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ALIGNMENT OF INNOVATION DIFFUSION AND PROJECT MANAGEMENT TO INCREASE LOGISTICS DIGITALIZATION

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Abstract. *Purpose* – This paper examines how integrating Innovation Diffusion Theory (IDT) with structured project management frameworks enhances digital technology adoption in logistics, addressing challenges in ineffective implementation.

Research methodology – A mixed-methods approach combines qualitative interviews with logistics executives and technology experts with quantitative analysis of adoption trends using case studies and industry data.

Findings – Results highlight the complexity of digital technologies and emphasize aligning decision-making frameworks – Agile, Scrum, Kanban, and Waterfall – with organizational goals to improve digital transformation. Structured project management methodologies help firms manage complexity, mitigate risks, and optimize project execution.

Research limitations – The study does not analyze all technology complexity levels or include all digital solutions in logistics. Additionally, not all technologies were linked to expert-identified success factors, limiting generalizability. Future research could use longitudinal or case-study approaches to explore long-term impacts.

Practical implications – Integrating IDT with project management frameworks and the Stacey Matrix helps logistics firms overcome adoption barriers and improve implementation success.

Originality/Value – This research provides empirical evidence on structured decision-making in digital adoption. By integrating expert insights and correlation analysis, it offers practical recommendations for optimizing innovation diffusion, mitigating risks, and aligning technology implementation with strategic goals in a rapidly evolving digital landscape.

Keywords: innovation diffusion theory, digital transformation, logistics, project management frameworks.

JEL Classification: O32, M10.

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1. Introduction

The adoption of digital technologies is crucial for maintaining competitiveness, yet many firms struggle to integrate innovations effectively into their operations. Poor implementation strategies often result in inefficiencies, wasted investments, and misalignment with organizational goals. Research indicates that up to 60% of companies fail to achieve the expected benefits from technology adoption due to a lack of structured diffusion strategies (Rogers, 2003; Hazen et al., 2014). This challenge is particularly pronounced in the logistics sector, where firms introduce advanced technologies – such as artificial intelligence (AI), the Internet of Things (IoT), and blockchain – without a clear framework for managing their diffusion and long-term impact (Kaminski, 2011). As a result, slow adoption rates and ineffective implementation hinder the transformative potential of these innovations (Sumarliah et al., 2023).

Given the increasing reliance on digital transformation, there is a critical need for structured approaches that align technology investments with strategic objectives and operational demands. While Rogers' Innovation Diffusion Theory (IDT) provides a valuable framework for analyzing how technologies spread within industries, its application in logistics has primarily focused on adoption determinants rather than structured diffusion processes. IDT explains that innovation adoption is influenced by key attributes, including relative advantage, compatibility, complexity, trialability, and observability (Rogers, 1995). In the logistics sector, IDT has been applied to examine adoption patterns; however, limited research explores how structured project management methodologies can facilitate diffusion processes (Hazen et al., 2014; Kamble et al., 2019). Studies indicate that firms implementing new technologies without fully considering diffusion dynamics often face resistance to change, poor resource allocation, and technological misalignment with operational needs. To ensure successful diffusion, it is essential to integrate IDT with project management strategies that account for complexity and risk mitigation (Lyytinen & Damsgaard, 2001; Wu et al., 2021).

To address these challenges, structured project management methodologies – such as Agile, Scrum, Kanban, Waterfall and the Stacey Matrix – offer strategic tools for managing complexity, mitigating risks, and enhancing the scalability of technological innovations in logistics operations. Recent studies have examined how these methodologies complement IDT by structuring adoption processes and reducing uncertainty in technology diffusion (Cooper, 1990; Brown & Vessey, 2003, Srivastava & Teo, 2012). The Stacey Matrix, in particular, provides a decision-making framework that helps organizations navigate uncertainty in innovation diffusion by categorizing projects based on complexity and agreement levels (Stacey, 2007). When applied alongside IDT, the Stacey Matrix can guide logistics firms in selecting appropriate implementation strategies based on the innovation's characteristics and industry conditions (Mettler & Rohner, 2009; Shenhar & Dvir, 2007). However, the interaction between these structured frameworks and IDT remains underexplored, creating a gap in research on how to systematically guide the diffusion of digital innovations.

This paper aims to bridge this gap by exploring how IDT, combined with structured decision-making frameworks, can enhance the adoption and long-term diffusion of digital technologies in logistics operations. The central research question of this study is: *How do structured project management methodologies influence the successful adoption and diffusion of digital technologies in logistics?* Specifically, the study investigates the role of project management and the Stacey Matrix in overcoming diffusion barriers and ensuring successful digital transformation in logistics firms.

To address this research question, the study employs a mixed-methods approach, combining qualitative research (semi-structured interviews with logistics executives and technology experts) and quantitative analysis of technology adoption trends based on case studies and industry data. This approach provides a comprehensive assessment of innovation diffusion strategies, integrating expert insights with empirical data to evaluate how structured implementation frameworks impact digital transformation success in logistics. The results section is divided into two parts: the comparative analysis and the correlation analysis. EViews facilitated precise and efficient correlation matrix transformation, systematically identifying relationships between digital technologies in logistics implementation.

The paper is structured as follows: Section 2 presents a literature review examining IDT, its application in logistics, and key decision-making and project management frameworks. Section 3 outlines the research methodology, detailing the mixed-methods approach used to analyze technology adoption trends. Section 4 presents the research findings, highlighting insights from expert interviews and data analysis. Finally, Section 5 discusses the implications of the findings and provides strategic recommendations for optimizing innovation diffusion in logistics.

2. Literature review

In today's global economy, digital transformation is essential for maintaining competitiveness, particularly in the logistics sector, which serves as the backbone of global supply chains. As logistics companies strive to improve efficiency, reduce costs, and enhance service quality, the adoption of digital technologies has become increasingly crucial.

Innovation Diffusion Theory (*IDT*), developed by Rogers (1995), provides a valuable framework for understanding how new technologies spread within industries. Many studies have expanded on Rogers' model to explore innovation diffusion across various fields such as business, healthcare, and information management (Wani & Ali, 2015). Rogers (1995) identifies five key attributes – relative advantage, compatibility, complexity, trialability, and observability – that influence the adoption of technologies in logistics. According to IDT, these five key attributes influence the rate at which innovations are adopted (Kaminski, 2011). Technologies that are perceived as advantageous, compatible with existing systems, and easily observable tend to spread more rapidly (Lou & Li, 2017). Rogers also outlines a five-stage adoption process: knowledge, persuasion, decision, implementation, and confirmation (Wani & Ali, 2015).

Innovation Diffusion Theory (*IDT*) *in the Context of Logistics*. In logistics, IDT offers valuable insights into the adoption of digital technologies, guiding organizations through the transformation process. Empirical studies show that logistics firms adopting digital solutions like AI, IoT, and blockchain can improve operational efficiency and customer satisfaction (Ding et al., 2021). Hazen et al. (2014) demonstrate that digital innovations, such as logistics enterprise architecture, enhance supply chain resilience. Kamble et al. (2019) examined the role of early adopters in promoting blockchain-based logistics solutions, focusing on perceived usefulness and organizational readiness. Song et al. (2024) explored technological innovations in supply chain resilience, which aligns with IDT's emphasis on technology adoption and diffusion. Sharma et al. (2024) highlighted that observability and trialability improve logistics managers' willingness to adopt AI and automation technologies. While these technologies offer significant benefits, their adoption is influenced by organizational readiness, market conditions, and technological compatibility (Akram, 2025). Logistics firms adopting digital solutions like AI, IoT, and blockchain can improve operational efficiency and customer satisfaction (Ding et al., 2021). However, barriers such as resistance to change and infrastructure limitations must be addressed (Kaminski, 2011).

The Application of IDT in Logistics Technology Adoption. Rogers' diffusion model has been widely applied to analyze the adoption of digital technologies, especially in complex systems such as those found in logistics, manufacturing, and operations management.

Rogers categorizes adopters into five groups: innovators, early adopters, early majority, late majority, and laggards, each exhibiting distinct characteristics in terms of risk tolerance, willingness to accept change, and reliance on social influences (Bakkabulindi, 2014). Early adopters and opinion leaders play a critical role in accelerating innovation diffusion within organizations (Sanson-Fisher, 2004). Wani and Ali (2015) suggest that firms with proactive innovation strategies are more likely to gain a competitive edge through early adoption. By analyzing adoption patterns of digital innovations in logistics, IDT helps identify barriers and strategies to expedite digital transformation. Technologies like Document Management Systems (DVS), Automated Guided Vehicles (AGV), and Autonomous Mobile Robots (AMR) typically experience adoption through the early adopter and early majority stages, following Rogers' curve. Studies by Leung et al. (2019) show that such technologies gain traction within organizations once their practical benefits become widely recognized.

More complex technologies such as MyDello, Ortec, TPS ABM Cloud, and Artificial Intelligence (AI) generally remain in the early adopter or even innovator stages due to the substantial investment and integration efforts required. Research by Nimmagadda et al. (2018) suggests that AI and similar disruptive technologies face slower adoption rates due to high implementation costs. However, industries with higher technical expertise, such as high-tech and finance, often adopt these technologies first.

Additionally, Geographic Information Systems (GIS) like ESRI/ArcGIS and Business Intelligence tools like Qlik are more likely to enter the early majority phase as organizations seek to improve operational efficiencies and decision-making processes (Côrte-Real et al., 2014).

The role of project management frameworks to gain competitive advantage through the implementation of innovations in Logistics. Project management frameworks play a crucial role in facilitating the adoption of innovations within logistics. Various methodologies, such as Agile, Scrum, Kanban, and Waterfall, provide structured approaches to managing logistics projects effectively. According to Tsai and Tang (2012), structured methodologies accelerate the diffusion of new technologies, while technologies with high uncertainty require adaptive strategies and iterative approaches (Hazen et al., 2014). Furthermore, the continuous use and adaptation of these frameworks are vital for ensuring long-term success in logistics technology implementation (Sumarliah et al., 2023). This aligns with Fichman's (2004) argument that the Innovation Diffusion Theory (IDT) should account for technology assimilation. Agile is an adaptive project management framework that prioritizes flexibility, iterative development, and customer collaboration. Agile methodologies are particularly beneficial in logistics innovation, where market conditions and technological advancements change rapidly. The iterative approach of Agile enables continuous feedback loops and incremental improvements, ensuring that logistics innovations align with evolving industry needs (Schwaber & Sutherland, 2020). Scrum, a subset of Agile, is widely used in logistics to manage complex projects through sprints – short, time-boxed development cycles. Scrum teams operate with defined roles, including a Scrum Master and Product Owner, to ensure clear responsibilities and streamlined decision-making. Logistics firms implement Scrum to enhance warehouse automation, optimize supply chain analytics, and improve route planning efficiency (Schwaber & Sutherland, 2020). Kanban is applied in logistics for inventory management, production scheduling, and transportation planning. By implementing Kanban boards, logistics teams gain real-time visibility into ongoing processes, improving coordination and responsiveness to demand fluctuations (Anderson, 2010). The Waterfall framework follows a sequential, phase-based approach, making it suitable for well-defined logistics projects with minimal uncertainty. Logistics firms use Waterfall for infrastructure development, regulatory compliance initiatives, and large-scale software implementations. The linear nature of Waterfall ensures thorough documentation and risk mitigation but may lack the flexibility required for rapidly changing logistics environments (Turner, 2021). Another critical framework in understanding how methodologies apply to solving logistics innovation challenges is the Stacey Matrix. Developed by Ralph Stacey (2007), this framework helps organizations determine the appropriate project management approach based on the complexity and uncertainty of the problem at hand. The matrix categorizes projects into four zones: simple, complicated, complex, and chaotic. For logistics innovations with high uncertainty, Agile and iterative approaches are recommended, while structured methodologies like Waterfall work better for predictable, low-uncertainty projects (Stacey, 2007).

Effective decision-making is crucial within project management frameworks to ensure successful innovation implementation in logistics. Decision-making processes vary based on the framework used and the complexity of the project. In structured methodologies like Waterfall, decision-making follows a linear and hierarchical approach, where predefined stages and approval checkpoints guide project progress (Turner, 2021). Conversely, Agile and Scrum emphasize decentralized decision-making, empowering teams to make real-time adjustments based on feedback and changing requirements (Schwaber & Sutherland, 2020).

The Increase of Logistics Digitalisattion. The rise of digital transformation has significantly influenced the logistics sector by integrating advanced technologies such as Artificial Intelligence (AI), cloud computing, and the Internet of Things (IoT). These innovations have reshaped the logistics ecosystem, enhancing supply chain visibility, improving predictive analytics, and enabling real-time decision-making (Christopher, 2020). AI-powered logistics solutions play a crucial role in route optimization and demand forecasting, leading to more efficient transportation and resource allocation. Meanwhile, IoT-enabled smart tracking systems improve shipment monitoring and asset management, ensuring real-time visibility of goods in transit (Hazen et al., 2014). Cloud computing further enhances agile project management by fostering collaboration among geographically dispersed teams and streamlining data-driven decision-making (Sumarliah et al., 2023). Blockchain technology is increasingly being integrated into the logistics sector to enhance transparency, reduce fraud, and streamline cross-border transactions (Kshetri, 2018). By enabling secure, decentralized record-keeping, blockchain ensures tamper-proof documentation of shipments, contracts, and payments. This technology helps logistics companies mitigate supply chain disruptions, prevent counterfeiting, and facilitate compliance with international trade regulations. Major logistics firms and freight forwarders are adopting blockchain to improve the traceability of goods, optimize customs processes, and reduce transaction costs (Francisco & Swanson, 2018). Despite its numerous benefits, digital transformation also presents challenges within the logistics ecosystem. Cybersecurity risks, data privacy concerns, and the need for workforce upskilling are among the key issues companies must address (Turner, 2021). Organizations must implement structured project management frameworks to facilitate the seamless adoption of emerging technologies while mitigating these risks. The integration of project management (PM) frameworks with digital transformation initiatives ensures structured and efficient technology adoption. Organizations that successfully leverage Intelligent Digital Transformation (IDT) alongside digital project management methodologies can enhance supply chain resilience, reduce operational costs, and achieve a competitive advantage in the evolving logistics landscape (Hazen et al., 2015). Implementing structured project management approaches ensures smooth adoption and scalability of these technological innovations (Tsai & Tang, 2012).

In conclusion, the application of Innovation Diffusion Theory (IDT) and project management frameworks plays a critical role in the successful adoption of digital technologies in logistics. Project management methodologies, particularly Agile and Scrum, provide the necessary flexibility and iterative processes to ensure the smooth integration of these technologies. By combining IDT with adaptive project management strategies, logistics organizations can improve operational efficiency and gain a competitive advantage in the rapidly evolving digital landscape.

3. Methodology

The research continues to analyse the data obtained from the survey conducted in EU countries in 2025.This study presents a five-stage methodology that systematically pursues the established research goals and objectives (Figure 1).

In the first stage, a questionnaire structure is developed for interviews to assess the impact of technology implementation.

The second stage involves selecting experts for semi-structured interviews – these are C-level executives and senior managers with more than 10 years of experience. These professionals provided valuable insights into the challenges and strategies of digital technology adoption, ensuring the reliability and relevance of the data.

In the third stage, semi-structured interviews are conducted with selected participants, and their responses are collected for further analysis.

In the fourth stage of this study, the correlation matrix method is applied to address the research questions by examining the interdependencies between variables and assessing the strength of their relationships. Both comparative and correlation analysis were utilized to explore these relationships, offering a comprehensive understanding of the data. The correlation matrix serves as a structured representation of Pearson correlation coefficients, quantifying the linear associations between variables. Pearson's correlation coefficient, first

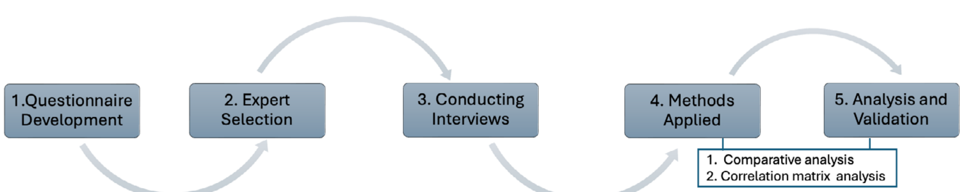

Figure 1. Research methodology stages

mathematically formalized by Pearson (1895), has since been widely used in various fields, including logistics. For instance, Baker and Halim (2007) used correlation matrices to examine the interrelationships between logistics service quality, customer satisfaction, and operational performance. Similarly, other researchers such as Ding et al. (2021), Zhao et al. (2011), and Ailawadi et al. (2001) have applied correlation analysis in logistics to explore interdependencies between organizational factors and logistics performance.

The following are the five research questions for this study:

Q 1. *The better an organization understands its needs and goals* (*ID*), *the better the results achieved in the technology implementation process* (*CC*).

Q2. Properly applied decision-making methods for technology deployment (*IDT*) *contribute to achieving higher technology implementation efficiency* (*CC*).

Q3. Organizational needs and goals (*ID*) *influence the choice of decision-making methods* (*IDT*), *as they determine which methods are most suitable for managing the technology implementation process.*

Q4. The use of the Scrum methodology (*S*) *increases technology implementation efficiency* (*CC*).

Q5. The better the project management methods (*PM*) *are chosen and implemented*, *the more successful the technology implementation* (*CC*) *will be*.

The correlation matrix method is essential for revealing the relationships between these variables. By computing Pearson's correlation coefficients, the study quantifies the strength of linear relationships and identifies potential dependencies. High correlation values indicate a stronger linear relationship, while low or near-zero values suggest minimal or no linear association. Negative correlations signify inverse relationships.

Numerous studies have demonstrated the effectiveness of correlation analysis in logistics. For example, Coyle et al. (2021) used correlation matrices to assess different logistical performance measures, and Gunasekaran and Ngai (2004) explored the role of information technology in logistics using correlation analysis. More recently, Naumenko et al. (2020) studied logistics optimization through technology adoption, applying correlation matrices to explore the relationship between strategies and performance in technology-driven projects.

In this study, the correlation matrix was applied to examine the relationships between digital technologies used in logistics and their implementation processes. This approach helps to identify significant relationships, offering valuable insights into technology adoption patterns and their strategic implications. The mathematical formulation for the Pearson correlation coefficient is given by the Equation:

$$r_{ij} = \frac{\sum\left(\times_i - \overline{\times}\right)\left(Y_j - \overline{Y}\right)}{\sqrt{\sum\left(X_i - \overline{X}\right)^2} \cdot \sqrt{\sum\left(Y_j - \overline{Y}\right)^2}}, \tag{1}$$

where r_{ij} represents the Pearson correlation coefficient between variables X and Y

- Higher correlation values indicate a stronger linear relationship between variables.
- Low or near-zero correlations suggest minimal or no linear association.
- Negative correlations highlight inverse relationships.

The use of EViews enabled a more precise and efficient transformation of the correlation matrix, ensuring a systematic approach to identifying meaningful relationships between digital technologies during the implementation process in logistics. This software facilitated the computation and graphical representation of correlations, enhancing the clarity and interpretability of the results.

Table 1 below provides an overview of the adoption stages of various digital technologies in the logistics sector, categorized by company size (see Appendix). Using Rogers' Diffusion of Innovations model, the Table 1 identifies whether a technology is adopted by innovators, early adopters, the early majority, or the late majority. Technologies such as Artificial Intelligence (AI) and Third-Generation Computed Tomography Security Scanners remain in the innovator or early adopter stage due to their complexity and high implementation costs. On the other hand, more mature technologies like Enterprise Resource Planning (ERP) and Warehouse Management Systems (WMS) have reached the early and late majority stages, indicating broader adoption in large organizations. The study also evaluates the adoption of medium-complexity technologies, such as Document Management Systems (DVS), Automated Guided Vehicles (AGV), Autonomous Mobile Robots (AMR), and Geographic Information Systems (ESRI/ArcGIS). These technologies present manageable challenges for companies. In contrast, the implementation of highly complex technologies like MyDello, Ortec, TPS ABM Cloud, and AI-based solutions requires significant resources due to intricate integration processes.

Table 1. Technology adoption stages by company size in the logistics sector

Adoption Stage	Technology	Company Size
Early Majority	Document Management Systems (DVS)	Small to Medium
Early Majority	Autonomous Mobile Robots (AMR)	Medium to Large
Early Majority	Geographic Information Systems (ESRI/ArcG	Medium to Large
Early Majority	Web-based Self-Invoicing	Small to Medium
Early Majority	Inventory Automation	Small to Large
Early Majority	Digital Integration	Medium to Large
Early Majority	Inventory Management	Medium to Large
Early Majority	Business Intelligence Tools (Qlik)	Medium to Large
Early Adopter / Innovator	MyDello	Medium to Large
Early Adopter / Innovator	Ortec	Medium to Large
Early Adopter	TPS ABM Cloud	Medium to Large
Innovator/Early Adopter	Artificial Intelligence (AI)	Medium to Large
Innovator/Early Adopter	Third-Generation (C3) ComputedTomographj	Large
Early Majority	Routing Solutions	Medium to Large
Early Majority / Late Majority	Warehouse Management Systems (WMS)	Medium to Large
Early Majority	Inventory Management Systems	Medium to Large
Early Majority	OperationalTime-Tracking Software	Medium to Large
Late Majority	SAP	Large
Early Majority/ Late Majority	Automated Guided Vehicles (AGV)	Medium to Large
Early Majority / Late Majority	Enterprise Resource Planning (ERP)	Large

In the fifth and final stage, the comparative analysis and correlation matrix analysis results were evaluated across the selected technologies, offering strong evidence to validate the research criteria.

4. Results

The results section is divided into two parts: the comparative analysis and the correlation analysis, each providing valuable insights into the relationships and differences among the variables under study.

Comparative Analysis of Technological Implementations. The comparative analysis indicates that the study employed the Waterfall methodology, ensuring a structured progression through the design, development, and testing phases. This approach is particularly suited for medium-complexity technological solutions. Consequently, the Waterfall methodology facilitated a systematic project implementation and efficient achievement of results. In contrast, Scrum was applied to more complex technologies.

The majority of the implemented technologies were deployed according to the planned schedule, with the Qlik business plan being executed ahead of expectations. Technologies such as DVS, DI, ESRI/ArcGIS, ERP, operation duration tracking systems, and digital integration were implemented efficiently, with most projects completed within 1 to 2 years. However, the implementation of DI and the web invoice solution was completed significantly earlier than originally planned. Conversely, the deployment of technologies like MyDello, DVS, TPS AMB Cloud, C3, routing solutions, ERP, and operation duration tracking systems faced unforeseen challenges, resulting in deviations from the initial project timelines. Not all phases were executed as originally planned, and for certain technologies such as DVS, AGV/AMR, TPS ABM Cloud, ERP, warehouse management systems, and routing solutions, it was necessary to modify the project trajectory to address these challenges. Surveyed experts identified that the most problematic aspect of implementing MyDello technology was the unexpected increase in development costs. The deployment of ESRI/ArcGIS faced challenges due to the project's large scale and the involvement of multiple stakeholders, which complicated coordination and execution. Additionally, the implementation of the Inventory Automation program encountered communication barriers, largely due to cultural and language differences among the involved stakeholders. The successful implementation of the Qlik program was attributed to strong collaboration with the technology provider, while the successful deployment of SAP was driven by robust business engagement and leadership support. The Inventory Automation program achieved notable success during its pilot phase in Europe, where its effectiveness had already been demonstrated. The successful launch of the DI project was largely influenced by effective communication between technical specialists on both sides, facilitated by comprehensive documentation that both parties could reference. The MyDello project has proven successful in the Baltic States and is now expanding its reach into Sweden, with efforts focused on broadening the service spectrum and offering more customer-centric options. Furthermore, the platform's implementation resulted in economic benefits by reducing human resource costs, as the technology automates a significant portion of tasks (e.g., eliminating the need for staff to send emails by automatically notifying customers of shipment status changes).

Correlation Matrix Analysis results. The correlation analysis was conducted to assess the relationships among the variables CC, ID, IDT, IM, K, PM, S, T, W, and AA. The correlation matrix reveals the strength and direction of the linear relationships between these variables, highlighting both strong and weak connections. The technology was implemented effectively, meeting organizational needs (ID), with decision-making methods applied successfully for efficient technology deployment (IDT). However, the process still needs improvement to enhance results and efficiency (T). Project management methods were critical for successful implementation (PM), and the organization's ability to adapt to changes played a key role in maintaining a competitive advantage (IM). Agile offered flexibility and iterative improvements (A), Scrum optimized the process through short cycles and close team collaboration (S), Kanban streamlined workflow management and task prioritization (K), and Waterfall followed a structured, step-by-step approach with limited flexibility for changes (W).

In Table 2 statistically significant correlations were identified, both positive and negative, indicating meaningful relationships.

Table 2. Key correlation findings

Correlation Probability	CC	ID	K	S
ID	0.40			
	0.09			
IDT	0.50	0.67		
	0.03	0.00		
PM	0.42		–0.53	
	0.07		0.02	
S	0.47	0.39		
	0.04	0.10		
T		–0.73		
		0.00		
W				–0.57
				0.01

Among the strongest positive correlations: IDT and ID ($r = 0.67$, $p = 0.0017$): A significant positive relationship, indicating that an increase in ID tends to correspond with an increase in IDT. CC and ID ($r = 0.40$, $p = 0.09$), CC and IDT ($r = 0.50$, $p = 0.03$), CC and PM ($r = 0.40$, $p = 0.07$), CC and S ($r = 0.47$, $p = 0.04$), ID and S ($r = 0.39$, $p = 0.10$): These correlations suggest that as one of these variables increases, the others also tend to increase, particularly in the case of CC, ID, and S.

The analysis identified significant positive correlations, particularly between Organizational Needs and Goals (ID) and Decision-Making Methods for Technology Deployment (IDT), indicating that an increase in organizational needs corresponds to an improvement in decision-making methods used for technology deployment. Additionally, moderate positive relationships were observed involving Technology Implementation Effectiveness (CC) and Scrum Team Collaboration and Process Optimization (S), suggesting that as one of these variables increases, the other tends to increase as well.

The explanations of the research questions are provided, along with arguments supporting their validity and connection to the research findings.

Q1. The better an organization understands its needs and goals (*ID*), *the better the results achieved in the technology implementation process* (*CC*). The correlation between Organizational Needs and Goals (ID) and Technology Implementation Effectiveness (CC) shows a moderate positive relationship ($r = 0.40$, $p = 0.09$), suggesting that a clearer understanding of organizational needs tends to contribute to more effective technology implementation.

Q2. Properly applied decision-making methods for technology deployment (*IDT*) *contribute to achieving higher technology implementation efficiency* (*CC*).

A significant positive correlation ($r = 0.50$, $p = 0.03$) was identified between Decision-Making Methods for Technology Deployment (IDT) and Technology Implementation Effectiveness (CC), indicating that effective decision-making methods lead to improved technology deployment efficiency.

Q3. Organizational needs and goals (*ID*) *influence the choice of decision-making methods* (*IDT*), *as they determine which methods are most suitable for managing the technology implementation process.*

The positive correlation ($r = 0.67$, $p = 0.0017$) between Organizational Needs and Goals (ID) and Decision-Making Methods for Technology Deployment (IDT) supports this hypothesis, showing that better-defined organizational goals are linked to more suitable decision-making methods in the deployment process.

Q4. The use of the Scrum methodology (*S*) *increases technology implementation efficiency* (*CC*). A moderate positive correlation ($r = 0.47$, $p = 0.04$) between Scrum methodology (S) and Technology Implementation Effectiveness (CC) was found, suggesting that effective use of Scrum increases the efficiency of technology implementation.

Q5. The better the project management methods (*PM*) *are chosen and implemented*, *the more successful the technology implementation* (*CC*) *will be.* The results showed a positive correlation ($r = 0.40$, $p = 0.07$) between Project Management Methods (PM) and Technology Implementation Effectiveness (CC), indicating that the proper selection and implementation of project management methods are linked to better technology deployment outcomes.

Notable negative correlations observed: T and ID ($r = –0.73$, $p = 0.0004$): A strong inverse relationship, where an increase in ID is associated with a decrease in T.

PM and K ($r = –0.53$, $p = 0.02$), W and S ($r = –0.57$, $p = 0.01$): Moderate negative relationships, indicating that as one of these variables increases, the other tends to decrease.

T and IDT ($r = –0.94$, $p < 0.0001$): The strongest inverse correlation, showing a near-perfect negative association between T and IDT. Notable negative correlations were found, including strong inverse relationships between Need for Improvement in Technology Deployment (T) and Organizational Needs and Goals (ID), as well as between Need for Improvement in Technology Deployment (T) and Decision-Making Methods for Technology Deployment (IDT). These findings suggest that as the organizational needs and decision-making methods improve, the need for further improvement in technology deployment decreases.

In conclusion, these findings underscore the importance of project management methods and organizational adaptability in successful technology implementation.

5. Conclusions

This study underscores the critical role of structured decision-making frameworks in advancing the adoption and diffusion of digital technologies within logistics operations. It highlights the necessity of aligning innovation diffusion strategies with robust project management methodologies to ensure successful technology implementation. Integrating IDT with frameworks such as Agile, Scrum, Kanban, Waterfall, and the Stacey Matrix can facilitate smoother technology diffusion. These methodologies help manage complexity, mitigate risks, and align technological adoption with strategic goals. While Agile and Scrum support iterative development in dynamic environments, Waterfall ensures structured execution in more predictable projects. The Stacey Matrix further assists in selecting appropriate approaches based on project complexity and uncertainty. As digital transformation accelerates, logistics firms must adopt adaptive decision-making and stakeholder engagement strategies to maximize technology adoption benefits.

This study introduces a systematic five-stage methodology for analyzing digital technology adoption in the EU logistics sector. By incorporating expert interviews, correlation analysis, and comparative assessments, the research evaluates the key factors influencing implementation success.

The findings reveal the varying complexity of digital technologies, from medium-complexity solutions to more advanced systems. The study stresses the importance of aligning decision-making frameworks – Agile, Scrum, Kanban, and Waterfall – with organizational goals to enhance digital transformation outcomes. By utilizing structured methodologies and statistical validation, the research provides valuable insights into how logistics firms can optimize technology implementation.

The comparative analysis demonstrated that Waterfall was best suited for medium-complexity solutions, ensuring a structured development process. In contrast, Scrum was more effective for complex projects, allowing for flexibility and iterative improvements. Although most technologies were implemented as planned, some projects faced unforeseen challenges, requiring adjustments to project execution.

The correlation analysis emphasized the significance of organizational preparedness and decision-making in successful technology deployment. A strong positive correlation between well-defined organizational needs and effective decision-making highlighted that clear goals lead to better implementation outcomes. Scrum methodology was also linked to higher technology deployment efficiency, underlining the role of agile approaches in enhancing project execution. Notably, negative correlations revealed that improvements in decision-making and planning diminish the need for further enhancements in technology deployment. The study also found that project management methodologies like Waterfall and Scrum are most effective when matched to the project's complexity and flexibility needs.

Despite these valuable contributions, certain limitations persist. The study did not examine the complexity of all technologies in detail, and not all implemented digital solutions within the logistics sector were explored. Furthermore, experts did not provide success factors for every technology, which could limit the generalizability of the findings. Future research could adopt longitudinal or case-study approaches to explore the long-term impact of digital transformation strategies. Further examination of additional decision-making criteria would provide a more comprehensive understanding of how firms can leverage digital technologies for sustained competitive advantage.

This study makes a significant contribution to the discourse on digital innovation in logistics, offering empirical evidence on how structured project management methodologies facilitate technology diffusion. It provides practical insights for firms looking to enhance their digital adoption strategies in an increasingly technology-driven business environment.

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APPENDIX

Table A1. The list of correlations alongside the covariance analysis results

Covariance Analysis: Ordinary
Date: 03/30/25 Time: 11:29
Sample: 1 19
Included observations: 19

Correlation Probability	CC	ID	IDT	IM	K	PM	S	T	W	AA
CC	1.000000									

ID	0.400063	1.000000								
	0.0897	-----								
IDT	0.499939	0.670694	1.000000							
	0.0293	0.0017	-----							
IM	−0.176997	0.025539	0.220174	1.000000						
	0.4685	0.9173	0.3651	-----						
K	−0.200865	−0.158739	0.022630	0.318980	1.000000					
	0.4096	0.5163	0.9267	0.1832	-----					
PM	0.419459	0.147702	0.173958	−0.409401	−0.532501	1.000000				
	0.0738	0.5462	0.4763	0.0817	0.0189	-----				
S	0.465800	0.393410	0.304086	−0.016385	−0.187032	0.553205	1.000000			
	0.0444	0.0956	0.2056	0.9469	0.4433	0.0140	-----			
T	−0.345983	−0.726310	−0.939051	−0.305310	−0.124841	−0.033486	−0.375179	1.000000		
	0.1468	0.0004	0.0000	0.2037	0.6106	0.8918	0.1135	-----		
W	−0.231482	−0.200799	−0.016498	−0.299794	−0.308148	−0.078111	−0.568391	0.102519	1.000000	
	0.3403	0.4098	0.9466	0.2124	0.1993	0.7506	0.0111	0.6762	-----	
AA	−0.081454	−0.074335	−0.253456	−0.004716	−0.164528	0.217057	0.038252	0.331120	−0.233360	1.000000
	0.7403	0.7623	0.2951	0.9847	0.5009	0.3721	0.8764	0.1661	0.3363	-----