supply chain network.

KEY WORDS
supply chain management (SCM), product lifecycle management (PLM), performance, management, PLM and SCM integration, benefits and challenges

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Introduction

Agile and flexible procedures are essential as the industrial sector moves towards Industry 4.0, which is characterised by more complex systems (Shakouhi et al., 2023). Industries must implement systems that not only keep pace with technological advancements but also encourage cooperation and coordination across different production phases. Information was formerly often disseminated via email or presentations, but in today's fast-paced world, these methods are insufficient (Stark, 2022). Companies that stick to antiquated procedures risk falling behind their rivals and becoming obsolete.

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In large enterprises, efficient information sharing is essential as goods get increasingly complicated over time. Product lifecycle management (PLM) is essential in this situation (Conlon, 2024). PLM manages data and procedures at every stage of a product's lifetime, including design, engineering, manufacturing, sales, and service, from the time of its conception until the end of its useful life. Supply chain management (SCM), on the other hand, covers the movement of goods and information from raw materials to the final customer and guarantees the coordination and control of all operations involved in the manufacture and delivery of services or products (PTC, 2024). Industries must adopt more efficient methods and processes to manufacture goods that satisfy consumer wants. By coordinating processes with strategic planning and promoting internal cooperation, the combination of PLM and SCM provides an answer (Triguero et al., 2023). Throughout the product lifecycle, this integration facilitates a smooth flow of data and procedures that improve productivity, lower costs, improve product quality, and shorten time-to-market (Vidergar et al., 2021). As a result, merging PLM and SCM can stimulate technological advancement by guaranteeing that all industry players are linked and coordinated on a single platform (Deteix et al., 2024).

The significance of this study can be seen from different points. Although PLM research has made great strides, it is generally agreed that more studies are needed to fully comprehend its place in Industry 4.0 (Meeshi et al., 2021). Because relatively few manufacturers provide such solutions, there is a gap in the analysis of the advantages of integrating maintenance data into PLM systems. The advantages of centralising data management are still mostly unknown, even though numerous studies have suggested frameworks for integrating PLM with other systems like CRM, ERP, and SCM at various phases of the product lifecycle. Interoperability is hampered by the lack of standards, and PLM solutions demand a significant time and financial commitment, which makes integration difficult, particularly when dealing with original equipment manufacturers (Conlon, 2024). Guidelines are essential to improve PLM and ERP system interoperability since they would lower the cost of maintaining various systems and encourage supplier and customer collaboration without the need for superfluous processes.

Moreover, an increasing number of studies support web-based methods that let original equipment manufacturers communicate product details in standard forms with suppliers (Meeshi et al., 2021). Research, however, is scarce on data transfer beyond computer-aided design, including product documentation and other related data (Deteix et al., 2024). Computer technology has improved SCM integration; yet empirical assessments of the effects of IT-enabled manufacturing processes on SCM performance are still scarce, especially when considering manufacturers' perspectives (Mulla et al., 2021). The literature also emphasises how important it is to cluster different supplier connections and create IT structures for data transmission while developing new products because these activities demand a lot of resources (Pang et al., 2021). Accordingly, this study aims to address this research gap and identify potential benefits and challenges of the integration between PLM and SCM, in a real case firm. The study answers the following research questions:

RQ1: In what ways can PLM systems improve the SCM process?

RQ2: What challenges might arise when implementing PLM systems within SCM?

This work makes several contributions to the subject of PLM and SCM integration. The study provides a detailed analysis of Sovelia PLM software's strengths, such as its ability to integrate with other systems, manage product data, and support engineering and business processes. Simultaneously, it highlights significant weaknesses, including the software's inflexibility, user interface challenges, and difficulties in handling mistakes and collaborating across departments. Moreover, this study offers tailored insights into how different departments within ABC TECH (i.e., Technology, Engineering, SCM, Business Systems, and After-sales) interact with and perceive the Sovelia PLM software. These insights help identify specific areas where the software meets departmental needs and where it falls short, providing a comprehensive view of its impact across the organisation. Furthermore, the study suggests specific improvements for Sovelia PLM software, such as enhancing user-friendliness, improving collaboration features, and increasing flexibility in handling errors and changes. These recommendations are informed by direct feedback from various departments and can guide future updates or customisations of the software to better align with ABC TECH's evolving needs. Finally, by examining the practical implementation and challenges of Sovelia PLM software in a real-world setting, the study adds valuable case-specific insights to the broader literature on PLM. It underscores the importance of aligning PLM software with organisational structures and processes, offering lessons that can be applied in similar industrial contexts.

The outline of the paper's structure is as follows: Background data and relevant literature on SCM and

PLM are presented in Section 1. The method of investigation used in this study is described in Section 2. The benefits and challenges of Sovelia PLM software are covered in Section 3, along with a meta-analysis of the department's use of the software. Section 4 explores the limitations of the study, practical implications and future avenues for research.

1. Literature review

1.1. Supply Chain Management

To generate net value, establish a competitive infrastructure, and align supply and demand, SCM is an essential discipline that includes the planning, delivery, supervision, and tracking of SC activities (Burke et al., 2023). Its inception can be linked to the development of operations management and logistics in the 20th century, when the main emphasis was on streamlining certain SC elements, including manufacturing, distribution, and procurement (Alzoubi, 2024; Hayrutdinov et al., 2020). However, the need for an integrated approach to managing these activities evolved as global trade increased and SCs grew more intricate and linked. By combining several operations from the procurement of raw materials to the delivery of the finished product to the customer, SCM developed to meet this need (Koc & Gurgun, 2021).

The smooth integration of these many elements and the capacity to react quickly to demand fluctuations, supply interruptions, and other unforeseen difficulties are prerequisites for effective SCM (Fernando et al., 2024). Strong channels of communication, cutting-edge data analytics, and cooperative partnerships with suppliers and partners are necessary for this (Burke et al., 2023). The need to strike a balance between speed and dependability, standardisation with innovation, and flexibility with cost-efficiency further complicates the relationships within the SC. Accordingly, SCM is now a strategic role in businesses and is necessary to stay competitive in a market that is becoming increasingly international and fast-paced (Chhetri et al., 2022).

An SC may be complicated if it includes the exchange of information and materials between several parties (Hayrutdinov et al., 2020). The multiplicity of interactions among the components that make up SCM is what makes it so complex. To guarantee the efficient movement of goods, information, and funding, these entities, which include manufacturers, distributors, suppliers, warehouses, and retailers, must cooperate (Shao et al., 2021). Because every step of the SC is interconnected, problems in one place might have repercussions for the entire system (Eby, 2023). If there are delays in obtaining raw materials, manufacturing bottlenecks may occur, hence influencing delivery timelines and ultimately customer satisfaction (Fernando et al., 2024). Furthermore, the worldwide scope of contemporary SCs adds yet another level of complexity, including handling various legal frameworks, overseeing cross-border transportation, and negotiating exchange rate swings (Vidergar et al., 2021). A greater amount of data must be shared due to the evolving hybrid nature of systems, businesses, and organisations, and everyone must be connected to one another in some way. This ultimately results in the creation of a system that is more complicated, and in this case, a more complex SC (Chhetri et al., 2022). Businesses that prioritise technology development and need to create, store, analyse, and process large amounts of data in a standardised way must use approaches that can be managed throughout the product lifecycle (Hayrutdinov et al., 2020).

1.2. Product lifecycle management

PLM offers a thorough method for overseeing a product's whole lifecycle, from conception to retirement. PLM systems collect vital data from multiple sources, including client needs, product data management systems, and experience-based learning (Stark, 2022). This data helps to map out the product design, and all product-related data, from design to manufacturing, is connected and functions as a whole (Shearon, 2018). An efficient tool for managing complicated product data and procedures is a well-implemented PLM system, which can store a variety of product-related information and provide functions like revision history, search, and quick modifications (Lim et al., 2020). A PLM system's ability to smoothly exchange information is crucial for enabling necessary upgrades and modifications, which keep the product development process flexible and adaptable (Pinna et al., 2018). Fig. 1 illustrates the PLM process. The figure illustrates various stages a product undergoes from its inception to its end-of-life (Eby, 2023). It starts with the concept phase, followed by development, prototyping, launch, and manufacturing. Once the product is in the market phase, it goes through distribution, use, and service stages (Eby, 2023). Finally, at the end of its lifecycle, the product enters the end-of-life phase, where it can be recycled. PLM is positioned at the centre, emphasising its role in overseeing and managing the entire product

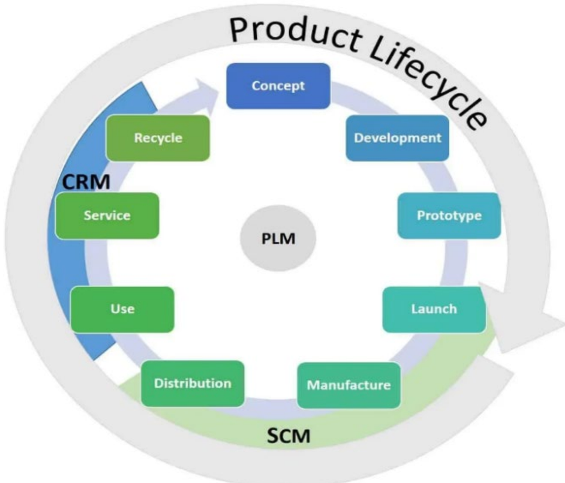

Fig. 1. PLM phases

Source: (Eby, 2023).

lifecycle (Eby, 2023). SCM in PLM covers all aspects of the launch and distribution, including manufacturing. CRM also encompasses everything that happens to a product once it is purchased, until its retirement or recycling (Eby, 2023).

Several prominent companies offer PLM systems: Dassault Systèmes offers PLM solutions through its 3DEXPERIENCE platform (Dassault, 2024); Oracle offers PLM software as part of its broader enterprise resource planning (ERP) suite (Oracle, 2024); PTC, which is well-known for its Creo CAD software and Windchill PLM platform (PTC, 2024); Siemens, which offers a comprehensive PLM suite, including Teamcenter (Siemens, 2024); and SAP, which offers PLM solutions integrated with its ERP system (SAP, 2024). Furthermore, there are open-source PLM systems, like open-source PLM, which are less popular than commercial solutions but still have choices for businesses with certain needs or limited resources (Technia, 2024). Moreover, several cloud-based PLMs that provide flexibility and scalability have emerged because of cloud computing's growing popularity (Technia, 2024).

For product development and delivery to be more efficient overall, PLM and SCM interaction is essential. Systems like Customer Relationship Management (CRM), ERP, and SCM are just a few of the enterprise systems that PLM systems are made to integrate with. Better departmental and system collaboration is encouraged by this integration, which guarantees smooth information flow throughout the company (Stark, 2022). Businesses can shorten lead times in the innovation process by integrating PLM and SCM, particularly in intricate new product development scenarios involving numerous departments (Eby, 2023). Because of the synergy between PLM and SCM, products can be conceived, manufactured, and delivered more effectively and with greater responsiveness to market changes.

Moreover, PLM systems offer the traceability and visibility required for efficient product lifecycle management when they are coupled with SCM (Corallo et al., 2020). For industries dealing with recalls, regulatory compliance, or material compliance issues, traceability is essential (Shearon, 2018). Additionally, by offering a thorough perspective of the product's lifespan, from design to delivery, the integration facilitates better decision-making (Pinna et al., 2018). By guaranteeing that every facet of the product's lifecycle is effectively handled, this holistic approach not only improves product quality and shortens time-to-market but also fosters innovation and supports sustainable business practices (Fernando et al., 2024).

1.3. Product lifecycle management applications in supply chain management

This section reviews the most relevant literature on PLM applications in SCM from the past five years. To ensure a focused and up-to-date overview of existing research, the literature included in this section was selected through a targeted search process. Academic databases, such as Scopus, Web of Science, IEEE Xplore, SpringerLink, and ScienceDirect, were consulted. The following keywords and Boolean combinations were applied: "Product Lifecycle Management" AND "Supply Chain Management", "PLM integration", "PLM SCM case study", "digital thread supply chain", "PLM Industry 4.0", and "lifecycle management supply chain". The search was limited to 2019–2024 to capture contemporary developments, as both PLM and SCM have evolved significantly in the context of digital transformation and Industry 4.0. Studies were included if they met at least one of the following criteria:

(1) examined PLM applications within supply chain contexts;

(2) proposed or evaluated PLM–SCM integration frameworks;

(3) investigated PLM implementation challenges affecting SCM processes; or

(4) provided empirical or conceptual models relevant to PLM-enabled supply chain visibility, traceability, sustainability, or collaboration.

Based on these criteria, the literature was organised into five thematic clusters representing recurring research streams: PLM in specific SCM industries,

Tab. 1. PLM applications in SCM

PLM focus	Study	Findings
PLM in specific SCM industries	Meeshi et al., 2021; Mulla et al., 2021	• PLM in the SCM aerospace industries. • PLM to data exchange, collaboration, and management across different domains.
	Burke et al., 2023	• PLM and SCM integration can support circular economy transitions.
	Triguero et al., 2023	• PLM is a key tool in implementing circular economy principles.
PLM system selection and evaluation	Enríquez et al., 2019	• Developing a quality model based on QuEF for selecting the most suitable PLM solution.
	Chhetri et al., 2022	• Alignment of SCM with product demand and design characteristics.
	Omerali & Kaya, 2022	• Proposing a multi-criteria decision-making method.
	Conlon, 2024	• Understanding industry practices and fostering innovative thinking.
SCM solutions based on PLM	Hayrutdinov et al., 2020	• Proposing an SCM model using blockchain for PLM information sharing.
	Shao et al., 2021	• Proposing a multi-stage implementation framework for Industry 4.0.
	McKendry et al., 2022	• Developing a PLM implementation framework.
	Tao et al., 2022	• Developed a product life cycle cost model.
Sustainability and lifecycle methodologies	Nilsson-Lindén et al., 2019	• Importance of sustainability managers and the business case in SCM.
	Elias Mota et al., 2020	• Identifying uncertainty sources in lPLM and their impact.
	Vidergar et al., 2021	• Importance of transparency and sustainability-oriented decision-making across various levels.
	Iveson et al., 2022	• Importance of shifting towards consumer-centric PLM modelling.
Traceability and lifecycle management	Corallo et al., 2020	• Reviewing the relationship between traceability and lifecycle management in the food industry.
	Pang et al., 2021	• Providing a framework combining digital twin and digital thread technologies to enhance production processes.
	Razak et al., 2021	• Developing a framework linking traceability to SC resilience.
	Deteix et al., 2024	• Exploring the impact of resource supply risk on life cycle assessments.
Barriers and challenges in PLM implementation	Singh & Misra, 2019	• Identifying critical barriers to PLM institutionalisation.
	Koc & Gurgun, 2021	• Investigating SCM risks in construction projects related to PLM.
This study		• Discusses the benefits and challenges of integrating PLM with SCM. • Provides several implications and future research directions.

PLM system selection and evaluation, SCM solutions based on PLM, sustainability and lifecycle methodologies, traceability and lifecycle management, and barriers and challenges in PLM implementation. Table 1 provides a structured summary of these studies.

PLM deployment has been investigated in a number of SCM businesses. Mulla et al. (2021) performed a systematic analysis of PLM literature, emphasising its use in the aerospace sector. The study emphasised the connections between PLM and other fields like ERP and SCM. According to their analysis, PLM is an effective instrument for information interchange, especially when it comes to data management and retrieval procedures (Mulla et al., 2021). Similarly, Meeshi et al. (2021) examined global communication procedures across and inside enterprises, highlighting the usefulness of PLM as a tool. In the aerospace industry, PLM has been found to be an essential business strategy and cooperation tool that greatly improves product lifecycle management (Meeshi et al., 2021). Furthermore, Burke et al. (2023) looked into how SCM and product design could work together in the context of a shift to a circular economy. The study clarified how important it is to incorporate the SC context into conventional notions of product design. It also underlined how urgently corporate models must be updated to conform to circular SC designs. A successful shift to a circular economy depends on the incorporation of end-of-life, circular, and innovative thinking into routine company operations; all of these must be supported by a strong organisational commitment to sustainability (Burke et al., 2023). Triguero et al. (2023) investigated how product design, including circular economy principles, affects environmental and economic outcomes. The results showed that PLM is a useful instrument for bringing circular economy ideas into practice, which enhances economic performance (Triguero et al., 2023).

Another stream of the literature focused on PLM system selection and evaluation. Enríquez et al. (2019) created a quality model based on the Quality Evaluation Framework (QuEF), which has been proven in the aviation sector, namely with Airbus. Similarly, Omerali and Kaya (2022) presented a multi-criteria decision-making technique to assist manufacturing companies in choosing the best PLM solution and overcoming the difficulties associated with subjective decision-making. Additionally, Chhetri et al. (2022) developed techniques to improve SC alignment by modelling the alignment of SC complexity with product demand and design features. Conlon (2024) discussed the insights, observations, and information obtained from an action research project that sought to create a PLM systems learning community. The results demonstrated that PLM produced an engaging learning atmosphere, which promoted the formation of a professional identity, encouraged critical and creative thinking, and enabled a thorough grasp of contemporary industry practices (Conlon, 2024).

In another theme, authors have proposed several solutions to enhance SCM using PLM. A blockchain-based SC coordination approach for sharing product lifecycle information was presented by Hayrutdinov et al. (2020), who also demonstrated higher chain-wide profitability. Parallel to this, Shao et al. (2021) suggested a multi-phase Industry 4.0 implementation strategy for SCs, emphasising enablers like culture, cross-functional methods, and continuous improvement. Additionally, McKendry et al. (2022) created a PLM implementation methodology that addressed issues of scale, complexity, and uncertainty specifically for high-value engineering-to-order initiatives. Furthermore, Tao et al. (2022) used revised multi-choice goal programming and multi-objective linear programming approaches to develop a product life cycle cost-based model with the goal of lowering rejections, late deliveries, and net costs. They designed a decision-making instrument tailored for use in sustainable procurement SCM at a high-tech Taiwanese light-emitting diode manufacturer. Using these two methods within the SC product life cycle cost model and changing for different parameters, managers can handle pertinent difficulties (Tao et al., 2022).

Another theme of literature focused on sustainability and lifecycle methodologies. Elias Mota et al. (2020) highlighted the sources of uncertainty in life cycle approaches and how they affect business and environmental initiatives, especially in the paper and pulp sector. Iveson et al. (2022) reviewed the literature on project lifecycle concepts and found that lifecycle modelling is shifting in favour of consumer-centric viewpoints. Comparably, Nilsson-Lindén et al. (2019) examined how corporate PLM was used in product chains, emphasising the function of sustainability managers and the significance of the business case in SCM. Furthermore, Vidergar et al. (2021) examined studies on food SCM and PLM, highlighting the significance of openness and sustainability in decision-making at all levels.

One more theme that has been given a lot of attention in the literature is traceability and lifecycle management. A thorough review examining the connection between traceability and PM, especially in the food industry, was performed by Corallo et al. (2020), with implications for a number of industries, including aerospace. On the other hand, Razak et al. (2021) created a conceptual framework that demonstrates the indirect and direct linkages between SC resilience and traceability, as well as flexibility, velocity, visibility, and collaboration. Comparably, Pang et al. (2021) offered a framework to improve information traceability and manufacturing processes in Industry 4.0 by fusing digital thread and digital twin technologies.

Finally, some studies focused on investigating the barriers and challenges in PLM implementation in SCM. Using an empirical investigation, Singh and Misra (2019) identified four primary barriers to PLM institutionalisation that include: lack of technical expertise, high investment costs, complex licensing policies, and training. Furthermore, by defining crucial decision entities and phases in construction SCM, Koc and Gurgun (2021) examined SCM risks in PLM-related building projects. Moreover, Deteix et al. (2024) examined how resource supply risk affected life cycle evaluations in the food business, demonstrating how resource risks and environmental effects may be traded off.

Despite the growing number of studies examining PLM frameworks, system selection, sustainability applications, and traceability solutions, the existing literature remains largely conceptual, with limited empirical evidence on how PLM systems are actually experienced and utilised across different departments within a single organisation. Very few studies provide multi-departmental, user-level insights into the practical challenges of PLM–SCM integration, particularly in firms with customised PLM solutions rather than standardised commercial platforms. Moreover, most prior work focuses on high-level benefits or technical models, offering little understanding of how operational realities, such as training, user interface issues, workflow integration, and data flow constraints, affect the success of PLM–SCM integration. To address this gap, the present study investigates the benefits and challenges of Sovelia PLM software within ABC TECH through department-specific qualitative analysis. This empirical focus directly informs the two research questions of the study by revealing how PLM systems can support SCM processes (RQ1) and identifying the integration challenges that organisations encounter in practice (RQ2).

2. Research methods

This study distinguishes itself from others in the field by offering an in-depth, department-specific analysis of Sovelia PLM software within a real-world industrial context at ABC TECH. Unlike many studies that focus on the theoretical benefits of PLM systems or general case studies, this research delves into the practical challenges and successes experienced by different departments (i.e., Technology, Engineering, SCM, Business Support, and After-sales). By capturing the unique perspectives and specific needs of each department, this study provides a nuanced understanding of how PLM software functions in a complex organisational environment. Additionally, it focuses on actionable recommendations for improvement, based on direct user feedback, and ensures that the findings are not only academically rigorous but also practically relevant to enhancing PLM implementations in similar industrial settings.

The data used in this study were gathered for the thesis in Khan and Iftikhar (2022). This study is based on a single qualitative case study, following the guidelines of Yin (2009). The case study design was selected because it allows an in-depth exploration of how PLM systems function within real organisational contexts (Yin, 2009). Data were collected using two qualitative methods: (1) semi-structured interviews with employees from multiple departments at ABC TECH, and (2) comprehensive on-site observations of work processes, systems usage, and information flows. These complementary qualitative techniques provided rich empirical evidence to understand the practical integration of Sovelia PLM software into SCM processes. A case study ought to contain research questions, propositions, logical connections between the data and the propositions, and an analytical unit, as stated by Yin (2009).

The claims that Sovelia PLM software will improve collaboration and traceability between various SCM process components are made under Section 2.2 (data collection and analysis). The logical linking of this article to literature is that PLM systems have been developed to integrate different components of SCM. Finding, evaluating, and reporting themes in the data is made possible by the thematic analysis technique (Alzoubi & Mishra, 2024). To create a comprehensive picture of common patterns and crucial insights, all significant remarks from each participant were gathered, compared, and contrasted (Alzoubi & Mishra, 2024). This study adhered to the four steps (data collecting, data reduction, data display, and conclusion drawing) outlined by Alzoubi and Gill (2021) to methodically examine and code the data that was gathered.

2.1. Case context

ABC TECH is a technology company established in 1990 as a spin-off from the main company's research and development division. They employ over 50 highly skilled professionals and focus on developing and delivering state-of-the-art, fully automated casting lines for the aluminium industry. Their core expertise lies in end-to-end aluminium cast house technology, utilising a combination of process know-how, mechanical engineering, electrical and automation engineering, project management, and SC expertise. Project deliveries are used to deliver ABC TECH goods to the end user. The selection of ABC TECH as the case company was intentional and theoretically justified. ABC TECH represents a highly relevant context because it is a technology-intensive manufacturing firm that relies heavily on engineering, customisation, and multi-departmental collaboration, conditions under which PLM–SCM integration is both critical and challenging. ABC TECH also uses a customised PLM solution (Sovelia), implemented across engineering, SCM, after-sales, business support, and technology functions. This makes the company an ideal setting for examining how PLM systems shape, enable, or constrain supply chain processes in practice. Furthermore, ABC TECH was chosen due to its willingness to provide full access to employees, systems, and internal workflows, allowing for rich qualitative insight that is rarely available in PLM research.

The Sovelia software does not support the following processes: budget/cost, milestones, communication/meetings, and documentation. Although Sovelia is a customised PLM system developed specifically for ABC TECH, its core structure and functionalities are comparable to mainstream PLM platforms such as Siemens Teamcenter, PTC Windchill, Dassault 3DEXPERIENCE, and SAP PLM. Like other PLM systems, Sovelia supports item management, engineering change management, document control, revision handling, and integration with CAD and ERP systems. However, Sovelia differs in two important ways: (1) it is highly customised and therefore reflects ABC TECH's legacy processes, and (2) it places a strong emphasis on engineering and design functions while offering more limited support for downstream supply chain operations. These characteristics make Sovelia an informative example for studying both the strengths and limitations of PLM–SCM integration in real industrial settings. Table 2 provides a breakdown of participants' demographics from various departments included in this study. It lists the participants' experience levels and their years of experience.

ABC TECH currently uses Sovelia PLM software that was created specifically for the company. The SC was not fully incorporated into this design when it was created because it was still evolving at the time. But now, as it fully developed, ABC TECH wants to find out how to better integrate SC with the PLM software. They also want to address the side issue of product traceability to stay competitive in the market.

Tab. 2. Participants' demographics

Department	Participant	Experience level	Experience (years)
SCM	JD	Middle	15–20
	TS	Senior	20–25
	FG	Middle	15–20
Engineering	MFW	New	1–5
	GAAN	New	1–5
	ABB	Senior	20–25
	RH	Junior	5–10
	RF	Middle	15–20
	SOS	Senior	20–25
Technology	MC	Middle	15–20
After-sales	HINT	Middle	15–20
Business support	EC	Junior	5–10

Their system will function smoothly and efficiently once these are in place. All participants in this study are employees of ABC TECH and were interviewed face-to-face on-site. Specifically, three participants from the SCM department (JD, TS, and FG), six participants from the Engineering Department (MFW, GAAN, ABB, RH, RF, and SOS), one participant (MC) from the Technology Department, one participant (HINT) from the After-sales Department, and one participant (EC) from the Business Department were interviewed.

2.2. Data collection and analysis

Four unstructured interviews were conducted with staff members from various departments of ABC TECH prior to the semi-structured interviews to better understand the SCM process as well as the Sovelia PLM software. This was crucial for formulating semi-structured interview questions and determining the primary theme for later stage coding. The four steps in thematic analysis used in this study are discussed in the paragraphs below.

Data collection: Semi-structured interviews were used in this step to get participants' in-depth insights. To complete the questionnaire, staff members from the departments of business support, marketing, engineering, SCM, and technology development were contacted. This is because each of these departments utilises the PLM software that is currently tailored by ABC TECH. The open-ended format of the questions made it easier to gather rich, qualitative information that gave rise to a complex knowledge of the experiences and viewpoints of the participants. The notes made during a two-month observation of the ABC TECH site were used to gather more data. 45–60 minutes were allotted for each interview. Each interview began with a series of generic inquiries about the interviewee's role. Then, the interviewee was asked the following pre-planned questions.

- How do you use different modules of Sovelia PLM software?
- Do you believe that using software enables you to collaborate with others?
- Does it interact with other programs, such as CAD, SCM, ERP, or CAD?
- What advantages do the existing Sovelia PLM software offer?
- What are the problems of using Sovelia PLM software?

Data reduction: Following data collection, the vast amount of qualitative data was systematically reviewed and condensed. This process involved identifying and coding recurring themes and patterns that emerged from the interviews, based on the predefined questions (Alzoubi & Gill, 2021). The goal was to distil the data into manageable, relevant segments that aligned with the research objectives, ensuring that the most significant information was retained while extraneous details were filtered out.

Data display: In this phase, the reduced data were organised and visually represented to facilitate further analysis. This involved creating charts, matrices, or tables that mapped out the key themes and subthemes, enabling a clear comparison of the findings (Alzoubi & Mishra, 2024). Data display helped in identifying relationships and trends within the data, making it easier to interpret the complex interconnections between PLM and SC performance.

Conclusion drawing: The final step involved synthesising the data displayed to draw meaningful conclusions about the research problem. This step required interpreting the patterns and themes identified during the analysis to understand their implications for optimising SC performance through PLM (Alzoubi & Gill, 2021). Conclusions were drawn based on the evidence gathered, providing insights that could inform both theoretical understanding and practical applications in the field of SCM (Alzoubi & Mishra, 2024).

3. Research results

This section presents the key insights derived from the semi-structured interviews and site observations conducted across the Engineering, SCM, Technology, Aftersales, and Business Support departments at ABC TECH. The findings reveal a dual pattern: while Sovelia PLM software provides clear benefits in terms of collaboration, process control, traceability, and data management, several challenges limit its full integration into SCM processes. These challenges relate particularly to system usability, workflow configuration, technical stability, and the limited support for downstream supply chain activities. To provide an overarching view of these insights, Fig. 2 synthesises the main themes emerging from the interviews, highlighting both the strengths and weaknesses of Sovelia PLM software as experienced across departments. The subsequent subsections elaborate on each theme in detail.

Sovelia encompasses a range of modules, including Item, Document, Engineering, Baseline, Task,

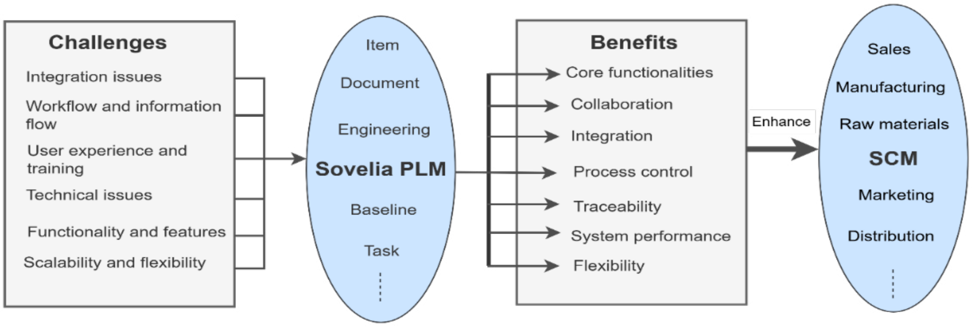

Fig. 2. Summary of the study findings

Operation, Design, SAP MM, Product, and Equipment, among others. Every department at ABC TECH uses Sovelia PLM software daily, except for one member from the engineering department and one from the technology department. This suggests that several people from different fields often rely on it. Most participants (over 60 %) felt that improvement in access, collaboration, and integration was required, with fewer reporting that it was already sufficient. Approximately half of the participants indicated that Sovelia PLM fulfils their requirements, although there were some who felt it could do better. Most participants perceived Sovelia PLM as up to date, with a smaller number feeling neutral.

Across all 12 participants, ten reported using Sovelia daily, indicating an 83 % active use rate across departments. Only two participants (one from Engineering and one from Technology) reported infrequent or limited use of the system. Moreover, the Engineering Department accounted for the highest number of daily users (6 out of 12 participants), followed by SCM (3 users), After-sales (1), and Business Support (1). Technology had the lowest number of active users (1). This distribution highlights that engineering-related tasks rely on Sovelia more heavily than downstream supply chain functions. Furthermore, 72 % of participants expressed mixed or negative perceptions of Sovelia's usability, while 66 % reported that integrations with other business systems need improvement. Conversely, 58 % of participants acknowledged Sovelia's value in supporting traceability, revision control, and document management.

3.1. Benefits of using Sovelia PLM software

The evaluation of Sovelia PLM software at ABC TECH reveals a generally positive perception of its functionalities and contributions to various operational processes. The software is widely used across multiple departments, including Engineering, SCM, Technology, Aftersales, and Business, indicating its integral role in the company's workflow. Participants highlighted Sovelia's capabilities in managing items, documents, projects, and equipment information, which are crucial for their day-to-day activities. Eleven out of 12 participants identified at least one benefit of Sovelia PLM software, with the most frequently mentioned benefits being traceability (mentioned by six participants), collaboration (five participants), and process control (four participants). Its ability to enhance collaboration, both within the company and with external stakeholders, was frequently noted, alongside its effective integration with other systems like SAP, E3-CAD, Inventor, and Vault. Furthermore, Sovelia was praised for its role in process control, traceability, and data management, with features like document linking, revision handling, and organised design/documentation significantly improving operational efficiency. The following paragraphs explain each of the benefits, supported by the participant quotes. Table 3 summarises these benefits and the feedback from participants.

3.1.1. Core functionalities and use

This theme focuses on how the participants use Sovelia PLM software in their daily operations. The core functionalities and modules of the software are integral to how various departments carry out their tasks, such as managing items, documents, projects, and equipment information (Conlon, 2024). MC used Sovelia for accessing the "Items module to find drawings and information about equipment", indicating that Sovelia is crucial for retrieving essential design and equipment data. HINT used Sovelia for multiple functions, including "Item, documents, Installed Base,

Tab. 3. Benefits of Sovelia PLM for ABC TECH's SCM.

Theme	Benefit	Participants
Core functionalities and use	Retrieving essential design.	MC
	Managing various aspects of the project.	HINT
	Managing complex engineering processes.	EC
	Streamlining daily task management.	MFW
	Supporting diverse tasks in a role.	RF
Collaboration	Facilitating teamwork.	TS, FG
	Supporting the dissemination of critical information.	JD, TS, FG
	Distributing reports across different platforms.	JD
	Supporting both internal and external collaboration.	EC
Integration	Working in conjunction with other software.	JD, TS
	Integration with ERP systems for streamlined operations.	FG
	Utility in specialised engineering tasks.	MC
	Integrating with design and document management systems.	RF
Process control and efficiency	Controlling and managing various operational processes.	JD
	Managing product changes.	GAAN
	Enhancing easier access and management.	ABB
	Improving the organisation and tracking of revisions.	SOS
Traceability and data management	Maintaining a clear record of changes and integrations.	TS
	Improving accessibility to critical design information.	MC
	Comprehensive data management capabilities.	RF
System performance and satisfaction	Satisfaction with the software's capabilities.	FG, EC
	Sovelia is adequate for their needs.	JD, MC
	The need for improvement.	TS
Customisation and flexibility	Satisfaction with the software's adaptability.	RH
	Meeting evolving business demands.	EC
	Flexibility for further development.	ABB

and projects", showing that Sovelia is central to managing various aspects of project work. EC reported using Sovelia for "Items, Documents, Engineering change management, Projects, Installed base management, and Baseline management", highlighting the software's broad functionality in managing complex engineering processes. MFW mentioned using Sovelia for "Items, Documents, 'My assigned tasks', and Project navigator", indicating that Sovelia helps streamline daily task management and project navigation. Finally, RF used Sovelia for "Items, Documents, Engineering Change Management, Installed Base Equipment, and Projects", showing that Sovelia supports diverse tasks in his role.

3.1.2. Collaboration

This benefit explores how Sovelia PLM software enhances collaboration within and outside the organisation. The ability to share reports and work collaboratively on projects is vital for efficient team coordination and cross-functional activities (Corallo et al., 2020). TS and FG highlighted that Sovelia PLM "enables collaboration", emphasising the software's role in facilitating teamwork. JD, TS, and FG mentioned that reports generated by Sovelia PLM software can be "shared with others", indicating that the software supports the dissemination of critical information. JD added that "Sovelia PLM can share reports produced by it with email, SAP, Sovelia, and SharePoint to nominated personnel", illustrating the software's versatility in distributing reports across different platforms. Furthermore, EC noted that Sovelia "fits well for collaboration with internal teams (ABC TECH) as well as external teams (suppliers and customers), an extranet module is required", showing the software's capacity to support both internal and external collaboration. These findings are in line with previous studies by Hayrutdinov et al. (2020) and Nilsson-Lindén et al. (2019).

3.1.3. Integration

Integration refers to how Sovelia PLM software interfaces with other software and systems used by the company. Effective integration ensures that data flows seamlessly between different platforms, enhancing overall system efficiency and reducing redundancies (Chhetri et al., 2022). JD and TS reported that Sovelia PLM software "integrates with other programs", highlighting its ability to work in conjunction with other software. FG specified that Sovelia integrates "especially with SAP", showing the importance of integration with ERP systems for streamlined operations. MC mentioned that Sovelia provides integration with the "E3-CAD program for electrical system", indicating the software's utility in specialised engineering tasks. Additionally, RF stated that Sovelia integrates with "Inventor, Vault, and SAP", demonstrating that Sovelia is well-integrated with other design and document management systems in use at ABC TECH. These findings are in line with previous studies by Burke et al. (2023), Meeshi et al. (2021), and Mulla et al. (2021).

3.1.4. Process control and efficiency

This benefit addresses how Sovelia PLM software contributes to controlling and optimising processes within the company. Process control and efficiency are crucial for ensuring that operations run smoothly and that tasks are completed within the required timeframes (Omerali & Kaya, 2022). JD reported that "it enables process control", highlighting Sovelia's role in overseeing and managing various operational processes. GAAN stated that Sovelia provides "full control of item revisions", indicating that the software allows for precise management of product changes. ABB mentioned that Sovelia offers "one place for all technical documents" and links documents to projects, demonstrating how the software centralises information for easier access and management. Finally, SOS noted that Sovelia enhances document revision by applying "unique tags to items and documents", showing how the software improves the organisation and tracking of revisions. These findings are in line with previous studies, such as by Omerali and Kaya (2022).

3.1.5. Traceability and data management

This benefit explores how Sovelia PLM facilitates traceability and effective data management, which are essential for tracking product history, managing revisions, and ensuring data integrity (Singh & Misra, 2019). TS reported that Sovelia "enables traceability and structure and integration", showing that the software helps maintain a clear record of changes and integrations. MC emphasised that Sovelia ensures "Product/project-related drawings and documentation are available for all", indicating that the software improves accessibility to critical design information. Lastly, RF listed several benefits, including "traceability, copy design of similar design, possibility to organise design/documentation. Document numbering/revision handling", illustrating Sovelia's comprehensive data management capabilities. These findings support previous findings, such as by Deteix et al. (2024) and Razak et al. (2021).

3.1.6. System performance and satisfaction

This benefit examines participants' perceptions of Sovelia PLM software's performance and their overall satisfaction with the software. It reflects how well the software meets user expectations and its standing relative to other tools on the market (Conlon, 2024). FG reported that Sovelia is "at par with the current market tech adoption", indicating satisfaction with the software's capabilities. JD and MC mentioned being "unaware of similar or alternative tools", suggesting that they find Sovelia adequate for their needs. TS commented that Sovelia is "not at par with the current market", pointing to some dissatisfaction and a desire for improvement. Additionally, EC noted that Sovelia "does not require any improvement as it complies with the Main companies' security policies", reflecting contentment with the software's current performance. These findings are in line with findings by Conlon (2024) and Iveson et al. (2022).

3.1.7. Customisation and flexibility

This benefit focuses on Sovelia PLM software's ability to be customised and its flexibility in meeting the specific needs of ABC TECH. Customisation is essential for aligning the software with unique business processes and requirements (Vidergar et al., 2021). RH pointed out that Sovelia "has a benefit over other PLM software in that it's possible to order custom functions which fit the customers", highlighting the software's adaptability. EC added that "Capabilities and features offered off-the-shelf did not fit with our requirements, therefore every year the software is improved based on business needs", showing that Sovelia is continually tailored to meet evolving business demands. Finally, ABB recognised the potential for customisation, stating that Sovelia offers "potential for comparing electrical and mechanical documentation for fabrication, potential for spare part lists, and potential for installed base", indicating that the software has room for further development to meet specific needs. These findings supported previous studies' findings, such as by Shao et al. (2021).

3.2. Challenges of Sovelia PLM software

Based on the feedback from participants, it appears that Sovelia PLM software has been a valuable tool for ABC TECH, providing benefits in areas such as collaboration, process improvement, data management, and traceability. However, there are areas where the software could be improved, such as user adoption, technical issues, and specific functionalities. Addressing these challenges will be crucial for improving the effectiveness and efficiency of Sovelia PLM within ABC TECH. Ten out of 12 participants identified at least one significant issue with Sovelia PLM. The most frequently mentioned concerns included user interface complexity (reported by five participants), technical problems such as freezes or downtime (four participants), and limited integration with other systems (four participants). These recurring issues indicate that challenges are not isolated to a single department but are systemic. Table 4 summarises these challenges and the feedback from participants.

3.2.1. Integration issues

This challenge addresses the issues related to Sovelia PLM software's integration with other software and systems (Eby, 2023). Participants expressed concerns over the need for improved integration, particularly with DCC, SAP, and other systems, which affect overall workflow and efficiency. JD reported that "this is especially needed for DCC". This indicates that Sovelia PLM requires enhancement in its integration capabilities, particularly for DCC. FG noted that better integration is required for Fiori and two-way communication. He said, "Fiori and the two-way communication require better integration". RH mentioned that "integration required between Sovelia and MS Office", indicating the need for integration between Sovelia and MS Office. Additionally, SOS highlighted the need for improved integration with SCM and CRM software to enhance information flow. He said, "integration with SCM and CRM software should be improved and re-configured".

3.2.2. Workflow and information flow

This challenge explores how well Sovelia PLM manages workflow and the flow of information within the company. Participants highlighted problems with the software's configuration, which was not designed with a holistic view, leading to inefficiencies in the workflow and information sharing (Koc & Gurgun,

Tab. 4. Challenges of Sovelia PLM software for ABC TECH's SCM

Theme	Challenge	Participants
Integration issues	Integration capabilities	JD, FG
	Integration between Sovelia and MS Office	RH
	Integration with SCM and CRM	SOS
Workflow and information flow	Information sharing	JD
	The focus only on the design phase; suboptimal data flow	SOS
	Limited collaboration using Sovelia	MC
User experience and training	Lack of user-friendliness.	RF
	Training and user interface improvement	FG
	Difficulties in teaching how to use it	RH
Technical issues	Frequent software freezes	ABB
	Downtime and server issues	MFW
	Software glitches	RH
Functionality and features	Improvements for the software's features	ABB
	Lack of fulfilment of business requirements	JD
	Workflows are hard to handle	SOS
Scalability and flexibility	Insufficient scalability	EC

2021). SOS stated that "the software is configured with the design-phase in mind, and less focus on the customer in a value chain", indicating that Sovelia was configured with a focus on the design phase, leading to challenges in procurement, production, installation, and after-sales. SOS also added that "the data flow is not optimal, because the software has (in some cases) been configured as workarounds", indicating that the data flow is not optimal due to workaround configurations. JD reported that "Sovelia PLM sometimes faces issues in information sharing", which indicates issues with information sharing within Sovelia. Finally, MC noted that "collaboration using Sovelia is quite limited", indicating that issues with collaboration between different departments using Sovelia are limited.

3.2.3. User experience and training

This challenge examines the user interface, ease of use, and the effectiveness of training for Sovelia PLM. Many participants reported that Sovelia is complex and difficult to use, with inadequate training provided to users, which hampers efficiency (Eby, 2023). RF commented on the complex interface and the lack of user-friendliness. He said, "UI is too complex (not user-friendly)". FG also emphasised the need for better training and user interface improvements. He said, "the major challenges of Sovelia PLM are the training and user interface". Additionally, RH highlighted difficulties in teaching people how to use Sovelia properly, saying, "it is hard to teach people how to use Sovelia properly and compliantly". These findings are in line with findings by Singh and Misra (2019).

3.2.4. Technical Issues

This challenge focuses on the technical problems encountered with Sovelia PLM software, including glitches, performance issues, and downtime (Eby, 2023). Participants across multiple departments reported significant technical challenges when using Sovelia PLM software. A central issue concerns the system's rigid locking mechanism, which prevents multiple users from working on related items simultaneously. When an item is opened or edited, it becomes fully locked and can only be released by an administrator. Several interviewees reported that this behaviour regularly disrupts workflows and creates avoidable delays. For instance, ABB described frequent interruptions due to item locking combined with system instability, explaining that "Sovelia freezes or stops working. Items get locked and can only be unlocked by admin". Similarly, RH observed that the system occasionally locks objects even when they are released correctly, noting that "there is a bug/glitch which locks released objects".

These recurring lockouts appear to stem from Sovelia's concurrency management model, which relies on hard item locks and administrator-controlled permissions. In legacy or heavily customised PLM environments, this type of locking model often becomes unstable when multiple users attempt to access interdependent items, causing unnecessary blocking and occasional corruption of lock states, consistent with RH's report of a glitch. In addition to locking issues, several participants highlighted system freezes, downtime, and server-related interruptions that affect productivity. MFW, for example, emphasised the unreliability of the system infrastructure, stating that "Sovelia has downtime and server issues". These performance problems likely originate from Sovelia's on-premise server architecture, which is more susceptible to resource saturation, delayed updates, and limited scalability compared to modern cloud-based PLM solutions. When the server experiences load spikes or fails to process concurrent requests efficiently, users encounter freezing or forced restarts, as also noted by ABB and others.

Another source of frustration relates to Sovelia's limited error-handling capabilities. Participants reported that even minor user mistakes often require restarting the operation or waiting for administrator intervention. As one participant summarised, the software "lacks a human error area and takes time to fix errors, nearly necessitating a restart in the event of a mistake". This indicates that Sovelia may not have robust transaction rollback or conflict-resolution mechanisms, which are essential in modern PLM platforms to prevent small errors from escalating into systemic disruptions.

Taken together, these challenges suggest that the underlying causes are rooted in (1) the system's legacy on-premise deployment, (2) extensive customisations that may reduce stability, and (3) outdated concurrency and error-handling logic (Benabdellah & Bennis, 2021; Duda et al., 2024). Addressing these issues would require a combination of technical and architectural improvements. Transitioning Sovelia to a cloud-based or hybrid infrastructure could help reduce downtime and improve performance scalability (Zhang et al., 2022). Enhancing its concurrency control mechanisms, for example, by introducing soft locks, version branching, or user-level conflict resolution, would reduce the frequency of lockouts (Alzoubi, 2024). Strengthening error-handling features, including automatic rollback and improved fault tolerance, would minimise the need for administrator intervention (Alzoubi, 2024). Finally, reviewing and modularising customisations could improve system stability and reduce the likelihood of glitches such as the one reported by RH (Tariq et al., 2025).

3.2.5. Functionality and features

This challenge addresses the limitations of Sovelia PLM software's functionalities and features. Participants noted that the software does not fully meet the business requirements, with certain functions lacking or being insufficiently developed (Koc & Gurgun, 2021). JD stated that Sovelia does not fulfil business requirements, particularly in document management. He said, "it is missing a user-friendly application for document management in a project, particularly for DCC". SOS added that the workflows are hard to handle and that the software is not standardised, saying "the workflows are hard to handle, difficult overview of status and progress". Finally, ABB suggested improvements for the software's features, including better report generation and stability, saying "improve functions like the Compare Function, and stability of application and server".

3.2.6. Scalability and flexibility

This challenge covers the difficulties in scaling and adapting Sovelia PLM software to meet the growing demands and specific needs of the company. Issues were raised about the software's lack of flexibility and its ability to scale according to evolving business requirements (Eby, 2023). When it comes to resolving errors and facilitating collaboration, Sovelia is typically rigid. The user frequently must restart the procedure from scratch if an issue arises during it. Furthermore, because the software was largely created to satisfy the demands of the engineering phase, it is not easily modified to accommodate future developments within ABC TECH. EC expressed the need for better scalability to meet the company's growing demands. He said, "better flexibility to scale up on demand as per the company requirements".

3.3. Meta-analysis from each department

Below is a comprehensive analysis of the insights from each department at ABC Tech regarding the use of the Sovelia PLM software. This analysis highlights the benefits, challenges, and suggestions for improvement as reported by the SCM, Engineering, Technology, Business Support, and After-sales departments.

3.3.1. SCM Department

The participants from the SCM department are regular users with limited access to the SC module. All respondents use Sovelia regularly in conjunction with SharePoint and SAP MM. Overall, they reported that Sovelia is seen as useful but limited by user interface and integration capabilities. However, they reported mixed experiences regarding software shutdowns. Also, they reported that Sovelia partially fulfils needs, but issues with user-friendliness affect effectiveness. They reported some benefits of Sovelia, including the effectiveness in controlling processes and maintaining traceability, as well as providing structural benefits and some level of integration.

However, they reported several challenges, including restricted access to specific modules, user-unfriendly software, and the need for improvement, as well as challenges in training due to the complex interface. They also reported mixed feelings related to Sovelia's integration with other software. Improvements are needed, especially for Dedicated Contract Carriage (DCC) with third-party logistics (3PL). Moreover, varied responses regarding problems in data sharing indicate inconsistent experiences. Finally, mixed perceptions were found on whether Sovelia is on par with market standards, with some participants noting that the market has moved towards more comprehensive, multi-module software. They provided several suggestions, including improving the interface to make it more user-friendly, implementing general metrology across the organisation, and enhancing collaboration features, possibly through an extranet module.

3.3.2. Engineering Department

This department has primary users with regular use. Almost all representatives use the software regularly, except for one. Overall, some participants believe Sovelia is on par with the market, while others disagree. The majority agree on technical issues, such as frequent shutdowns due to server downtime and limited supplier knowledge, making maintenance challenging. Additionally, they provided mixed responses on whether the software meets work requirements, with concerns about high costs and inflexibility. They reported several Sovelia benefits, including seamless integration with other engineering tools, the ability to revise from scratch with full control, effective traceability of components and changes, efficient organisation and document numbering.

However, they also reported several challenges, including unexpected Sovelia freezes or stops, items getting locked, requiring admin intervention to unlock, inability to reverse item statuses without admin's help, high number of objects (45,000+) leading to rigidity, user-unfriendliness with a difficult overview of status and progress, requiring significant manual operations without standardisation, time-consuming training for new colleagues, expensive and resource-intensive efforts to correct and implement issues, partial integration with other software; mixed opinions on effectiveness, lack of holistic approach beyond the design phase, excess documents are sometimes shared due to software inflexibility, and challenges in exporting files in desired formats without excess data. They provided several suggestions to enhance the capabilities of Sovelia's development, a more user-friendly interface, an update to a more up-to-date PLM system that meets internal customer needs, improve collaboration capabilities and system stability, and enable the production of effective reports.

3.3.3. Technology Department

The role of a participant was more of an observer than a primary user. The use of Sovelia was minimal compared to other departments like Engineering or Business Support. The participants were generally satisfied and able to access detailed information from the equipment they had designed and worked on. Generally, the department does not experience significant problems with the software. However, he reported difficulty in accessing the software efficiently. As well as challenges in collaborating with other software and locating necessary documents. He also suggested implementing a single sign-on and transitioning to a web-based platform to enhance accessibility. Also, he suggested improving the ability to collaborate with other software and streamline document retrieval processes.

3.3.4. Business Support Department

This department has regular users with access to multiple modules. All respondents use Sovelia regularly. Overall, the participants from this department reported that Sovelia is strong in managing and integrating product data, needs ongoing adjustments to better fit business requirements, and requires enhancements to better scale with company growth and needs. He reported that Sovelia has effective management of product data and changes, well-integrated with other systems, allowing data sharing in formats like PDF/JPEG, and utilises various modules such as items, documents, engineering change management, projects, installed base management, and baseline management. However, he reported that Sovelia has occasional shutdowns due to server and network issues and suggested that an ongoing annual improvement is needed based on business needs, implement an extranet module to enhance external collaboration, and improve flexibility to scale up according to company requirements. Furthermore, he acknowledged that the market trend towards cloud-based platforms, though the implications of switching have not been evaluated.

3.3.5. After-sales Department

This department encompasses daily users with specific module access. The participant reported that some improvements have been implemented, including master data (ERP) and metadata from Sovelia to BPA (CRM). However, overall, he suggested that the software does not fully meet the after-sales department's needs due to complexity and incomplete data migration. He also added that Sovelia is limited to after-sales modules, such as items, documents, Installed Base, and projects. Also, not all old projects and documentation have been moved to Sovelia, leading to the use of multiple systems. Accordingly, the system is perceived as very complex and time-consuming for after-sales tasks since it is a "Java" version, which is not preferred and needs improvement. Hence, he suggested improving the software access method, possibly moving away from the Java-based version, simplifying the system to make it less complex and more time-efficient for after-sales operations.

4. Discussion of the results

This study aims to explore the function of the PLM system in the SCM process. To do this, RQ1 was addressed (i.e., how PLM boosts the SCM process). In addition, by answering RQ2 (challenges with integrating SCM and PLM systems). Section 3 addressed these two questions. The implications of Section 3 findings, future research directions, and study limitations are covered in this section.

4.1. Practical implications

This paper provides valuable insights for businesses using PLM solutions. Maintaining inventory accuracy and avoiding delays in product releases are dependent on the efficient handling of human data input and mistakes, which may be greatly reduced through the integration of PLM and SCM systems. Businesses may attain maximum profitability and efficacy by guaranteeing that product data is synced in real-time between the two platforms. Furthermore, the results show that integrating PLM and SCM systems can save SCM costs by preventing overspending and enhancing inventory control (Singh & Misra, 2019). For businesses like ABC TECH that must handle intricate SCs with several suppliers and components, this might be very helpful. Moreover, the difficulties ABC TECH had with its specially designed Sovelia PLM indicate that although personalisation can meet certain requirements, it can also result in higher maintenance costs and ineffective operations (Vidergar et al., 2021). Businesses should compare the advantages of tailored solutions against the affordability and adaptability of cloud-based, standardised systems (Singh & Misra, 2019).

Business success requires effective collaboration with stakeholders, including manufacturers, suppliers, partners, and customers (Koc & Gurgun, 2021). The study demonstrates that by offering a single, unified platform for communication and data exchange, PLM integration with other business systems improves cooperation. This is essential for ABC TECH's operating procedures and project delivery. Furthermore, acceptance and efficient use of PLM systems depend on their user-friendliness (Singh & Misra, 2019). The results show that poor user engagement and challenges in onboarding new staff can be attributed to Sovelia PLM's sophisticated and inflexible interface (Burke et al., 2023). The necessity to create more user-centric PLM systems with simple user interfaces that lower learning curves and boost user engagement is another practical implication. The overall feeling suggests a strong desire for improvement in access and collaboration, with a more mixed perception regarding integration. While Sovelia PLM is generally perceived as meeting the requirements of participants, there is still room for enhancement in these areas.

4.2. Theoretical implications

By shedding light on the benefits and challenges of real-world integration, the study advances theoretical debates on PLM and SCM integration. The study emphasises how PLM and SCM are interrelated and how their complementary functions improve SC efficiency and product development. It highlights the need to create systems that are flexible and adaptive to changing business demands and the requirement for theoretical models that consider the challenges of such integrations (Koc & Gurgun, 2021). It is important for theoretical models to investigate the trade-offs between standardisation and personalisation. Although customisation could appear desirable for some business requirements, the study reveals that it can result in long-term problems, including increased expenses, troublesome maintenance, and a delayed capacity to adjust to changing market demands. Ways to standardise PLM systems and enhance their compatibility with other business tools, such as ERP and CRM systems, should be further investigated in research. This can entail creating industry-wide standards or protocols that make data interchange and system integration simpler.

The study highlights the value of multidisciplinary methods in system design, where engineering, SCM, and IT departments contribute (Burke et al., 2023). This reveals a flaw in the way that present theoretical frameworks frequently concentrate on one domain without properly integrating the demands of other domains (Vidergar et al., 2021). The creation and uptake of cloud-based PLM systems, which provide more affordability, scalability, and flexibility than conventional on-premises versions, should be the subject of future study. Additionally, by enabling improved interaction with additional cloud-based business tools, this change would improve overall operational efficiency. To increase user satisfaction and productivity, research might concentrate on creating PLM systems that are simpler to use and require less extensive training.

Furthermore, the study advances knowledge of lifecycle management in PLM systems, especially regarding how modifications, mistakes, and historical data are handled. It implies that additional study is required to create PLM systems that can smoothly connect with other systems and dynamically adapt to changing business processes. Future research should investigate how PLM and SCM systems can benefit from the integration of emerging technologies like artificial intelligence, machine learning, and the

Internet of Things (IoT) to further improve their capabilities, especially in areas like automation, real-time decision-making, and predictive analytics.

4.3. Research limitations

There are several limitations to this study to consider. The handful of vendors that were accessible and the studies that concentrated on PLM integration limited the study's scope. Because of this restriction, it is challenging to extrapolate the results to other businesses or industries that use alternative PLM systems. Also, since the study was carried out during the COVID-19 epidemic, communication and information exchange may have been delayed, and the capacity to arrange direct meetings was impacted. This restriction could have affected the breadth and promptness of the information gathered. Furthermore, the study concentrated on a specially designed PLM system (Sovelia) for ABC TECH, which might not accurately represent the advantages or disadvantages of utilising more conventional PLM systems. The results may not be as applicable in other situations because of this customisation. Moreover, issues with the incomplete transfer of historical data to the new PLM system are brought to light in the research. This restriction could distort the findings since the challenges with data management and traceability can be specific to this implementation rather than a sign of wider patterns.

Conclusions

Integration of PLM systems with SCM processes has proven to be challenging for companies that attempt it, with limited empirical research available on this topic. Consequently, this study aimed to explore whether the implementation of PLM systems can enhance SCM within an organisation. The study followed a single qualitative case study design, drawing on semi-structured interviews and site observations conducted at ABC TECH. The data was collected from ABC TECH, which utilises Sovelia as its PLM software. This study provides new empirical insights into how a customised PLM system (Sovelia) supports and constrains supply chain-related activities within a technology-intensive manufacturing environment. The key conclusions are summarised below:

- Sovelia provides clear benefits across departments, particularly in:
- Improving traceability and revision control,
- Enhancing the collaboration between engineering and SCM,
- Increasing process visibility and document consistency,
- Supporting lifecycle documentation and quality assurance.

However, several challenges limit its full integration into SCM, including:

- System freezes, downtime, and performance instability,
- Rigid item-locking mechanisms that interrupt workflows and require administrator intervention,
- Limited error-handling and rollback capabilities,
- Difficulty integrating Sovelia with other operational systems used by SCM and After-sales.

User experience issues are widespread, with participants highlighting:

- Interface complexity and unintuitive workflows,
- High dependency on administrator rights,
- Limited flexibility for non-engineering departments.
- Adoption and utilisation vary across departments, with Engineering relying heavily on Sovelia while downstream supply chain functions use it less frequently due to functional gaps.
- Overall, Sovelia is effective for engineering-driven PLM tasks but insufficiently optimised for SCM needs, particularly for real-time collaboration, data exchange, and operational planning.

  Improvement opportunities include:
- Migrating to a cloud or hybrid infrastructure,
- Introducing soft locking, version branching, or improved concurrency controls,
- Enhancing integration with ERP and operational systems,
- Simplifying customised workflows to increase stability and usability.
- The findings contribute to PLM–SCM research by offering rare, department-level insights into practical system usage, complementing the largely conceptual or technical focus of prior studies.

To create a system that satisfies the demands of the whole business, input from several departments is essential. Research is still needed to create standardised PLM systems that are simple to link with other business tools, which will lessen the difficulties associated with data management and interoperability.

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