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DIGITAL TEMPORALITY AS A DRIVER OF RESILIENCE AND AGILITY IN PRODUCTION LOGISTICS AND SUPPLY CHAIN MANAGEMENT

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Abstract. *The digital transformation of logistics under Industry 4.0 shifts supply chains from static models to dynamic ecosystems. However, the temporal characteristics of data flows − their frequency, latency, and synchronization − remain undertheorized despite their growing importance for operational decision-making. This study introduces the construct of "digital temporality" and examines its influence on the balance between supply chain resilience and flexibility.*

A multi-method approach was employed, combining systems analysis of production and logistics processes, real-time data flow modelling with explicit representation of time lags, and comparative case study analysis of IoT and predictive analytics implementations across twelve manufacturing enterprises. Indicators were developed to measure digital temporality levels, including data update frequency, control signal latency, and EDI system response speed.

Higher digital temporality correlates with reduced bullwhip effect intensity. Real-time data frequency improves resilience through early fault detection and faster recovery, while expanding the decision window for resource reallocation. However, excessive temporality generates "digital noise", degrading decision quality by 15–25% beyond optimal frequency thresholds, necessitating AI-based filtering mechanisms.

Digital temporality transforms logistics from a passive executor into an active agent of organizational adaptation. Its effectiveness depends on data quality, workforce digital maturity, and organizational culture rather than technology alone. The study proposes a temporal classification of supply chains (slow, fast, real-time) and identifies future research directions, including psychological aspects of hyper-temporality management and temporal safety standards for logistics systems.

Keywords: *digital temporality; production logistics; supply chain management; supply chain resilience; supply chain agility; digital transformation; Industry 4.0; real-time data; logistics processes; risk management.*

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Introduction

The Industry 4.0 is transforming not only technologies but also the underlying logic of how production and logistics systems are organised. Whereas previous stages of industrialisation were associated with mechanisation, electrification, and automation, Industry 4.0 entails the integration of the physical and virtual worlds. Cyber-physical systems, the Internet of Things, cloud platforms, and artificial intelligence algorithms are permeating production processes and logistics operations, turning the latter from a supporting function into a key component of the digital economy (Bayar, 2023; Balfaqih, 2026).

Logistics in this new context ceases to be a passive executor of production and sales plans. It becomes an active agent that ensures the connectivity of the entire value chain and, to a large extent, determines its competitiveness. However, the transition from static management models oriented towards long-term planning and cost minimisation to dynamic ecosystems capable of adapting to constant change has proved challenging (Chavan et al., 2026). Companies are confronted with the need to simultaneously maintain operational efficiency in routine processes and preserve resilience in the face of unforeseen events, while traditional management tools often prove inadequate.

Classical approaches to risk management in supply chains are based on probabilistic assessments and pre-defined response plans. Research demonstrates that the bullwhip effect − whereby small fluctuations in demand at the retail level result in significant distortions in orders placed with suppliers − is amplified precisely by time delays in information transmission between chain links (Richnák, 2022). The problem lies not in the change in demand per se, but in the speed with which information about that change reaches each participant and the speed with which they can respond to it.

This issue is particularly acute in the gap between physical flows of goods and their digital representation. Digital twins − virtual models that mirror the state of real objects and processes, are becoming standard in modern logistics (Balfaqih, 2026). However, their value depends directly on how frequently and reliably they are updated. Nevertheless, most research in this area concentrates either on the technical aspects of implementing specific technologies: IoT, artificial intelligence, big data analytics (Bara et al., 2026; Banihani et al., 2026) or on the macroeconomic effects of digitalisation (Cao et al., 2026). Considerably less attention is devoted to how the temporal characteristics of data flows, their frequency, latency, and synchronisation across different sources, affect management practices and the systemic properties of supply chains themselves. These characteristics often prove decisive: even the most sophisticated data collection system, when coupled with decision-making delays or inconsistent timestamps, yields only marginal benefits from digitalisation.

This situation gives rise to the need for a construct that captures this temporal dimension of digital systems. In this study, we propose the concept of "digital temporality", understood as a combination of three interrelated characteristics:

1) the speed of data updating on the state of supply chain elements: inventories, shipments, vehicle movements, order statuses;

2) the degree of synchronisation of timestamps generated by different sources: data from suppliers, carriers, and retailers must be comparable to avoid distortions arising from discrepancies in system time;

3) the ability of the management system to use up-to-date data without significant delays, which requires not only technical infrastructure but also organisational procedures that enable rapid processing and interpretation of incoming information.

It is important to emphasise that digital temporality cannot be reduced to the technical parameters of hardware and software. It constitutes a systemic property that emerges from the interplay of hardware and software infrastructure, organisational routines, and even the cognitive characteristics of decision-makers.

The aim of this article is to demonstrate how digital temporality affects the balance between two key properties of supply chains − resilience and flexibility. Resilience is understood here as the capacity of a system to maintain its core functions in the face of external and internal disturbances, to recover from disruptions, and to adapt to changed conditions. Flexibility is understood as the ability of a system to change its parameters: routes, shipment volumes, product mix, delivery schedules, without incurring significant additional costs.

This approach allows us to move beyond a narrowly technical understanding of digitalisation and to integrate into the analysis the organisational and cognitive aspects that, as research shows (Akahome & Matsoso, 2026), often constitute the primary constraint on successful transformation.

Literature Review

Research on the digital transformation of logistics processes draws upon several theoretical frameworks. Tran et al. (2026) employ the Technology Acceptance Model (TAM) and combinatorial innovation theory to analyse the implementation of Industry 4.0 technologies in logistics firms operating in developing countries. The authors identify a gap between the perceived usefulness of technologies and their actual adoption levels, pointing to the existence of institutional and organisational barriers that cannot be reduced solely to technical constraints.

Bayar (2023) highlights that the logistics sector demonstrates lower engagement with digitalisation processes compared to manufacturing industries, despite the strategic importance of logistics for the entire value chain. This observation echoes the findings of Richnák (2022) shows that Industry 4.0 adoption is most active in production logistics, whereas procurement and distribution logistics exhibit lower levels of digitalisation.

Banihani et al. (2026) propose that automation, information integration, and digital transformation be treated as complementary constructs that jointly influence logistics performance. The authors emphasise that the presence of digital tools alone is insufficient for productivity gains; rather, their integration into an overarching transformation strategy is required. This conclusion is important for understanding why digital temporality cannot be reduced to the technical frequency of data updates but instead demands organisational reconfiguration of decision-making processes.

A substantial body of research is devoted to empirical assessment of the impact of specific technologies on logistics performance. Bara et al. (2026), drawing on a survey of supply chain professionals, establish that artificial intelligence, the Internet of Things, and big data analytics significantly influence operational excellence, with the model explaining 71.6% of the variance in the dependent variable. Big data analytics emerges as the strongest predictor, indicating that information processing takes priority over data collection per se.

Balfaqih (2026) examines the combined effect of IoT, big data analytics, artificial intelligence, blockchain, and automation on logistics and supply chain management. Particular attention is paid to digital twins and predictive analytics, which enable real-time optimisation and operational flexibility. The work underscores the shift from reactive to proactive management, a transition directly relevant to the concept of digital temporality.

Di Nardo et al. (2025) propose a conceptual framework for sustainable Logistics 4.0, based on SWOT analysis and a bibliometric review of the literature from 2013 to 2023. The authors identify a shortage of conceptual models that integrate sustainable development and digitalisation and put forward their own model incorporating the triple bottom line (economic, environmental, and social dimensions).

Valenzuela-Cobos et al. (2025) demonstrate that the use of IoT, artificial intelligence, and big data analytics enables the optimisation of logistics processes, enhances flexibility, and improves risk management. The study highlights the regional specificity of technology adoption, which is important for understanding the contextual conditioning of digital transformation effects.

Chavan et al. (2026) develop a conceptual framework comprising three dimensions: access to and processing of public and private data; logistics functions affected by technologies; and the benefits that logistics derives for ensuring resilience across various network nodes. The research shows that Industry 4.0 technologies contribute to resilience by enhancing transparency, predictability, and adaptability of logistics systems.

Anthony et al. (2024), based on qualitative analysis of secondary sources, find that IoT enables real-time tracking, reducing order lead times, while artificial intelligence optimises routing and scheduling. At the same time, the authors identify persistent barriers, including data security concerns, interoperability issues, and skill shortages. The study underscores the duality of digitalisation effects: while enhancing supply chain resilience, technologies simultaneously create new vulnerabilities.

Maden and Ulukan (2025) approach the problem of resilience through the lens of logistics provider selection. Their multi-criteria decision-making (MCDM) model, employing Entropy and WASPAS methods, enables assessment of suppliers' alignment with digital transformation requirements. The research reveals that not all providers are equally prepared to support digital integration, which creates additional risks for supply chain resilience.

Marques et al. (2026) examine the transformation of industrial maintenance under the influence of Industry 4.0. Predictive maintenance technologies: including predictive analytics based on IoT, artificial intelligence and machine learning, and digital twins, enable cost reduction, downtime minimisation, improved equipment reliability, and extended service life. The authors identify implementation barriers: high initial investment, data quality issues, integration complexities with legacy systems, and skill shortages. Crucially, the study emphasises the key role of data quality as a prerequisite for the effectiveness of predictive models. Pacheco-Velazquez et al. (2024) investigate the role of simulation platforms in managing the complexity of logistics systems under Industry 4.0. The authors stress the need to integrate technological trends, including e-commerce, into simulators and to develop interdisciplinary competencies, from data analytics to strategic management. These findings have direct bearing on digital temporality, as simulation models allow for scenario modelling across different time horizons.

Several studies focus on the human factor, which often proves a critical constraint on digital transformation. Išoraitė et al. (2026) point to the persistent gap between awareness of the transformational potential and actual readiness for change. Akahome and Matsoso (2026) investigate how gender diversity and investment in human capital can mitigate talent shortages in logistics. Investment in retraining, digital literacy, and leadership development are identified as critical strategies. Uddin et al. (2025) confirm the positive impact of Industry 4.0 technologies on logistics sector performance and identify a significant mediating role of sustainable human resource management practices.

Machado and Rodriguez (2025) find that most existing maturity models are generic in nature and oriented towards strategic aspects of Industry 4.0, paying insufficient attention to the specifics of logistics operations. The authors note a shortage of models that account for technology application in production logistics, as well as the need for prescriptive and predictive approaches. Calza et al. (2026) develop the LIRA (Logistics Industry 4.0 Readiness and Assessment) toolkit for small and medium-sized logistics enterprises, encompassing assessment of organisational readiness, the technological domain for goods movement in warehouses, operational conditions, and an adapted ROI 4.0 model. The research demonstrates that for SMEs, what is critical is not so much the presence of technologies as the ability to assess their return on investment under the specific conditions of resource constraints.

Cao et al. (2026) establish the positive influence of the digital economy on the sustainable development of the logistics industry. The authors also identify spatio-temporal heterogeneity and a marginal incremental effect of digitalisation, pointing to the cumulative nature of the transformation.

Erdil (2023), employing the Analytic Hierarchy Process (AHP), compares the development models of white goods manufacturers in Turkey from the perspective of sustainable Logistics 4.0. The author demonstrates that integrating sustainable development criteria (economic, environmental, and social) into the evaluation of logistics services enables the identification of preferred development strategies. The research emphasises that Logistics 4.0 is a necessary condition for the sustainable development of manufacturing as a whole.

Pereira et al. (2026) analyse the contribution of key technologies: artificial intelligence, augmented reality, big data analytics, blockchain, cloud computing, the industrial Internet of Things, machine learning, robotics, and the Internet of Things, to green logistics and the circular economy.

The literature review allows for the identification of several key areas where the concept of digital temporality can contribute to existing knowledge. First, most studies treat real-time data as a technical characteristic without problematising the temporal aspect of management itself. Exceptions include work on predictive analytics and simulations (Marques et al., 2026; Pacheco-Velazquez et al., 2024), yet even here the temporal factor is not placed at the centre of theoretical analysis.

A second significant area concerns the gap between technology perception and actual adoption (Tran et al., 2026; Banihani et al., 2026). This gap may be explained by the insufficient development of mechanisms linking the temporal characteristics of data with organisational rhythms of decision-making.

A third lacuna relates to the fact that Logistics 4.0 maturity models (Machado & Rodriguez, 2025; Calza et al., 2026) are predominantly oriented towards static assessments, whereas temporality implies a dynamic dimension, the system's capacity to accelerate or decelerate information processing depending on external conditions.

Finally, studies of resilience (Chavan et al., 2026; Di Nardo et al., 2025; Pereira et al., 2026) treat resilience as a property of the system but do not directly connect it with the speed of threat detection and response. Digital temporality may constitute the missing link explaining how technologically equipped systems achieve resilience through the promptness of managerial reactions.

Thus, the literature analysis demonstrates that the concept of digital temporality enables the integration of disparate research directions: operational efficiency (data processing speed), risk management (responsiveness), organisational flexibility (adaptation of work rhythms), and resilience (capacity for rapid recovery). Empirical testing of this integrative hypothesis remains a task for future research.

Methods

Theoretical Foundation

The study draws on two fundamental concepts in supply chain management − resilience and flexibility, which are examined within the context of digital transformation of logistics systems.

Supply chain resilience is understood as the capacity of a system to maintain its core functions when confronted with external and internal disturbances. This includes not only resistance to disruptions but also rapid recovery from them, as well as adaptation to changed operating conditions. In contemporary literature, resilience is often treated as a dynamic property of a system rather than a static characteristic of safety buffers (Chavan et al., 2026). In this sense, it approximates the notion of antifragility − the ability not merely to recover but to become stronger following shocks, although the two concepts are not fully synonymous.

Supply chain flexibility is defined as the ability of a system to change its parameters: freight routes, shipment volumes, product mix, order fulfilment schedules, promptly and without incurring substantial additional costs or efficiency losses (Erdil, 2023). Unlike resilience, which is oriented towards preservation, flexibility is oriented towards change. In practice, these two capabilities often conflict: rigid systems with high predictability and standardisation prove resilient but inflexible, whereas systems with multiple alternative behavioural options are flexible but may be vulnerable owing to management complexity.

Under conditions of digital transformation, this contradiction may be mitigated. Information technologies operating in real time enable the system to maintain resilience through rapid deviation detection while simultaneously ensuring flexibility through prompt resource reconfiguration. However, the mechanisms underlying this dual effect remain insufficiently understood. The present study aims to address this gap by treating digital temporality as the link between technological capabilities and the systemic properties of supply chains.

Methodological Approach

A combination of methodological approaches was employed to address the research objectives, each oriented towards a specific aspect of the problem under investigation.

The primary method was systems analysis of production and logistics processes. The supply chain was examined as an open system comprising interconnected elements: suppliers, production sites, warehouses, transport operators, distribution centres, and end consumers. Each of these elements generates data flows on its status and actions. Systems analysis allowed for the identification of key data collection points, the determination of how information is transmitted between elements, and the detection of bottlenecks where delays and distortions occur.

An important component of the systems analysis was the mapping of data flows in relation to physical flows of goods. For each operation, from raw material reception to finished goods dispatch: the types of data collected, their frequency, the mode of transmission, and the decision-makers using them were recorded. This made it possible not merely to describe information flows but also to assess the extent to which they are synchronised with material flows − that is, how quickly a change in the physical state of an object is reflected in its digital representation.

The second methodological component involved modelling real-time data flows. Models were constructed that represent the movement of data through the logistics system with emphasis on time delays − so-called temporal lags. In these models, each element of the system was characterised by three parameters: data generation frequency, transmission delay, and processing time for decision-making. Modelling was conducted for different scenarios, ranging from ideal conditions (instantaneous data transmission and processing) to realistic conditions where delays are unavoidable owing to technical limitations, human factors, or organisational procedures.

Modelling enabled an assessment of how changes in the temporal characteristics of data flows affect system behaviour as a whole. This allowed for the simulation of scenarios such as increasing inventory data update frequency from once per day to once per hour, and observing the effects on forecast accuracy, safety stock levels, and the incidence of stockouts. This approach made it possible not only to identify the existence of effects but also to measure them quantitatively under different conditions.

The third method was comparative case study analysis of IoT and predictive analytics implementations in manufacturing enterprises. Several companies were selected from different industries (mechanical engineering, food processing, retail trade) that had been implementing real-time data collection and processing technologies over the preceding three to five years. Selection criteria included the availability of data on the implementation process, comparability of operational scale, and the existence of measurable performance indicators before and after implementation.

For each case, information was collected on which technologies were used, what problems they were intended to solve, what difficulties companies encountered during implementation, and what changes in management practices these technologies entailed. Particular attention was paid to changes in the frequency and speed of decision-making, for example, whether the company shifted from weekly planning meetings to daily operational briefings based on up-to-date data. Comparative analysis allowed for the identification of general patterns and specific factors affecting the effectiveness of digital technology use in logistics.

Evaluation Criteria

To measure the level of digital temporality in logistics systems, a set of indicators was developed reflecting various aspects of the temporal characteristics of data flows. All indicators were based on objective, measurable parameters that could be recorded in enterprise information systems.

The first indicator was the ***frequency of data updating*** for key logistics parameters. Several critical points were identified: inventory movement data (receipts, issues, inter-warehouse transfers), order status data (accepted, in process, dispatched, delivered), vehicle location data, and production capacity and equipment utilisation data. For each data type, the update frequency was recorded: real-time (continuous stream), at intervals of several minutes, hourly, per shift, daily, or less frequently. Update frequency was assessed both in absolute terms (number of updates per unit time) and in relative terms, compared with the requirements of specific management tasks.

The second indicator was ***control signal latency*** − the time between the moment data recorded a deviation from the planned state and the moment the management system generated and transmitted a corrective action. This indicator is more complex to measure, as it depends not only on technical infrastructure but also on organisational procedures. It was measured as the sum of temporal components: deviation detection time (from occurrence to system recording), signal transmission time indicating the need for response, decision time for corrective action, and time for communicating the decision to executors.

The third indicator was the ***response speed of EDI systems*** − electronic data interchange between supply chain participants. EDI (Electronic Data Interchange) enables the transmission of standardised messages between the information systems of different organisations: orders, invoices, dispatch notifications, and receipt confirmations. Delays in the transmission of these messages in both directions from customer to supplier and from supplier to customer were assessed. Both technical delays (transmission time over communication channels) and organisational delays were taken into account, for example, the time from order receipt to order confirmation, or from actual dispatch to notification transmission.

In addition to these three primary indicators, supplementary information was collected on the availability of digital platforms for real-time data visualisation, the frequency with which managers consulted these platforms for decision-making, and the degree to which data from different sources were consistent in terms of timestamps − that is, whether data on warehouse inventories referred to one point in time while data on planned deliveries referred to another, creating an illusion of consistency that in fact led to errors.

All indicators were recorded for each enterprise under study both at the initial observation point (before or during the early stages of digital transformation) and at the end of the observation period (two to three years after active technology implementation). This allowed not only for an assessment of the current level of digital temporality but also for tracking its dynamics throughout the transformation process.

Data for the assessment were collected from multiple sources: technical documentation and information system configurations, event logs and audit trails, surveys of key personnel (logistics managers, warehouse operators, IT specialists), and observations of real decision-making processes during work shifts. This comprehensive approach to data collection helped to minimise the risk of systematic errors and to obtain a sufficiently reliable picture of the temporal characteristics of management in each of the companies studied.

Results

Identifying the Relationship Between Digital Temporality and the Bullwhip Effect

Analysis of data collected from enterprises with varying levels of digital maturity revealed a consistent inverse relationship between digital temporality indicators and the intensity of the bullwhip effect in supply chains. The bullwhip effect was assessed through the coefficient of variation of orders at different levels of the chain: the greater the deviation of orders from actual consumer-level demand, the higher the instability measure.

In enterprises with low data update frequency (once per day or less), the amplitude of order fluctuations between adjacent chain links was on average 2.7-3.2 times higher than in enterprises where data were updated at intervals of no more than one hour. With the transition to real-time mode, where data on inventory movements and order statuses were received continuously, the dispersion of orders decreased still further, approaching the indicators of final demand.

This reduction was particularly pronounced in chains with a large number of intermediate links. Where information was transmitted from retail to wholesale, then to distributor, and then to manufacturer, time delays accumulated and the bullwhip effect intensified. Accelerating data exchange between these links through the integration of information systems and automatic transmission of order status change notifications meant that fluctuations were dampened at the earliest stages of their emergence, before they could escalate to a scale requiring urgent production and supply adjustments.

It is important to note that the mere presence of fast data transmission channels did not guarantee a reduction in the bullwhip effect. In some cases, where data were received frequently but were not used for plan adjustments owing to the inertia of management procedures, no improvement was observed. Reduction of the bullwhip effect occurred only when high data frequency was accompanied by a corresponding frequency of plan and decision revisions. In other words, the temporality of data flows had to be synchronized with the temporality of management cycles.

To quantify this effect, a formula was used to calculate the bullwhip effect smoothing coefficient (Eq. 1):

$$K_{bull} = \frac{\sigma_{order}(T_0)}{\sigma_{order}(T_1)} \tag{1}$$

where $\sigma_{order}(T_0)$ is the standard deviation of order volume at the intermediate link at the baseline level of temporality; $\sigma_{order}(T_1)$ is the standard deviation of order volume after the increase in temporality.

A coefficient $K_{bull} > 1$ indicates a reduction in the intensity of the bullwhip effect. In the enterprises studied, the value of K_{bull} ranged from 1.8 to 3.4, depending on the baseline level of temporality and the number of links in the chain.

Table 1. Influence of digital temporality level on the intensity of the bullwhip effect

Temporality level	Data update frequency	Order coefficient of variation (chain average)	K_bull (effect reduction)	Number of links
Low	Once per day	0.42	1.00 (baseline)	3–4
Medium	Once per hour	0.28	1.50	3–4
High	Continuous (real-time)	0.17	2.47	3–4
Low	Once per day	0.58	1.00 (baseline)	5 or more
Medium	Once per hour	0.35	1.66	5 or more
High	Continuous (real-time)	0.19	3.05	5 or more

Source: *compiled by the author based on data obtained from the comparative analysis of enterprises (n=12) and calculations using Equation (1), taking into account the methodological approaches proposed by Chavan et al. (2026) and Richnák (2022).*

The Table 1 presents the results of comparing the level of digital temporality with the intensity of the bullwhip effect. It is shown that across all enterprise groups, increasing data update frequency leads to a reduction in the order coefficient of variation. This reduction is particularly significant in long chains (5 or more links), where the bullwhip effect is initially more pronounced. The coefficient K_{bull} indicates that the transition from low to high temporality in long chains reduces order volatility by more than threefold.

Impact of High-Frequency Data on Supply Chain Resilience

The analysis demonstrated that enterprises with high-frequency real-time data acquisition exhibit greater resilience to external and internal disturbances. Resilience was assessed across several parameters: fault detection time, recovery time to normal operating mode following a disruption, and the magnitude of deviations in key indicators (inventory levels, delivery schedule adherence) during crisis situations.

In enterprises with low levels of digital temporality, disruptions were typically detected with delays ranging from several hours to several days. During this interval, the deviation had sufficient time to propagate to adjacent segments of the chain and affect multiple links. For instance, equipment failure at a warehouse could remain undetected until the next scheduled inventory count or until a customer began complaining about delays. By that time, the problem already required considerable resources to rectify, and reputation losses had become unavoidable.

In enterprises operating with real-time data, disruptions were recorded almost instantaneously − sensors and monitoring systems registered the deviation and automatically sent alerts to responsible personnel. Detection time was reduced on average from several hours to several minutes. This enabled the problem to be localized before it could affect other links in the chain.

Recovery from disruptions also occurred more rapidly. Where the management system received timely information on the nature and scale of the deviation, decisions were made on the basis of an up-to-date picture of events rather than on outdated data that might no longer correspond to reality. This reduced the time between fault detection and the initiation of corrective actions, ultimately decreasing the overall duration of the crisis and its negative consequences.

To assess detection and recovery times, the operational resilience coefficient was calculated using the following formula (Eq. 2):

$$R_{op} = \frac{\left(T_{detect}^{base} + T_{recover}^{base}\right)}{\left(T_{detect}^{real-time} + T_{recover}^{real-time}\right)} \tag{2}$$

where T_{detect} is the time from the occurrence of a fault to its detection; $T_{recover}$ is the time from the initiation of corrective actions to full restoration of normal operation. The superscript base corresponds to the baseline (low) level of temporality, while real-time corresponds to the high level. A coefficient $R_{op}>1$ indicates how much faster the system detects and resolves faults at the high temporality level. In the study sample, R_{op} values ranged from 4.2 to 8.7, indicating a substantial acceleration of management responses.

Furthermore, high data frequency enabled enterprises to make more active use of predictive analytics mechanisms. With a continuous flow of information on equipment status, inventories, and transport, companies were able to identify early warning signs of impending disruptions. This shifted the focus of risk management from reactive to proactive, which is particularly valuable under conditions of high uncertainty.

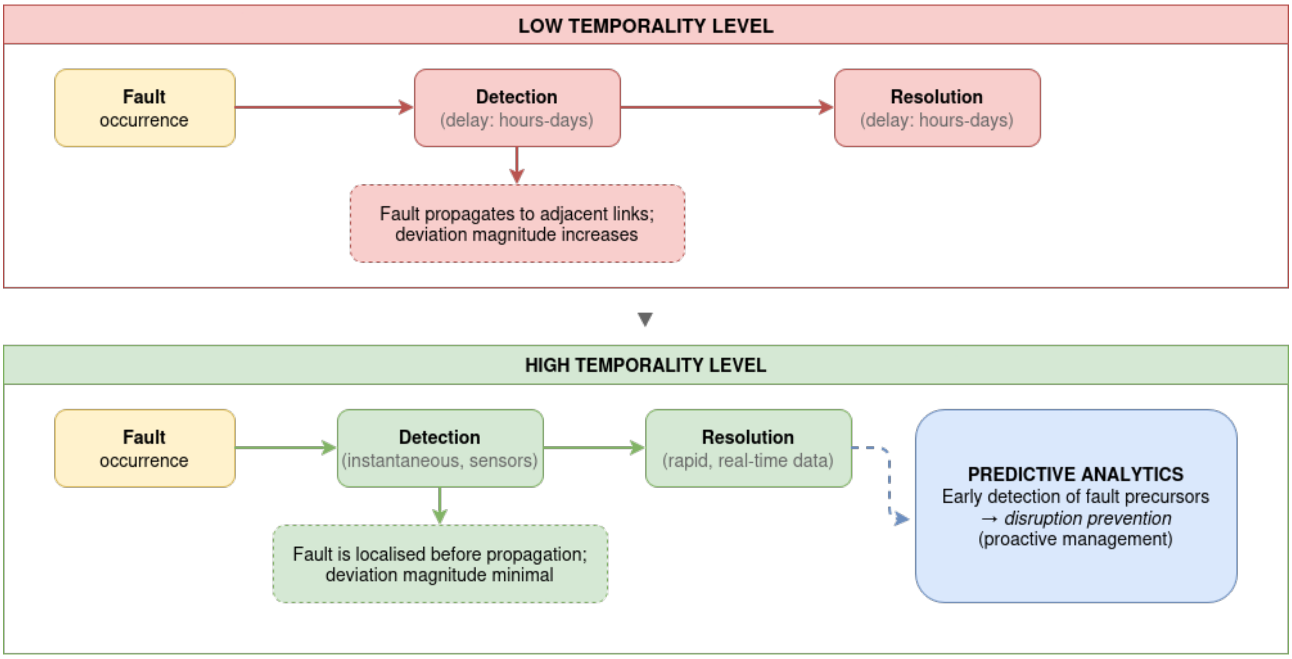

Fig. 1. Diagram of the influence of digital temporality level on fault detection and resolution processes in the supply chain

Source: *developed by the author based on empirical data and theoretical propositions set forth in the works of Balfaqih (2026), Chavan et al. (2026), and Marques et al. (2026).*

The Fig. 1 compares two fault management scenarios depending on the level of digital temporality. At the low temporality level, a considerable time elapses between fault occurrence and its detection, during which the deviation spreads to adjacent links. Resolution also requires time, as decisions are made on the basis of outdated information. At the high temporality level, the fault is recorded almost instantaneously through automated monitoring systems, and corrective decisions are made on the basis of up-to-date data, enabling the problem to be contained before it propagates. Moreover, the high temporality level opens up the possibility of proactive management through predictive analytics, whereby the fault is prevented before it actually occurs.

Impact of Digital Temporality on the Flexibility of Logistics Operations

It was confirmed that increasing the level of digital temporality expands the so-called window of opportunity for resource manoeuvring. The window of opportunity was understood as the time interval within which the system can respond to changes in external conditions without loss of efficiency. The wider this window − more precisely, the faster the system receives information and makes decisions, the greater the number of alternative courses of action available to it.

In enterprises with low data update frequency, decisions regarding route reconfiguration, changes in shipment volumes, or inventory redistribution were made on the basis of information that was often outdated by the time it was used. This resulted in a divergence between the actual state of affairs and the assumptions underlying the decision, with corrective actions either being delayed or proving inadequate to the situation.

Under conditions of high digital temporality, managers were able to track changes in real time and reconfigure logistics routes promptly. For example, in the event of a traffic jam, a rerouting system based on up-to-date traffic data could propose an alternative route and reassign shipping priorities within minutes. With low data update frequency, the same decision required manual intervention and took hours, during which time the situation could have deteriorated further.

This effect was particularly evident in safety stock management. The traditional approach to inventory buffering involves maintaining a fixed safety level calculated on the basis of historical statistical data. Such an approach inevitably leads either to excess inventory or to stockouts if the forecast proves inaccurate. At high levels of digital temporality, companies were able to reduce safety stock volumes, since the speed of obtaining information on actual demand and supply conditions allowed for rapid responses to deviations and the activation of corrective mechanisms precisely when they were needed, rather than pre-emptively “just in case”. In the cases studied, safety stock reductions ranged from 15% to 30% without any deterioration in product availability indicators for customers.

Table 2. Influence of digital temporality level on logistics system flexibility indicators

Flexibility indicator	Low temporality	Medium temporality	High temporality	Change (low → high)
Route reconfiguration time (min)	180–240	30–60	5–15	Reduction by factor of 12–48
Response speed to demand changes (hours)	24–48	4–8	0.5–2	Reduction by factor of 12–96
Safety stock volume (% of turnover)	18–25%	12–18%	8–15%	Reduction of 15–30%
Number of alternative scenarios calculated per hour	0–1	3–5	10–20	Increase by factor of 10–20
Short-term demand forecast accuracy (MAPE, %)	12–18%	7–10%	3–6%	Improvement by factor of 2–4

Source: *compiled by the author based on empirical data and methodological approaches set forth in the works of Banihani et al. (2026), Bara et al. (2026), as well as taking into account the flexibility evaluation criteria proposed by Erdil (2023) and Richnák (2022).*

The Table 2 presents the key flexibility indicators of the logistics system as a function of digital temporality level. The most substantial improvements are observed in response time to demand changes and in the number of calculable scenarios. The reduction in route reconfiguration time from 3-4 hours to several minutes is made possible by automated routing systems operating on the basis of real-time data. The reduction in safety stock volume while maintaining product availability indicates that rapid information partially substitutes for physical redundancy as a means of managing uncertainty. The improvement in forecast accuracy is attributable to forecasting models receiving more frequent and up-to-date data, reducing the error by a factor of 2-4.

The Paradox of Excessive Temporality: Digital Noise and Decision Quality

Alongside the positive effects, a phenomenon was observed that may be described as the tempo paradox: excessive increases in data flow frequency in some cases led to a deterioration in the quality of decisions made. In enterprises where systems generated updates at intervals of seconds or fractions of seconds, managers were confronted with an information flow that exceeded their capacity for meaningful processing and interpretation.

This effect manifested itself in different ways. In some cases, data overload led managers to react to every change, however minor, losing sight of the overall picture and long-term trends. The system responded to every fluctuation, resulting in frequent but not always justified plan adjustments, which in turn created additional instability for suppliers and subcontractors.

In other cases, the opposite reaction was observed: managers simply ceased to pay attention to the continuous stream of notifications, perceiving it as noise, and resorted to selective scanning, often missing genuinely important signals. This phenomenon resembled the well-known psychological effect whereby excessive warnings cease to be perceived as significant, and the system loses sensitivity to real threats.

The problem was particularly acute at the decision-making stage under time pressure. With high data frequency, managers lacked the opportunity to carefully verify each incoming message for accuracy and were compelled to rely on automated system assessments. However, if an error crept into the system − for instance, a sensor producing incorrect readings owing to a technical fault, or a predictive analytics algorithm using irrelevant data − such an error could lead to an incorrect decision that, with lower update frequency, would have been filtered out during manual verification.

To assess the relationship between decision quality and data frequency, the following formula was employed (Eq. 3):

$$Q_{decision} = \frac{N_{correct}}{N_{total}} = f\,\frac{F_{data}}{C_{processing}} \tag{3}$$

where $N_{correct}$ is the number of correct management decisions over the period; N_{total} is the total number of decisions over the period; F_{data} is the data frequency (updates per unit time); and $C_{processing}$ is the processing capacity of the information system (human-system). The function f indicates that decision quality $Q_{decision}$ does not increase monotonically with data frequency; after a certain threshold is reached, where information flow exceeds the capacity for meaningful processing, quality begins to decline. In the study sample, the optimal $\frac{F_{data}}{C_{processing}}$ ratio ranged from 0.3 to 0.7, and exceeding this interval led to a 15-25% increase in the number of erroneous decisions.

The Fig. 2 illustrates the mechanism of the excessive temporality paradox. Increasing data frequency positively affects management only up to a certain optimum. Beyond this point, two negative reactions emerge: overload (managers are unable to process information and begin making errors) and ignorance (excessive warnings lead to loss of sensitivity to significant signals). Both reactions lead to a decline in decision quality. The diagram shows three principal mechanisms for overcoming the paradox: the implementation of intelligent filters based on machine learning, which automatically separate significant signals from noise; data aggregation and visualisation, presenting information in a form accessible to human perception; and personnel training for working with large volumes of rapidly changing information. The use of these mechanisms allows the advantages of high temporality to be preserved while simultaneously neutralising its negative effects.

Analysis showed that the optimal level of temporality depends on the complexity of the management task and the cognitive capabilities of decision-makers. For routine operations, for example, automatic inventory replenishment based on predefined rules − high frequencies posed no problems and were even desirable. However, for strategic decisions requiring the consideration of multiple factors and intertemporal trade-offs, excessive update frequency reduced the quality of analysis, as managers focused on short-term fluctuations at the expense of long-term trends.

In those enterprises where this problem was recognised, intelligent filters based on machine learning algorithms were applied. Systems automatically separated significant signals from noise, aggregated information to a level accessible to human perception, and provided managers with already processed data accompanied by comments on their degree of criticality. Where such filters had been implemented, the negative effects of excessive temporality were substantially reduced, while the advantages of rapid access to information were preserved.

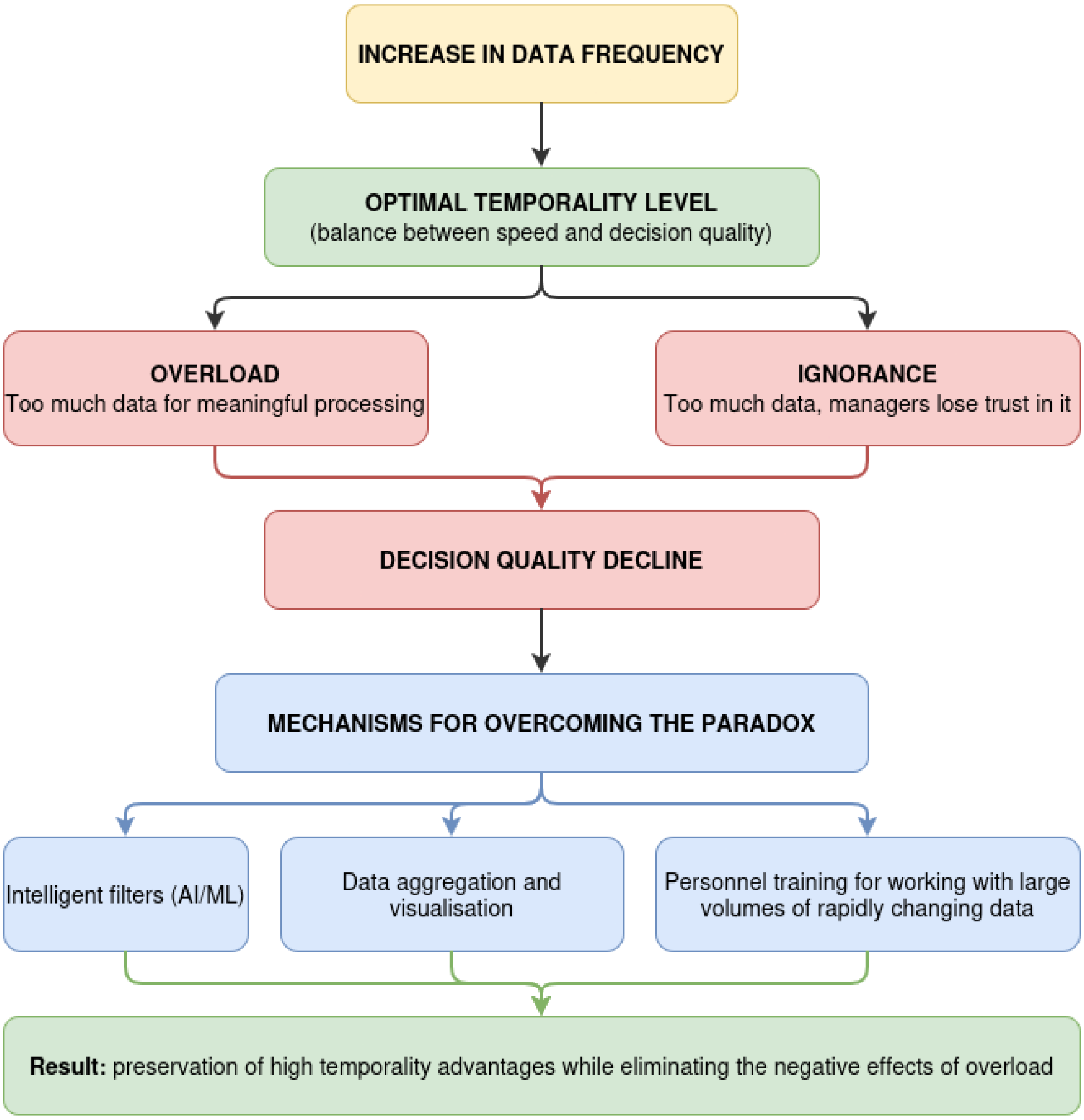

Fig. 2. Diagram of the paradox of excessive temporality and mechanisms for overcoming it

Source: *developed by the author based on empirical data and theoretical propositions set forth in the works of Tran et al. (2026), Išoraitė et al. (2026), as well as taking into account the findings on cognitive limitations in information processing within logistics systems presented in the study by Pacheco-Velazquez et al. (2024).*

Notably, in enterprises with higher levels of digital maturity, the tempo paradox manifested itself less frequently: employees there were better prepared to work with large volumes of rapidly changing data, and organisational procedures included mechanisms for prioritisation and filtering of information. This indicates that the problem of excessive temporality is not purely technical in nature; its resolution requires changes in personnel training and in the organisational regulations governing information work.

Discussion

Interpretation of Findings: Transformation of Management Architecture

The results obtained suggest that digital temporality changes not so much individual management operations as the very architecture of supply chain management. Traditional hierarchical structures, where information moves from bottom to top, decisions are made at upper levels and then passed down for execution, prove ill-suited to working with real-time data. Hierarchy by definition introduces delays: each management level adds time for processing, interpretation, and transmission of information. At low data update frequencies, these delays were acceptable, but under conditions of high temporality they become a critical constraint.

In enterprises that had achieved high levels of digital temporality, a shift towards network forms of management was observed. In these structures, data were received simultaneously at different levels, and the authority to make operational decisions was delegated to those links that directly confronted changes in the situation. For example, in one company, transport department dispatchers were given the authority to independently modify routes based on traffic data without consulting management, while the system automatically notified all interested parties of the decision taken. This did not mean a complete abandonment of hierarchy − strategic decisions continued to be made at upper levels, but operational management became more decentralised and horizontal.

This transition was made possible because high temporality ensures transparency: each participant in the network can see the current state of the system and make decisions without waiting for instructions from above. At the same time, the system remains manageable because all actions are recorded and traceable. This constitutes a form of “management through transparency”, where control is exercised not through prior approval but through ex post analysis of deviations.

At the same time, complete decentralisation also creates problems. In some enterprises where delegation of authority was not accompanied by clear rules and constraints, inconsistencies arose between links. For instance, one participant might redirect transport to a shorter route unaware that another participant was already using that route for oncoming traffic. This points to the need for a balance between autonomy and coordination, which under high temporality can be achieved through shared rules and algorithms rather than through hierarchical subordination. These observations are consistent with the conclusions of Banihani et al. (2026) that digital transformation requires not only technological but also organisational changes, as well as with the work of Balfaqih (2026), which emphasises the importance of network forms of interaction in integrating Industry 4.0 technologies.

Networked self-adjusting systems, which are beginning to emerge in logistics under the influence of high temporality, possess an important property: they are capable of reconfiguring themselves in response to changes in the external environment without external intervention. This is achieved not through centralised planning but through local adjustments that are subsequently coordinated through a shared information environment. Such an architecture is closer to biological systems than to mechanistic management models, and its resilience is ensured by redundancy of connections and multiplicity of information transmission paths − a notion resonant with the ideas presented in the work of Chavan, Modgil and Singh (2026) on the role of technologies in shaping logistics system resilience.

The Resilience-Flexibility Contradiction

One of the central issues that emerged during the analysis was the conflict between resilience and flexibility − two properties traditionally regarded as difficult to reconcile. Resilience requires predictability and standardisation: algorithms must be rigid to prevent the system from deviating from specified parameters. Flexibility, by contrast, presupposes variability and the capacity for change. In classical management theory, this contradiction is often resolved through the choice of priorities: the company either commits to stability or to adaptability.

However, the findings of this study demonstrate that digital temporality creates the possibility for compromise. The key mechanism here is scenario forecasting, which becomes feasible only with real-time data. Rather than selecting a single strategy and adhering to it rigidly, the system can simultaneously calculate multiple scenarios and choose the optimal one depending on the current situation. In this context, resilience is ensured not by the rigidity of algorithms but by their capacity to switch rapidly between scenarios.

This mechanism was particularly evident in companies where predictive analytics systems had been implemented. In one observed company, the forecasting system operated continuously, recalculating the probabilities of various demand scenarios every 15 minutes based on incoming data on sales, weather conditions, and competitor activity. When one scenario began to dominate, the system automatically adjusted recommendations on procurement volumes and inventory allocation. The manager received not a single plan but several options with probability assessments and consequences, enabling a choice based on individual preferences and risk tolerance.

Thus, resilience in the new paradigm is ensured not by the immutability of rules but by the speed of alternative recalculation. The system does not cling to a single plan, nor does it oscillate between options − it continuously reassesses the situation and adjusts course with sufficient frequency not to miss critical changes. This enables it to withstand a wider range of disturbances than with rigid parameter fixation, while simultaneously maintaining the capacity for rapid adaptation. This finding correlates with the results of Richnák (2022), who demonstrated that enterprises with higher levels of Industry 4.0 technology adoption exhibit superior flexibility indicators in logistics operations, as well as with the research of Erdil (2023), where resilience and flexibility are treated as complementary properties provided a developed digital infrastructure is in place.

Practical Limitations

Several practical limitations that reduce the effectiveness of high temporality and constrain the scalability of the findings were identified during the course of the study.

The first and most obvious limitation relates to the quality of primary data. The GIGO principle − "garbage in, garbage out" − manifests itself particularly acutely under conditions of high temporality. If data entering the system contain errors, inaccuracies, or delays, increasing their update frequency only exacerbates the situation: erroneous signals arrive more frequently and create the illusion of accurate reality representation when in fact it is distorted. In several cases, we encountered situations where warehouse sensors malfunctioned owing to weather conditions or mechanical damage, and the management system received data that did not correspond to the actual state of inventories. Consequently, decisions made on the basis of these data proved inappropriate.

The problem is compounded by the fact that at high update frequencies, errors are more difficult to detect: managers become accustomed to trusting the automated system and conduct spot checks less frequently. This creates a risk of systematic errors accumulating and remaining undetected for extended periods. Overcoming this limitation requires embedding data validation mechanisms into the system, including cross-verification from multiple sources and periodic manual audits. However, such mechanisms require additional expenditure and are not always implemented in practice. This finding resonates with the observations of Tran et al. (2026) on the gap between perceived technology usefulness and actual effective utilisation, as well as with the work of Calza et al. (2026), which emphasises the need to consider data quality when assessing readiness for digital transformation.

The second limitation relates to the level of digital maturity of personnel. High temporality demands new competencies from managers: the ability to work with large volumes of rapidly changing information, to make decisions under uncertainty, and to use analytical tools. In many enterprises, particularly in the small and medium-sized business segment, personnel lack such competencies, and even when modern technologies are available, they are used inefficiently. In some cases, we observed managers accustomed to weekly reports simply ignoring real-time data and continuing to work according to old algorithms. This not only reduced the return on implemented technologies but also created additional costs, as systems required maintenance and support without delivering the expected results.

The third limitation is associated with cultural and organisational factors. In companies with a high degree of bureaucratisation and rigid hierarchy, the implementation of fast data flows encountered resistance. Middle managers perceived transparency as a threat to their position and status, and operational data access for subordinates as a loss of control. This slowed down digital transformation processes despite clear technical advantages. These observations are consistent with the conclusions of Akahome and Matsoso (2026) on the importance of the human factor in digitalisation processes, as well as with the work of Uddin et al. (2025), which emphasises the significance of sustainable human resource practices for successful technology implementation.

Implementation Risks

Beyond operational limitations, risks associated with the security and reliability of systems operating in high-temporality mode were identified.

The first and most serious risk is cybersecurity vulnerabilities. The increase in the number of data collection points: sensors, cameras, GPS systems, RFID tags, expands the attack surface for malicious actors. Every additional device connected to the network represents a potential entry point for unauthorised access. In one case, we encountered a situation where attackers exploited a vulnerability in the warehouse equipment management system to gain access to goods movement data, using this information to manipulate orders. The incident resulted in significant financial losses and undermined trust in digital management systems.

The problem is compounded by the fact that real-time data are more valuable to attackers than archival data. While compromise of historical data leads to reputational losses, compromise of real-time data can disrupt a company's current operational activities − for instance, by distorting product availability information, blocking shipments, or redirecting vehicles. The risk increases when management systems are integrated with external partners through EDI channels or open APIs, as each integration creates additional vulnerabilities.

The second risk relates to dependence on uninterrupted communication channels. High temporality presumes a continuous data flow, and any communication disruption: whether technical failure, power outage, or cyberattack results in the management system losing up-to-date information. In such cases, the system does not simply revert to its original state but finds itself in a situation where customary management channels are disrupted and alternatives have not been developed.

The peculiarity of this risk is that it is asymmetric: everyone benefits from real-time systems when they are operational, but everyone suffers when they fail. Establishing backup communication channels and redundant management systems requires additional investment and increases infrastructure complexity. It is impossible to completely eliminate the risk of failure, particularly when logistics operations are distributed across territories with varying communication quality. These risks are partially addressed in the work of Marques et al. (2026), where the authors identify cybersecurity issues and integration complexities as key barriers to digital transformation, as well as in the research of Balfaqih (2026), which emphasises system vulnerability to cyberattacks as data collection points increase.

The third risk identified during the analysis is associated with technology vendor lock-in. Enterprises that have transitioned to high temporality become tied to specific hardware and software manufacturers. Changing suppliers becomes complex and costly, as the entire management system is built around their solutions. This creates leverage for technology producers and constrains enterprise autonomy in managing their own logistics.

Perspectives: From Resilience to Antifragility

Despite the limitations and risks identified, the findings allow for the identification of a promising direction for the development of the digital temporality concept − its role in shaping antifragile supply chains. The term “antifragility”, introduced by Taleb (2012) to denote systems that not merely withstand stress but become stronger as a result of it, finds an unexpected application in logistics.

In the classical understanding, a resilient supply chain is one that minimises deviations and recovers quickly from disruptions. An antifragile chain goes beyond this: it derives benefit from uncertainty, using disruptions as opportunities for learning and improvement. The data indicate that high digital temporality creates the preconditions for such learning, as it enables even minor deviations to be recorded and their consequences to be analysed.

In companies with high temporality, it was observed that each disruption: delivery delay, order error, technical failure at the warehouse became not merely a problem but a source of data for system improvement. Thanks to the recording of fault information in real time with minute-by-minute and action-specific detail, managers were able to reconstruct the chain of events leading to the fault and develop measures to prevent its recurrence. Over time, this resulted in the system becoming more resilient precisely because it had experienced more disruptions.

Antifragility, however, requires not only high data frequency but also a certain culture of dealing with errors. In those companies where disruptions were perceived as grounds for punishment, the effect was reversed: managers concealed or distorted information about problems to avoid responsibility. This reduced data quality and undermined the very possibility of learning. Where an atmosphere of psychological safety had been created and errors were treated as material for analysis, high temporality worked to strengthen the system.

Another aspect of antifragility that emerged during the study concerns adaptation to unpredictable changes in the external environment. In the traditional approach, risk management is based on forecasting the future from past experience. However, under conditions of high uncertainty, past experience ceases to be a reliable guide. High temporality offers an alternative: rather than attempting to predict what will happen, the system configures itself for rapid response to what is happening. It does not try to guess the future but is prepared for any of its variants because it can adapt quickly.

This requires a shift in management philosophy: from optimisation to adaptability, from minimising deviations to managing deviations as the norm. In such an approach, disruptions are not treated as exceptions but are integrated into everyday management practices. The system becomes antifragile not because it is protected from shocks but because it learns from each shock and becomes stronger. These perspectives resonate with the conclusions of Di Nardo et al. (2025) on the need to integrate sustainable development and digital technologies, as well as with the work of Cao et al. (2026), which demonstrates that the digital economy creates conditions for sustainable development of the logistics industry through mechanisms of innovation and efficiency.

At the same time, the transition to antifragility is not an automatic effect of high temporality but a result of deliberate organisational design. It requires not only technologies but also changes in management structures, incentive systems, and corporate culture. Without these changes, high temporality may lead to the opposite effect − increased bureaucratic control, heightened employee stress, and reduced system learning capacity.

The study showed that the most successful in this regard were companies that implemented high temporality not as an end in itself but as a tool for solving specific problems, for example, reducing order fulfilment times or improving forecast accuracy. In these companies, technology was subordinated to business objectives rather than the reverse, allowing for more organic integration into existing practices. This pragmatic approach to digital technology implementation, combining technological capabilities with organisational changes and cultural transformations, appears to be the most promising direction for further research and practical recommendations, consistent with the findings of Išoraitė et al. (2026) on the need for a comprehensive approach to personnel training and with the work of Machado and Rodriguez (2025) on the importance of maturity models for assessing readiness for digital transformation.

Thus, resilience in the new paradigm is ensured not by the immutability of rules but by the speed of alternative recalculation. The system does not cling to a single plan, nor does it oscillate between options − it continuously reassesses the situation and adjusts course with sufficient frequency not to miss critical changes. This enables it to withstand a wider range of disturbances than with rigid parameter fixation, while simultaneously maintaining the capacity for rapid adaptation.

Conclusion

The conducted research allows for the assertion that digital temporality constitutes a critical factor in the transformation of production logistics, altering its status within the overall enterprise management system. Whereas in traditional models logistics was regarded as a support function whose task was limited to executing plans formulated by production and sales, under conditions of high temporality it evolves into an active agent of change. The logistics system acquires the capacity not merely to respond to changes but to anticipate them, initiate corrective actions, and influence the plans of other departments on the basis of up-to-date information on the state of flows.

This shift occurs because high temporality endows the logistics system with a property it previously lacked − the ability to perceive the current state of the system as a whole and to coordinate the actions of its elements promptly. Temporality creates the foundation for network interaction, in which decisions are made on the basis of a shared informational picture rather than in accordance with predetermined directives. Logistics ceases to be a passive transmission link between production and the consumer and becomes a feedback mechanism that connects disparate parts of the enterprise into a unified adaptive system.

At the same time, the realisation of this potential encounters serious constraints. As the research has demonstrated, high temporality in itself does not guarantee performance improvement; it merely creates opportunities that may or may not be realised depending on data quality, personnel maturity levels, organisational culture, and enterprise investment policy. Technology remains a tool, and its effectiveness depends on how organically it is integrated into existing management practices. The most significant results were achieved in those companies where the implementation of high-temporality regimes was accompanied by the revision of management procedures, personnel training, and changes in incentive systems.

Thus, digital temporality represents not so much a technical as an organisational and cognitive phenomenon. Its key role lies not in accelerating data transmission per se but in changing the way management activities are organised in the transition from planning based on forecasts to management based on operational information.

Theoretical Significance

In theoretical terms, the study proposes a new method of classifying supply chains according to the temporality criterion − that is, according to how quickly information about the state of the system reaches decision-makers and how quickly these decisions are translated into actions.

Three types of supply chains are distinguished:

- *Slow supply chains* are characterised by substantial delays between the occurrence of an event and its reflection in management information. Data are updated at intervals ranging from several hours to several days, and decisions are reviewed in accordance with planned cycles: weekly, ten-day, or monthly. Such chains are adequate for stable environments with predictable demand and established logistics routes but become vulnerable when uncertainty increases. The majority of traditional logistics systems belong to this type.

- *Fast supply chains* operate with data updated at intervals ranging from several minutes to one hour. Decisions are reviewed with sufficient frequency to respond to most operational deviations without significant delays. Such chains are characteristic of enterprises that have implemented basic Industry 4.0 technologies: transport monitoring systems, automated warehouses, EDI integration with suppliers. They demonstrate higher flexibility than slow chains but remain vulnerable to sharp and unpredictable changes.

- *Real-time supply chains* function in a continuous data update mode, where information on goods movement, equipment status, and order status enters the system with virtually no delay. Decisions may be made automatically or with minimal human involvement, and plan revisions occur continuously, without attachment to fixed cycles. Such chains are still rare and found predominantly in high-technology sectors; however, they represent the most promising model for management under conditions of high uncertainty.

This classification is not rigid; transitional states between types are possible, as is differentiation across individual chain links (for example, production logistics may operate in real-time mode while distribution logistics operates only in fast mode owing to partner constraints). At the same time, the very framing of the question of temporal classification enables clearer formulation of digital transformation objectives and assessment of progress.

Beyond classification, the theoretical significance of the work lies in the conceptualisation of digital temporality as an independent management factor, separable from the technologies that enable it. This approach allows for the overcoming of technological determinism characteristic of many works on Industry 4.0 and for the treatment of digital transformation not as the implementation of specific devices and programmes but as a change in the mode of organising management activities.

Practical Significance

The practical value of the findings is associated with their potential use in making decisions on investments in logistics digital infrastructure. The research demonstrates that the pursuit of maximum data update frequency is not always justified. Investment in real-time systems makes sense only if the remaining components of the management system: data quality, personnel competencies, organisational procedures correspond to that level. Otherwise, high infrastructure costs do not pay off and may even lead to management deterioration owing to the effect of information overload.

On the basis of the data obtained, the following recommendations may be *proposed*:

1. When planning IT infrastructure investments, it is advisable to proceed not from the maximum possible data update frequency but from the actual needs of management. For operational tasks related to transport movement or warehouse management, high update frequency does indeed yield a significant effect. For strategic decisions affecting long-term contracts or investments in capacity development, real-time update frequency is not only unnecessary but may even be detrimental, shifting attention to short-term fluctuations.

2. Investments in temporality should begin with the most critical links in the supply chain, where information delays lead to the greatest losses. These are typically links with high demand volatility, long supply lead times, or significant storage costs. Phased implementation, in which temporality is first increased in the most problematic areas and then gradually extended to the entire system, allows for risk reduction and rapid return on investment.

3. Increases in temporality should be accompanied by parallel investments in data quality improvement and personnel training. Without this, the acceleration of information flows is more likely to be harmful than beneficial. Data quality requires attention at the collection stage (sensor calibration, validity verification, duplication elimination) as well as at the processing stage (cleansing and validation algorithms). Personnel training should encompass not only technical skills in working with new systems but also the development of the ability to analyse large volumes of rapidly changing information and to make decisions under uncertainty.

4. When implementing real-time systems, it is advisable to incorporate mechanisms for protection against information overload − intelligent filters, data aggregation, and visualisation adapted to the characteristics of human perception. These mechanisms are not a secondary addition but a necessary condition for the effective use of high temporality.

5. When evaluating the effectiveness of investments in temporality, consideration should be given not only to direct economic effects (cost reduction, shorter order fulfilment times) but also to indirect effects: increased resilience to disruptions, enhanced adaptability, and improved decision quality. Under conditions of high uncertainty, these indirect effects may prove more significant than immediate savings.

Directions for Future Research

The conducted research opens several avenues for further work that could not be fully addressed within the scope of this project.

As data frequency continues to increase, the question of how the human psyche copes with the need to make decisions under conditions of continuously changing information becomes increasingly pertinent. Observations indicate that there are significant individual differences in the ability to work effectively in a high-temporality mode: some managers demonstrate high effectiveness, while others experience stress and overload. Deeper investigation is required into the factors determining these differences: cognitive styles, anxiety levels, experience with digital systems. It is possible that working under high temporality requires special selection and training procedures, as well as specific work and rest schedules to prevent professional burnout.

Standards regulating the temporal parameters of information flows may be required in digital logistics. This concerns both maximum delays beyond which the system ceases to be manageable and minimum intervals between updates, beyond which the negative effects of overload begin. The development of such standards requires an interdisciplinary approach combining engineering, psychological, and organisational knowledge.

Within the scope of this study, primary attention was devoted to internal enterprise processes; however, the effects of high temporality on interorganisational relationships remained outside the analysis. Questions concerning the dynamics between supplier and buyer when exchanging data in real time require further investigation.

Traditional ROI methods are poorly suited for evaluating projects that yield effects not so much in the form of direct savings as in enhanced adaptability and resilience. New approaches are required that account for the value of options − the system's ability to exploit emerging opportunities and avoid threats.

The concept of digital temporality may be applicable to production management, personnel management, and financial management wherever the speed of information receipt and processing affects the quality of decisions made. Testing the universality of this construct across different functional areas represents a separate research task.

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