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Assimilation of Technologies vs. Technological maturity of industry 4.0: the case of the dairy processing sector in Poland

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Abstract
The transition toward Industry 4.0 in the agri-food sector necessitates a nuanced understanding of how digital technologies are assimilated within operational and strategic contexts. This study investigates the relationship between technology assimilation and technological maturity in the dairy processing industry – an often-overlooked yet critical segment of the food production value chain. Drawing on a CATI survey of 68 Polish dairy manufacturing companies, we operationalized (5-point Likert scale) assimilation and maturity through principal component analysis (PCA), identifying two core dimensions of assimilation (integration and cybersecurity; digital competencies and data analytics) and four dimensions of maturity (digital technologies and data use; process automation and sustainability; IT flexibility; AI). The results reveal strong correlations between strategic integration of digital transformation and maturity in process automation and sustainability, as well as between digital skills and IT system adaptability. Notably, AI remains at an early adoption stage, reflecting infrastructural and human capital constraints. Our findings underscore the need for aligned strategy, secure digital environments, and workforce development, and support phased digitalization with targeted training and infrastructure investment.

Keywords
technology assimilation; digital maturity; cybersecurity; dairy industry; digital transformation; food manufacturing; PCA.

Introduction

The literature emphasizes the importance of technology assimilation as a key element of an organization's digital transformation (Zhu et al., 2006; Lu, 2024; Trivedi et al., 2023). Assimilation is not limited to the mere adoption of new technologies but involves their actual integration into operational processes and embedding in the daily functioning of the organization (Meyer & Goes, 1988). In the context of Industry 4.0, effective assimilation of digital technologies can directly influence an organization's level of technological maturity – its ability to strategically and efficiently use technology to streamline processes and enhance competitiveness (Martínez-Caro et al., 2020; Machado et al., 2020).

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Despite growing interest in Industry 4.0, there is still a lack of in-depth analyses exploring the relationship between the assimilation of these technologies and technological maturity, especially within specific industries such as dairy processing (Saeedi et al., 2022). Most existing studies focus on general aspects of implementation, often overlooking sector-specific conditions and practical barriers and challenges (Tripathi et al., 2023; Rikalovic et al., 2022). This knowledge gap hampers a full understanding of how companies can effectively navigate the digital transformation process.

This article aims to address this gap by analyzing the relationship between the assimilation of Industry 4.0 technologies and technological maturity in dairy processing companies. The main goal is to identify the interplay between these two categories and determine the factors that facilitate or hinder their interaction. Specifically, the study focuses on:

1. identifying key Industry 4.0 technologies used in the dairy processing sector
2. analyzing the relationship between technology assimilation and technological maturity

3. determining the main drivers of successful digital transformation
4. formulating practical recommendations for managers and policymakers

This study contributes to the literature on digital transformation in the food sector by proposing an empirically tested model of the relationship between technology assimilation and technological maturity in the dairy industry. Unlike previous studies that focused either on implementation barriers (e.g., Ghobakhloo et al., 2022) or the potential of specific technologies (e.g., Cui et al., 2024), this research simultaneously examines both dimensions, highlighting the key role of strategic alignment, digital competencies, and cybersecurity as enablers of digital maturity. As a result, the article offers not only an industry-specific diagnostic model but also a basis for future cross-sectoral comparisons. Given the exploratory nature of the study, we focus on identifying latent structures rather than testing directional hypotheses.

The analysis of results is grounded in the existing literature on production management and Industry 4.0, providing a clearer understanding of digital transformation processes in dairy processing. This can serve as a foundation for designing strategies for implementing Industry 4.0 technologies. The article is structured as follows: after this introduction, a literature review is presented, covering Industry 4.0 technologies, assimilation processes, and technological maturity in the dairy sector. The third part discusses the research methodology, including data collection and analysis techniques. The fourth part presents the empirical findings, followed by their interpretation in light of previous research. The paper concludes with a summary of findings, research limitations, and suggestions for future studies.

Literature review

The implementation of Industry 4.0 technologies, as part of the so–called Fourth Industrial Revolution, entails the integration of advanced solutions such as the Internet of Things (IoT), artificial intelligence (AI), big data analytics, robotics, and cyber–physical systems into production processes (Serôdio et al., 2024; Ryalat et al., 2024; Jagatheesaperumal et al., 2022). Recent studies emphasize that digital transformation in agribusiness contributes to operational flexibility and productivity growth, thereby strengthening the rationale for technological assimilation in food–related sectors (Cui et al., 2024). The use of Big Data in food production chains not only increases process accuracy but also enhances traceability and food safety, particularly when integrated with real–time monitoring frameworks (Ahearn et al., 2016).

In the context of dairy processing, these new solutions and concepts play a significant role in improving operational efficiency, ensuring high product quality, and increasing the flexibility and responsiveness of companies to changing market conditions (Chuprina et al., 2022; Burke et al., 2018; Sangode, 2024). The implementation of IoT allows for real–time monitoring and management of production processes, while the use of AI and big data analytics supports data-driven decision-making, thus improving process control and predictability (Mhapsekar et al., 2024). Automation and robotics increase operational precision and reduce the risk of errors, which is especially important in milk and dairy product processing and packaging (Khoroshailo & Kozub, 2020; Kozub et al., 2020). Moreover, recent studies emphasize the importance of digital integration tools that enable real–time coordination and data harmonization along food–processing value chains. In this context, the work of Zawadzki & Żywicki (2016) on ERP integration for mass customization provides an important sector–relevant perspective, demonstrating how advanced ERP architectures support flexibility, production synchronization, and end–to–end information flow – capabilities that are increasingly relevant for dairy processors seeking to modernize legacy systems. The growing relevance of blockchain–based traceability further strengthens the rationale for including blockchain technologies within the digital technologies and data analytics dimension. While blockchain was previously mentioned only briefly in literature, research by Casino et al. (2020) highlights its concrete applications in the dairy sector, including immutable records, improved traceability, and reduced information asymmetry across the supply chain. These insights underline the importance of secure, transparent data environments in advancing dairy–sector digital maturity.

In this context, the concept of *Dairy 4.0* has emerged, referring to the adaptation of Industry 4.0 solutions to the specific needs of dairy processing. Dairy 4.0 includes the integration of IoT sensors into production lines, the use of AI systems for raw material quality forecasting, and the application of big data to optimize milk logistics in real time. Increasingly, operational decision–making is being automated, and intelligent, self–organizing processing systems are being developed (Hassoun et al., 2023).

Technology assimilation refers to the extent to which technological solutions are embedded in operational practices and become part of the organization's daily routines (Meyer & Goes, 1988).

This is a staged process, encompassing evaluation, adoption, and implementation, and its course depends on contextual factors (e.g., industry), the nature of the technology itself, and their interaction. Effective assimilation enhances the absorptive capacity of the organization, thereby increasing its agility and efficiency (Martínez-Caro et al., 2020).

Previous research has highlighted the importance of organizational, technological, and environmental factors as determinants of assimilation processes Amin et al. (2024). Among them, organizational culture and leadership commitment are considered critical components shaping organizational readiness for innovation (Marcon et al., 2021; Chatterjee et al., 2021). Equally important are access to technological resources and the advancement of technical infrastructure, which significantly influence the likelihood of successful Industry 4.0 implementation (Ghobakhloo et al., 2022; Amin et al., 2024). External conditions also matter – competitive pressure, institutional support, and public policy may act both as drivers and barriers to adoption (Kumar & Bhatia, 2021; Amin et al., 2024).

The literature also points to the phenomenon of the *assimilation gap* – a situation in which a technology has been formally adopted but not effectively integrated into organizational routines, resulting in a misleading perception of its diffusion (Fichman & Kemerer, 1999). In this context, the notion of *technological maturity* becomes increasingly relevant, understood as the level of effective technology use for process improvement, enhanced competitiveness, and innovation development. Technological maturity may be viewed as an outcome of successful assimilation: the deeper the integration of technology into the organizational structure, the greater the firm's potential to derive sustainable benefits from digitalization (Machado et al., 2020; Martínez-Caro et al., 2020). In many countries, the dairy industry remains a sector with a relatively low degree of digitalization. This is due, among other factors, to high investment costs, limited access to specialized knowledge, and technological conservatism in production management (Hassoun et al., 2023; Wangen et al. (2021)).

Materials & Methods

Aim and data collection

Previous studies have typically focused on large manufacturing companies, while food–processing sectors and their specific implementation challenges have been analyzed far less frequently (Birkel & Müller, 2021; Beltrami et al., 2021). Therefore, the main objective of this study was to examine the relationship between the assimilation of Industry 4.0 technologies and the level of technological maturity in dairy processing companies.

A quantitative research approach was applied, using a structured questionnaire due to its suitability for analyzing perceptions, practices, and attitudes across many companies. The study was cross–sectional in nature and conducted in the second quarter of 2024. Data were collected through a survey questionnaire composed of 25 items divided into two sections: Technology assimilation (ASSIM) – 11 questions / items, and 2) Technological maturity (MATUR) – 14 questions / items. Responses were coded on a 0–4 scale, where 1 = strongly disagree, 4 = strongly agree, and 0 = don't know/don't have an opinion. Substantive agreement responses were therefore interpreted on a 1–4 scale. The questionnaire was validated through a pilot study in two dairy companies to ensure clarity and relevance. Based on pilot feedback, minor adjustments were made to improve readability and comprehension. The main study was conducted using the Computer–Assisted Telephone Interview (CATI) method. All respondents provided informed consent, and data collection was carried out in full compliance with confidentiality and anonymity standards. Each interview lasted approximately 25–30 minutes and adhered to ethical research guidelines.

The respondents were individuals holding key decision–making positions, such as company owners, quality directors, production managers, and technologists. Their expertise ensured that the responses reliably reflected both strategic and operational dimensions of digital transformation in the dairy sector. The sample was drawn from publicly available registries of dairy processing companies classified under NACE code 10.51 in Poland, which lists 476 companies. Ultimately, 68 valid responses were obtained, resulting in a response rate of 13.9%. Sample structure:

- Small companies: $n = 27$
- Medium companies: $n = 33$
- Large companies: $n = 8$

Data analysis and operationalization of variables

Data were analyzed using IBM SPSS software, applying Principal Component Analysis (PCA). PCA was chosen for its effectiveness in reducing many interrelated variables and identifying key components that determine technology assimilation and technological maturity. The suitability of the data for factor analysis was confirmed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. The KMO values indicated high sampling adequacy, while Bartlett's test was statistically significant (ASSIM: $\chi^2 = 619.58$, $p < 0.001$; MATUR: $\chi^2 = 1107.32$, $p < 0.001$).

To assess the internal consistency of the scales derived from PCA, we calculated Cronbach's alpha for each of the extracted components. The results confirmed strong reliability across all constructs, with final alpha coefficients falling within a high and satisfactory range (0.86–0.91). These values exceed the commonly recommended threshold of 0.70 and demonstrate that the constructs are internally coherent and stable. The consistently high alpha levels also support the robustness of the factor structure obtained through PCA and justify the use of these dimensions in subsequent analysis despite the modest sample size.

Components with eigenvalues greater than 1.0 were extracted. Items with factor loadings below 0.40 were excluded from further analysis. Technology assimilation (ASSIM) was operationalized through two dimensions:

- ASSIM1 – Integration and cybersecurity
- ASSIM2 – Digital competencies and data analytics

Technological maturity (MATUR) was divided into four dimensions:

- MATUR1 – Digital technologies and data analytics
- MATUR2 – Process automation and sustainable practices
- MATUR3 – IT system flexibility
- MATUR4 – Advanced technologies (AI)

Figure 1 illustrates the conceptual framework developed in this study, which links two core dimensions of technology assimilation with four dimensions of technological maturity in the context of Industry 4.0 implementation.

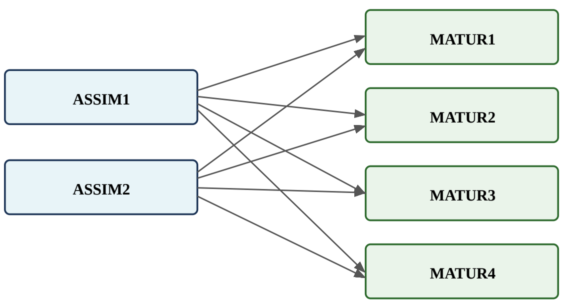

Fig. 1. Conceptual model of the relationship between technology assimilation and digital maturity

The model assumes that the extent to which digital technologies are embedded in organizational routines (assimilation) significantly influences the firm's ability to effectively leverage these technologies (maturity). It also reflects the complementary nature of strategic alignment, employee competencies, and IT infrastructure as enablers of sustainable digital transformation.

Results and discussion

This section presents a detailed statistical analysis based on the data collected from 68 dairy processing companies in Poland. It includes the assessment of sample adequacy for factor analysis (using KMO and Bartlett's tests), the results of Principal Component Analysis (PCA) for the two main study areas – technology assimilation (ASSIM) and technological maturity (MATUR) – and a correlation matrix between the extracted components, along with their interpretation in the context of digital transformation.

To contextualize the empirical examination of how technology assimilation shapes technological maturity in the dairy sector, the following analysis synthesizes the average levels of assimilation and maturity across firms of different sizes, highlighting the structural disparities that underpin the sector's heterogeneous digital transformation trajectory. The empirical results demonstrate a discernible size-dependent gradient, whereby both technology assimilation and digital maturity exhibit a consistent and incremental rise in proportion to firm scale. The mean assimilation value calculated for the entire sample was 1.86, with small companies achieving an average of 1.55, medium companies 1.88, and large companies 2.83 (in a scale 1–4). A similar pattern is evident in the context of digital maturity, where the overall average is 1.72, in comparison to 1.45 in small companies, 1.73 in medium companies, and 2.59 in large companies. This finding suggests that larger companies possess significantly stronger strategic readiness, more advanced digital competencies, and more established cybersecurity frameworks, frequently achieving values in the 3.0–3.4 range in areas related to data use, IT systems, and employee capabilities, while small companies remain around 1.4–1.7.

The maturity indicators further confirm this divide – large companies demonstrate advanced automation and real–time data integration across all major production stages (often 2.5–3.4), whereas small and medium companies operate at a more basic digitalization level (1.4–2.0). It is important to note that across all size categories, the adoption of advanced technologies such as AI, digital twins, or blockchain remains low. In small and medium–sized companies, the adoption rate is typically between 1.1 and 1.2, and in large companies it is between 1.6 and 2.1. This highlights the early stage of algorithmic capabilities in the sector. The data indicates that the dairy industry is undergoing a gradual, staged transformation trajectory. It is evident that only companies achieving intermediate levels of capability (approximately 1.8–2.4) appear positioned to progress towards higher–order digitalization and data–driven operations.

Sample adequacy for factor analysis

In the first stage, the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity were conducted to assess the suitability of the dataset for PCA. High KMO values (above 0.7) indicate that the data are appropriate for dimension reduction Hair et al. (1998), while the significance of Bartlett's test confirms the presence of correlations among the variables, justifying the application of factor analysis (Table 1).

Table 1
KMO and Bartlett's test parameters

Parameter	ASSIM (Assimilation)	MATUR (Maturity)
KMO	0.874	0.725
Bartlett's chi-square	619.580	1107.323
Degrees of freedom (df)	55	210
Significance (p)	0.000	0.000

The results show that for both domains (assimilation and technological maturity), the KMO values exceed the recommended threshold of 0.70. Additionally, Bartlett's test is highly significant ($p < 0.001$), which confirms the presence of sufficient correlations among the variables for factor analysis.

Principal Component Analysis (PCA) – Technology assimilation (ASSIM)

The PCA for technology assimilation aimed to identify the most important components (factors) that explain the variance in responses regarding the adoption and integration of Industry 4.0 solutions in dairy companies. Based on the criterion of eigenvalues > 1.0, two components were extracted, jointly explaining nearly 78% of the total variance. The high cumulative variance indicates that these two dimensions sufficiently capture the nature of assimilation processes in the studied companies (Table 2).

Table 2
Eigenvalues and explained variance – ASSIM

Component	Eigenvalue	% of variance	Cumulative %
ASSIM1	7.311	48.620	48.620
ASSIM2	1.237	29.083	77.702

The first component (ASSIM1) explains nearly half (48.62%) of the total variance, suggesting the existence of a dominant dimension of technology assimilation, reflecting core digital adoption elements. The second component (ASSIM2) contributes nearly 29%, offering a complementary view of the internal capabilities required for effective implementation.

The next step was to examine the factor loadings to determine which survey items best define each dimension (Table 3).

Table 3
Factor loadings – ASSIM

Survey item	ASSIM1	ASSIM2
Understanding of digital transformation	0.652	
Integration of digital strategy	0.639	
Acceptance of Industry 4.0 initiatives	0.701	
Cybersecurity	0.798	
Core technologies in the company	0.710	
Understanding of digitalization processes		0.928
ERP/BI system use		0.892
Data analysis capabilities		0.922
Investment in digital training		0.704

Based on these loadings, two core dimensions of technology assimilation were identified:

1. ASSIM1 – Integration and cybersecurity – this component reflects general strategic awareness, organizational acceptance of digital transformation, and awareness of data protection and cybersecurity. High scores in this dimension suggest that companies perceive Industry 4.0 as an integral part of corporate strategy, contributing to coherence and long–term investment commitment.
2. ASSIM2 – Digital competencies and data analytics – this dimension is related to employee skills and the ability to use advanced IT tools (e.g., ERP/BI systems) in daily operations. A strong loading on "data analysis" (0.922) indicates that the ability to process and interpret production–related data is key for deeper digital assimilation.

This factor structure is consistent with prior studies on Industry 4.0 implementation in the food sector, which emphasizes that successful adoption requires both managerial support and workforce development (Marcon et al., 2021; Amin et al., 2024).

Principal Component Analysis (PCA) – Technological Maturity (MATUR)

The next stage of the analysis focused on identifying key components that describe the level of technological maturity in companies with respect to the use of advanced Industry 4.0 solutions. Using the same procedure (eigenvalue > 1.0), four components were extracted, together accounting for 78.06% of the total variance (Table 4).

Table 4
Eigenvalues and explained variance – MATUR

Component	Eigenvalue	% of Variance	Cumulative %
MATUR1	10.430	27.644	27.644
MATUR2	3.166	25.590	53.233
MATUR3	1.768	17.733	70.966
MATUR4	1.027	7.088	78.055

The first two components (MATUR1 and MATUR2) together explain over 53% of the total variance, confirming their dominant role in shaping the differentiation of technological maturity levels among dairy companies. The additional two dimensions (MATUR3 and MATUR4) refine the model by indicating more specific areas of implementation (e.g., IT flexibility and AI). The variable loadings for each component are shown in Table 5.

Table 5
Factor loadings – MATUR

Technology/ Process	MATUR1	MATUR2	MATUR3	MATUR4
IoT	0.652			
Big Data	0.860			
Blockchain	0.783			
Water purification		0.926		
Packaging		0.839		
Recycling		0.863		
IT systems flexibility			0.912	
Process automation			0.795	
Artificial Intelligence (AI)				0.861

Based on the results above, four dimensions of technological maturity were identified:

1. MATUR1 – Digital technologies and data analytics. This component includes technologies such as IoT, Big Data, and Blockchain – core foundations of Industry 4.0. High scores indicate the organization's ability to gather and analyze production data effectively, enabling data–driven decision–making.
2. MATUR2 – Process automation and sustainable practices. This dimension encompasses physical process automation (e.g., packaging) and the implementation of environmentally sustainable solutions such as recycling. In the dairy industry, these are particularly important due to strict hygiene standards and growing sustainability requirements.
3. MATUR3 – IT system flexibility and automation – This component highlights the role of flexible ERP systems that allow adaptation to dynamic production and market conditions. High scores suggest that the organization can reconfigure production parameters efficiently using its IT infrastructure.
4. MATUR4 – Advanced technologies (Artificial Intelligence). This component captures the adoption of AI–based technologies. In the dairy sector, this may include predictive quality assessment using IoT sensors or real–time production optimization. The isolated emergence of this factor may reflect the currently low level of AI diffusion in the industry.

Although artificial intelligence (AI) was identified as a distinct component of technological maturity (MATUR4), its implementation remains limited across the studied sample. Unlike foundational technologies such as IoT or Big Data, AI often represents an advanced or aspirational stage of digital transformation. Its effective deployment requires not only a stable analytical infrastructure and high–quality standardized data, but also significant investments in human capital and technical expertise. Therefore, its inclusion in the maturity model reflects a strategic direction for the future rather than a commonly achieved state among dairy processors.

Correlation matrix between components

To better understand the relationships between assimilation dimensions (ASSIM1, ASSIM2) and maturity dimensions (MATUR1–MATUR4), Pearson correlation coefficients were calculated. All reported correlations below are statistically significant at $p < 0.01$ (denoted "**", Table 6).

A very strong correlation between ASSIM1 and MATUR2 ($r = 0.897$) may indicate that companies integrating digital strategy and placing a strong emphasis on cybersecurity (ASSIM1) are significantly

Table 6
Correlation matrix of components

Correlation	ASSIM1	ASSIM2	MATUR1	MATUR2	MATUR3	MATUR4
ASSIM1	1	0.693**	0.722**	0.897**	0.332**	0.481**
ASSIM2		1	0.722**	0.738**	0.707**	0.464**
MATUR1			1	0.722**	0.591**	0.438**
MATUR2				1	0.379**	0.386**
MATUR3					1	0.215
MATUR4						1

more advanced in implementing process automation and sustainable practices (MATUR2). From a managerial standpoint, this suggests that a secure and digitally mature IT environment fosters effective modernization of production lines and facilitates the adoption of eco-friendly solutions. Similar conclusions were drawn in a study of the food industry by Wangen et al. (2021), which emphasized that a secure IT environment not only acts as a protective barrier against cyber threats but also strengthens employee trust in newly introduced digital solutions. In the dairy sector, the integration of digital initiatives into the core corporate strategy is even more critical due to the highly perishable nature of raw milk and strict food safety requirements. This is supported by research from Hassoun et al. (2023), which found that real-time digital monitoring of production parameters (e.g., temperature, pasteurization time) yields the best outcomes when embedded within a broader quality management and information security policy. The link between digital strategy integration (ASSIM1) and the adoption of process automation and sustainability practices (MATUR2) illustrates a kind of feedback loop – where strategic decisions directly support the implementation of advanced operations – affirming the hypothesis of complementarity between organizational and technological resources (Teece, 2018).

The strong correlation between ASSIM2 and MATUR3 ($r = 0.707$) suggests that digital competencies – such as proficiency in ERP/BI systems and data analysis – are closely associated with IT system flexibility and advanced automation. In other words, having a skilled workforce may serve as a key driver that enables companies to dynamically reconfigure processes, for example, in response to variable raw material supply or market demands. These findings align with Ahearn et al. (2016), who emphasized that the effective use of Big Data and AI requires not only access to information resources but also the competencies to apply them in practice. Similarly, Höhler & Kühl (2019) highlighted how companies adopt varied approaches depending on their organizational and infrastructural readiness. Our results expand this perspective by showing that even within a single sector (dairy), companies can be typologized by distinct trajectories of technological maturity. Chatterjee et al. (2021) concluded that the ability to use ERP/BI systems and perform data analysis enables better adaptation of production to change conditions. In the dairy industry, this may translate into, for example, the rapid reconfiguration of production lines depending on milk quality (e.g., varying fat content) or seasonal milk availability. Furthermore, companies that invest in employee training are better able to utilize advanced ERP modules for dynamic production resource management, making them more agile and resilient to market fluctuations (Ghobakhloo et al., 2022). Developing digital competencies appears essential for fully leveraging flexible IT platforms. Without such capabilities, companies often fall into the so-called "assimilation gap" (Fichman & Kemerer, 1999), where new technologies are formally adopted but not used effectively in everyday operations.

The interpretation of weaker correlations with MATUR4 (AI) is more complex. The implementation of artificial intelligence appears to require a high level of digital awareness, yet it is not as strongly associated with the primary dimensions of assimilation (e.g., $r = 0.464$ with ASSIM2). This may be due to the fact that AI requires a stable analytical infrastructure and significant human capital investments – conditions that are still uncommon in the dairy sector. The results suggest that the adoption of IoT, Big Data, and Blockchain (MATUR1) provides a foundational base for further transformation stages (MATUR2 and MATUR3), while the implementation of artificial intelligence (MATUR4) remains relatively rare and only modestly correlated with other components (correlations ranging from 0.215 to 0.481). These findings are consistent with Beltrami et al. (2021), who found that AI in the food sector is predominantly adopted by highly experienced companies with well-developed real-time data collection infrastructures. As a result, the literature advocates a staged Industry 4.0 implementation model, wherein companies first develop IoT capabilities and analytical systems before moving on to machine learning applications once a solid competency base has been established (Tripathi et al., 2023).

The study's findings reflect a broader trend in manufacturing organizations, where digital transformation is a multi-stage process driven by both internal factors (e.g., leadership, organizational culture) and external pressures (e.g., competition, government regulation) (Kumar & Bhatia, 2021). In the case of dairy, the perishability of raw materials and strict food safety requirements (e.g., sanitary regimes) further emphasize the need for robust data security during implementation phases (Saeedi et al., 2022). Dairy companies should treat digitalization as a long-term strategic initiative, co-developed by top management and key departments (production, logistics, IT, and quality). Investing in the development of employees' digital competencies is essential for the effective integration of Industry 4.0 solutions, as highlighted by Chatterjee et al. (2021), who underscored the human factor in digital transformations, particularly in traditional sectors such as dairy. The deployment of AI technologies (e.g., vision systems, predictive algorithms, chatbots) should be preceded by the establishment of a robust IoT infrastructure and employee training – an approach supported by Machoka et al. (2022), who argue that AI only becomes meaningful when based on standardized and secure production data. Furthermore, digitalization should support sustainable practices such as recycling and energy-efficient packaging, as evidenced by our findings and by Burke et al. (2018), who noted the growing importance of environmental and social responsibility in the food sector.

When compared with cross-national evidence on dairy digitalization (e.g., Saeedi et al., 2022), the Polish dairy sector appears to follow a similar staged trajectory of Industry 4.0 adoption, albeit shaped by stricter EU regulatory requirements and a relatively fragmented supply chain structure. These institutional and structural conditions may strengthen the role of strategic integration and cybersecurity in enabling process automation and sustainability, while simultaneously slowing the diffusion of more advanced technologies such as artificial intelligence.

Conclusions

Strategic responses of dairy companies to sector–specific challenges are often shaped by structural market dynamics and their position within the supply chain, which in turn influence both the pace and the scope of digital transformation (Höhler & Kühl, 2019). The results of this study indicate that effective assimilation of Industry 4.0 technologies is closely linked to achieving higher levels of technological maturity. Digital transformation in the dairy sector follows a multi–stage trajectory and rests on mutually reinforcing pillars – from deliberate and well–aligned strategy, through the development of human capital, to the implementation of the most advanced AI–based solutions.

Findings from the principal component analysis (PCA) and the correlation matrix reveal that organizations which treat Industry 4.0 technologies as an integral element of corporate strategy and ensure appropriate cybersecurity mechanisms are more likely to advance process automation and implement sustainability practices. Additionally, well–developed digital competencies among staff – especially data analytics skills and proficiency in operating advanced IT systems such as ERP or BI – correlate with greater process flexibility. This enables companies to respond quickly and efficiently to fluctuations in market conditions or the quality of raw milk. In the sample studied, the implementation of artificial intelligence remains at an early stage of adoption. This may stem from an underdeveloped data infrastructure, limited human capital, or insufficient investment levels.

The study yields the following managerial implications. First, preparing the infrastructure and collecting reliable, standardized data sets should be seen as a prerequisite for subsequent AI adoption. Second, managers must ensure proper employee motivation and training (Cabrera et al., 2021) to avoid the so–called *assimilation gap*, where newly adopted technologies remain unused due to mental or skill–related barriers. Third, executives should embed Industry 4.0 technologies within long–term corporate strategy while simultaneously developing robust cybersecurity systems. This dual approach facilitates not only efficient process automation but also supports the integration of sustainability practices.

Our study is subject to several limitations that should be considered in interpreting the results. First, the correlational nature of the analysis does not allow for a definitive conclusion as to whether a high level of technology assimilation causes technological maturity or vice versa – that maturity fosters faster adoption. Second, the geographical (Poland) and sectoral (dairy processing) focus limits the generalizability of findings to other food sectors or countries with different legal and economic environments. Third, although the number of valid responses ($n = 68$) was sufficient for preliminary analysis, future research should aim to expand the sample size to improve statistical power and inference accuracy.

Our findings and research limitations point to several future research directions. First, the proposed model should be tested in other branches of the food industry (e.g., meat, bakery) to enable comparison of technology assimilation dynamics across different production contexts – considering the nature of raw materials, logistics challenges, and manufacturing traditions. Second, researchers should consider applying structural equation modeling (SEM) to identify mediating and moderating effects, such as the role of institutional support or ownership structure. Third, incorporating ESG (environmental, social, governance) variables could extend the analysis to include sustainability and regulatory compliance, particularly within the EU context. Lastly, future research should delve deeper into advanced technologies such as artificial intelligence and blockchain (Casino et al., 2020) and explore factors that may accelerate – or hinder – their adoption in the daily operations of dairy companies.

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