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Impact of Market Drivers on the Digital Maturity of Logistics Processes in a Supply Chain

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Abstract: Logistics processes allow for the movement of goods along the supply chain to the customers. Companies are using digital solutions more widely to support their logistics processes. Current studies focus mainly on the intrinsic perspective of the digital maturity of logistics processes. Rarely do previous studies consider the impact of external factors (e.g., market trends, as external drivers at the strategic level) on the digital maturity of logistics processes. In this paper, our aim is to propose a novel generic approach to measuring the level of adoption of digital technologies in logistics processes. We applied the maturity model theory to provide a generic framework for the assessment of different partners in supply chains (suppliers, manufacturers, retailers, e-tailers, logistics service providers) in a homogeneous way. We propose the five levels (Avoiding, Discovering, Adopting, Improving, Excelling) to measure the frequency of the application of the digital technologies with high intelligence in the domain of logistics processes. Furthermore, we investigate the relationship between the selected market trends, which are external drivers at the strategic level, and the digital maturity of logics processes. We conducted the survey among a group of 38 companies to classify their maturity level and then to test which market trends motivate them to digitalize their processes. We applied Bayesian statistics to test the level of the relationship between the digitalization of logistics processes and four market trends, namely, the sustainability, e-commerce, sharing economy, and speed-orientation of customers. The results show that all the trends tested moderately and positively influence the digital maturity of logistics processes.

Keywords: maturity; digitalization; Logistics 4.0; Bayesian statistics; sustainability; sharing economy; E-commerce

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1. Introduction

The COVID-19 pandemic has put a lot of pressure on the functioning of supply chains [1] due to disturbances in the availability of crucial logistics infrastructure (e.g., ports closure) and the absence of staff. Companies have focused on building the resilience against uncertainty and looking for the higher digitalization of their processes [2] to improve efficiency and reduce dependency on the staff availability [3]. Furthermore, the pandemic triggered the rapid development of e-commerce [4] and increased the demand for quick deliveries (e.g., less than 24 h) [5]. These changes in the behavior of customers [6,7] from traditional to digital logistics channels further trigger the application of digital tools in a supply chain [8,9].

Digital technologies allow for innovating logistics processes and moving towards a higher level of efficiency and responsiveness to changing market conditions and enable increased agility and higher performance [10,11]. The digitalization of logistics processes requires a “combination of information, computing, communication, and connectivity technologies” [12].

The digitalization of logistics processes is an evolutionary process [13,14]; thus, maturity theory is a suitable approach to investigating this phenomenon. The maturity in the context of digitalization can be analyzed from the perspective of the digital capacities of a company (how intensively a company applies digital technologies) and the management capabilities (e.g., governance or leadership) [15]. The ongoing academic discussion leans towards distinguishing between the broader context of the digital transformation of companies (capability to introduce the change) and digitalization sensu stricto (application of digital technologies). In this paper, we will focus on how intensively (measured by frequency) companies apply digital technologies in logistics processes and define this as the digital maturity of logistics processes.

The aim of this paper is to propose a generic approach to measuring the level of adoption of digital technologies in logistics processes. Furthermore, we investigate the relationship between the selected market trends, which are external drivers at the strategic level, and the digital maturity of logics processes.

To the best of our knowledge, there has been no previous research on the relationship between the digital maturity of logistics processes and key market trends, e.g., the shift to sustainable practices, the shift to e-commerce, the speed of delivery, and the sharing economy. Thus, this paper contributes to the existing literature by:

- Proposing a novel generic maturity model for the assessment of the digitalization level of logistics processes.
- Providing results on the relationships between the selected market trends and a company's willingness to digitalize logistics processes.

The remainder of this paper is organized as follows. Section 2 summarizes the literature review. Section 3 discusses the materials and methods. Section 4 presents the results of this study. Section 5 includes a discussion on the results. In Section 6, the final conclusions are stated, and further research is presented.

2. Literature Review

2.1. Digitalization of Logistics Processes—Leading IT Solution

The digitalization of logistics processes is defined here as the application of IT solutions to facilitate the flow of goods and information in a supply chain [16,17]. Digitalization enables the improvement of processes in a supply chain, such as procurement, logistics, scheduling, and planning [18]. A dynamic, real-time, customer-oriented adaption of market trends is important to achieving the objectives of logistics processes, decreasing costs, and mitigating market risks [19].

Yang et al. [20] have distinguished different degrees of technological intelligence when adopting digital technologies in a supply chain. The low degree of technological intelligence describes traditional information management systems such as MRP/ERP systems. In these IT systems, data collection, visualization, and processing serve descriptive purposes [21]. The high level of technological intelligence refers mainly to Logistics 4.0 solutions, where real-time data collected by smart sensors serve predictive and prescriptive purposes and support prediction and real-time logistic planning. Such solutions allow for data-driven decision making [20]. The typical digital solutions with high technological intelligence, which are suitable for applications in a supply chain, are [2,19,22–25]:

- Internet of Things (IoT);
- Big Data Analytics;
- Cloud computing;
- Blockchain;
- Intelligent Transport Systems;
- Robotic process automation.

Ben-Daya [26] defined IoT as "a network of physical objects that are digitally connected to sense, monitor and interact within a company and between the company and its supply chain". IoT enables the tracking and monitoring of the materials flow and sharing information [27], thus improving supply chain management for timely deliveries of customer-oriented services.

Big Data Analytics allow for an enhanced availability of data across the physical flow of goods in a supply chain and increased cooperation among the SC partners [28,29]. Cloud computing is an "IT service model where computing services are delivered on demand to customers over a network in a self-service mode, independent of device and location" [30]. The application of the cloud computing in a supply chain allows for improved logistics processes due to the resource sharing, flexibility, and low cost (e.g., pay-per-use) [31].

Blockchain (DTL distributed ledger technology) is a consecutive list of time-stamped records linked using cryptography into a distributed asset database that is shared across a network of an organization [32,33]. The application of blockchain in the supply chain domain is still in its infancy stage [33]. Blockchain technologies allow for cooperation and data sharing among partners in a supply chain with increased trust. This results from enhanced possibilities for the tracking of information, cash, products, and services flows [34]. DTL allows for the automatization of contracts (smart contracts), leading to streamlined and more efficient supply chain processes [35].

Intelligent Transport Systems (ITS) are another disruptive technology in the domain of the supply chain. ITS apply digital technologies to physical transport systems to improve the flow of materials or passengers in the transportation network and reduce the environmental impact [36,37]. ITS studies predominantly focus on the macro-scale (city logistics) [37], but benefits can be achieved at the micro-level of a company or the meso-level of a supply chain [38].

Robotic process automation plays an important role in the increased performance of logistics processes, especially during the pandemic, when companies experienced shortages of staff and lockdowns [39]. Robotic Process Automation (RPA) approach combines artificial intelligence, and machine learning capabilities to automate tasks in processes [40]. Companies implement the RPA to optimize the repetitive tasks and lower cost, reduce the process time, and improve resource utilization [41].

In summary, the literature review provides examples of implementing digital technologies in various logistics processes, such as:

- Transportation [42–44];
- Warehousing, packaging, and materials handling [45,46];
- Procurement [47–50];
- Distribution [51,52].

Digital technologies for logistics processes in the supply chain must allow for connectivity, integration, cooperation, and adaptability (CICA criteria) [14].

Previous research has mainly considered the digital solutions in logistics and supply chains with a focus on one solution or a combination of two solutions. The novelty of this paper comes from considering a portfolio of digital solutions and their impact on the level of the digital maturity of logistics processes. In this paper, we do not distinguish between logistics processes or types of supply chain participants (supplier, logistics service provider, etc.); we propose a new generic assessment approach. We consider technologies with a high technological intelligence. The technologies mentioned above allow one to merge the physical flows of materials in the supply chain with a virtual process, by the integration and optimization of information [53], and meet the CICA criteria. Thus, we will focus on them in our survey.

2.2. Drivers for the Digitalization of Logistics Processes

Understanding why a company adopts digital technologies is essential [54]. The motivation of companies to digitize processes in a supply chain has been investigated from different angles (e.g., strategic and operational). Yadegaridehkordi et al. [55] have investigated the impact of technological, environmental, and organizational drivers on the adoption of digital technologies for improving processes in a supply chain from a manufacturer perspective. The internal drivers for the implementation of digital technologies at an operational level in the supply chain by the manufacturer were studied, with a focus on cost reduction and improving efficiency [56], enabling lean or agile processes [57].

At the strategic level, the drivers for digitalization in a supply chain lead to proactive process rather than a bottom-up and reactive approach, and they are aligned with the fulfilment of long-term goals [58].

In a systematic review, Yang et al. [20] classified the external drivers for the adoption of digital technologies in a supply chain into three categories related to customers, other partners in a supply chain (e.g., suppliers), and competitors. They stated that "driven by customer needs, companies provide digital products and services to better meet market demands and manage customer relationships" [20]. The digitalization of one partner in the supply chain often triggers the adoption of the digital technologies by the other partners, as they do not want to be left behind [59]. The competitors' behavior shapes the technological landscape in a sector; thus, it is a strong driver for following up on digitalization [60].

In this paper, we focus on the market's trends with regard to the digitalization of logistics processes, which are related to the customers, competitors, and other supply chain partners, namely:

- Shift to E-commerce;
- Environmental sustainability in a supply chain;
- Pressure from customers on the shorter delivery cycles;
- Sharing Economy.

The pandemic has triggered a shift in the distribution towards omnichannel distribution, where companies need to combine their operations in offline and on-line modes [51,61]. It can be assumed that the shift to brick-and-click requires a digitalization of logistics processes; however, this link was not sufficiently investigated in the literature.

Previous studies have identified the link between the digitalization of processes in a supply chain and environmental sustainability [62–67]. Big Data Analytics and IoT have been shown to be efficient in improving energy efficiency in logistics processes (in particular, transport) and reducing related carbon emissions [45,63]. Ji and Su [68] analyzed the application of the E-Commerce Big Data Platform for offering the low-carbon-footprint transport services in China. Garcia-Torres et al. [69] identified that access to real data in tracking the flows in a supply chain allowed for finding the source of pollution in processes and taking of the necessary mitigation actions in a timely manner. Park and Li [70] presented case studies on the application of blockchain in a supply chain to reduce waste and increase sustainable resource management. Previous studies have not explored the focus on the relationship between the sustainability in a supply chain and the level of application of digital solutions in logistics processes.

Time plays a crucial role in supply chain management, but at the same time, the pressure of time negatively influences the optimization of logistics processes due to the lower consolidation of deliveries, the increase in the number of trips, and the lower load factor of vehicles [71–73]. Previous studies have indicated that the application of digital technologies could help solve this problem [5,74,75]. Previous studies have not explored the relation between the speed-driven consumer's expectation in a supply chain and the level of application of digital solutions in logistics processes.

The Sharing Economy (SE) in a supply chain can be triggered by customers, competitors, or other partners. SE involves platforms that enable the sharing of resources among at least two market players [76]. Current practices include the sharing of the logistics infrastructure or integrating shipment schedules or pooling services between different companies in a supply chain in order to increase the resource utilization and meet customer needs in a more cost-efficient way [66,77,78]. Guo et al. [78] analyzed the potential of the application of the Internet of Things in cooperation with the vehicle manufacturer and external service providers. Bellein [77] studied the benefits of the sharing transport infrastructure in a supply chain. Castellanos et al. [79] investigated the impact of technology on shared mobility—for example, ride-sharing, car-sharing, car-pooling, and freight-sharing). Bienhaus et al. focused on the digitalization of the procurement process [56]. Dellaert [80] analyzed how the digitalization of a supply chain can empower customers towards the Sharing Economy. The studies on the relationship between the rise of the Sharing Economy and the digitalization of logistics processes are very limited. Most studies focus on the consumer's perspective.

In this paper, we contribute to the existing research gap by taking into consideration the relationships between the market trends (external drivers at the strategic level) and their impact on a company achieving a higher level of digital maturity of logistics processes.

2.3. Maturity Models Theory

The maturity model is defined here as "a structured collection of elements that describes the characteristics of effective processes at different stages of development" [81] They allow for a transition towards more mature, effective logistics processes. Maturity models are used to position and benchmark a company and allow for guiding the transformations of a company to progress from the current state (as is) to the future desired stage [82–85]. The main advantages of maturity models are the simplicity of their application, their universality (qualitative and/or quantitative description of criteria), and their evolutionary character (step-by-step transition towards digitalization).

The models for the digital maturity of logistics processes predominantly consider the Logistics 4.0 approach and focus either on the holistic perspective or a particular logistics process (e.g., distribution, transportation). For example, Facchini et al. [86] proposed the maturity model to position companies on their way towards Logistics 4.0 by addressing macro-aspects, such as the company's attitude towards Industry 4.0, the current use of digital technologies, and investment levels in Industry 4.0 technologies. Werner-Lewandowska and Kosacka-Olejnik [83] defined maturity models for the classification of capabilities toward the implementation of Logistics 4.0 technologies in services. Krowas and Riedel [87] proposed a maturity model for Intra-Logistics 4.0. Modice et al. [88], through a systematic literature review, investigated the potential of the implementation of Logistics 4.0 technologies in transport processes in a supply chain. The previous studies have focused on a company's readiness, capacities, and attitude towards the adoption of the Industry 4.0/Logistics 4.0. This study provides a generic framework for measuring the digital maturity level of logistics processes.

All works highlighted the strong link between the implementation of digital technologies and the need to align with a company's strategic objective. Current studies focus mainly on the intrinsic perspective of the digital maturity of logistics processes. They do not consider the impact of external factors (e.g., market trends, as external drivers at the strategic level) on the digital maturity of logistics processes. Correani et al. [54] stated that digital transformation often fails due to the disconnect between strategic goals and the implementation of technologies; thus, it is crucial to investigate the drivers and current conditions of a company. Taking into account that the adoption of high-intelligent digital technologies shall facilitate the rapid response to the changing environment [20,60], our article aims to investigate the link between market drivers (responsible for changing the business environment) and the level of digital maturity of logistics processes. Thus, we contribute to the existing research gap by linking the reason for implementing the digital technologies (why) with the level of their adoption (what).

3. Materials and Methods

3.1. Research Methodology

Previous studies applied maturity models to measure the level of adoption of digital technologies in the domain of logistics for manufacturers [89,90] or logistics service providers [91]. In this study, we aim to propose a generic maturity model for the assessment of the level of adoption of digital technologies with high intelligence in logistics processes. The research questions addressed in this work are:

- RQ1: How can the level of adoption of high-intelligence digital technologies in logistics processes be measured?

- RQ2: How does the importance of market trends for a company affect the level of digital maturity of its logistics processes?

  The conceptual model for this study is presented in Figure 1.

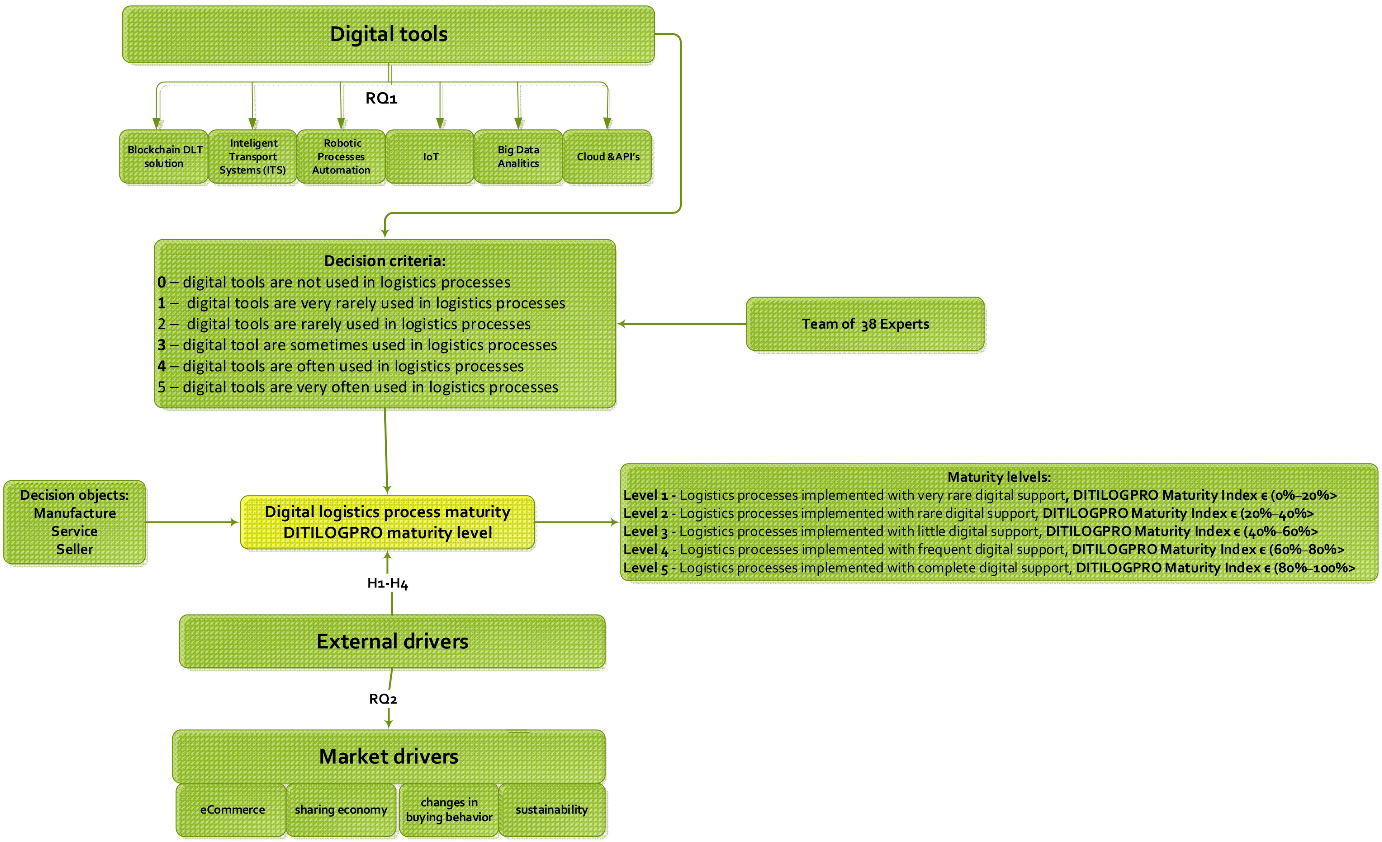

Figure 1. Conceptual model.

In the conceptual model, we link market drivers with the adoption of the digital technologies, which is measured by level of the digital maturity of logistics processes.

We test four hypotheses:

Hypothesis 1 (H1). *The level of importance of E-commerce for a company influences its level of digital maturity of logistics processes.*

Hypothesis 2 (H2). *The level of importance of the Sharing Economy for a company influences its level of digital maturity of logistics processes.*

Hypothesis 3 (H3). *The level of importance of speed-oriented customer behaviors influences its level of digital maturity of logistics processes.*

Hypothesis 4 (H4). *The level of importance of the sustainability focus for a company influences its level of digital maturity of logistics processes.*

We follow the research procedure presented in Figure 2.

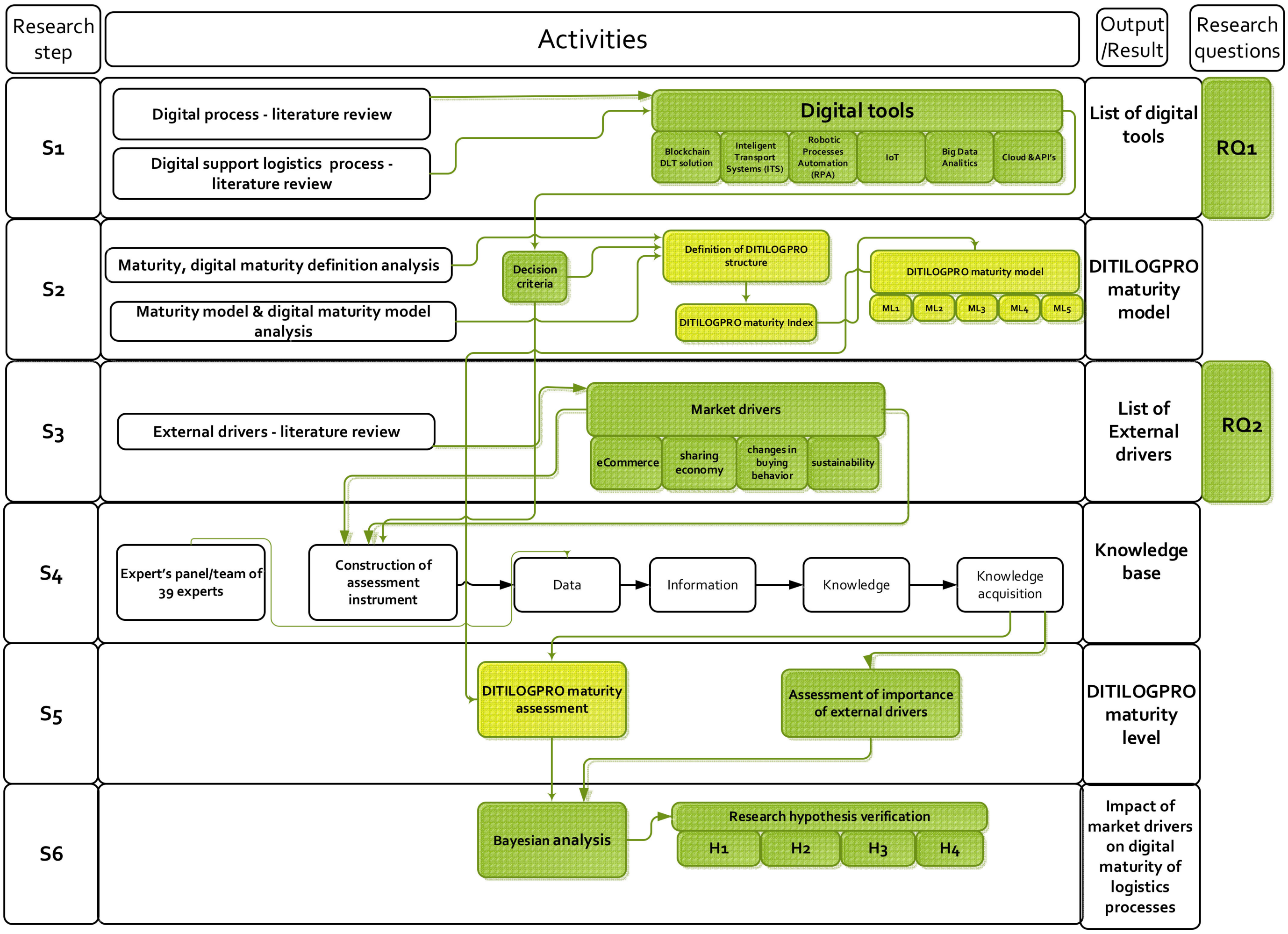

Figure 2. Research methodology.

3.2. Design of the Maturity Model

The Digital Maturity Model for Logistics Processes (DITILOGPRO) is designed to measure the level of adoption of high-intelligence digital technologies in companies in a generic way. The model includes five levels, and companies are positioned based on the value of the DITILOGPRO Maturity Index, which is calculated according to the following formula (Equation (1)):

$$\text{DITILOGPRO Maturity Index} = \frac{\sum_{i=1}^{5} a_i}{30} \times 100\% \tag{1}$$

where a_i means an assessment of the frequency of use of the i-th IT tool in an enterprise; $a_i = \{1, 2, 3, 4, 5\}$.

For simplicity, the range of the DITILOGPRO Maturity Index is even for each level, as presented in Table 1.

Table 1. Maturity level—the classification rules.

	DITILOGPRO Maturity Index		Maturity Level
IF	<0–20%)	THEN	ML1
	<20–40%)		ML2
	<40–60%)		ML3
	<60–80%)		ML4
	<80–100% *>		ML5

* reference level.

The maturity levels are defined as follows:

ML1 (Avoiding)—the frequency of adoption of the high-intelligence digital solutions for logistics processes is very low
ML2 (Discovering)—the frequency of adoption of the high-intelligence digital solutions for logistics processes is low
ML3 (Adopting)—the frequency of adoption of the high-intelligence digital solutions for logistics processes is medium
ML4 (Improving)—the frequency of adoption of the high-intelligence digital solutions for logistics processes is high
ML5 (Excelling)—the frequency of adoption of the high-intelligence digital solutions for logistics processes is very high

The designed maturity model is presented in Figure 3.

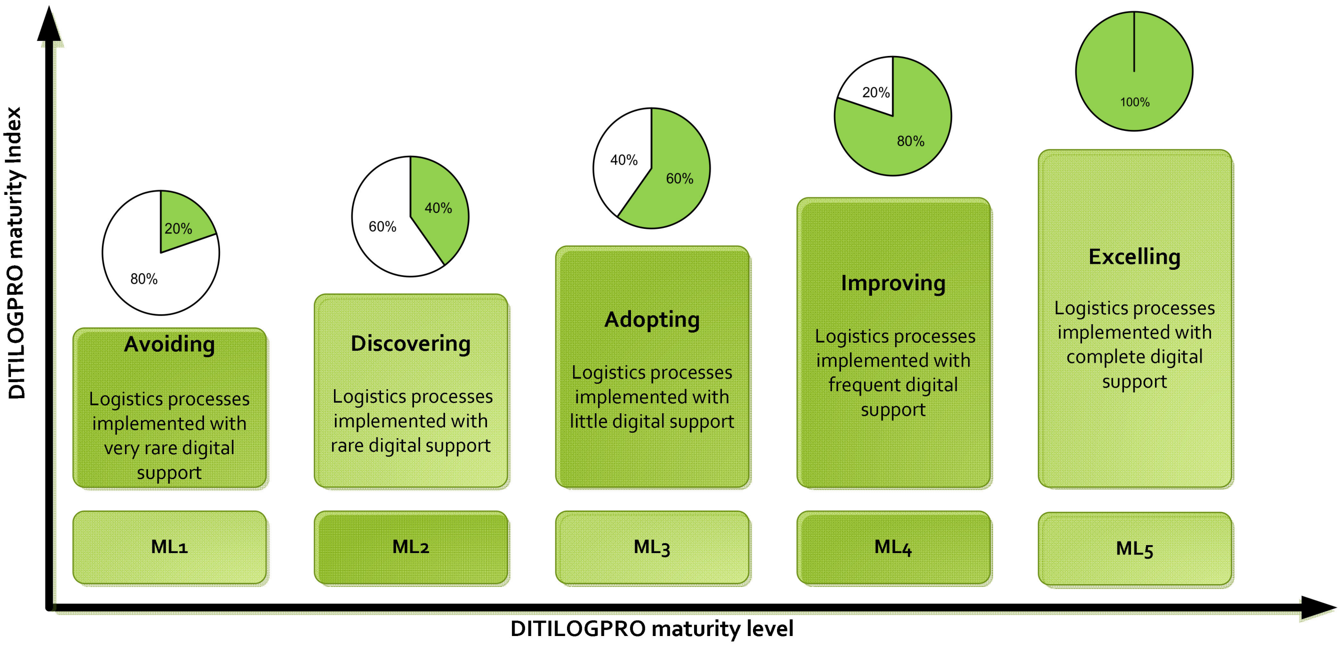

Figure 3. Digital Maturity Model for Logistics Processes (DITILOGPRO).

3.3. Data Sampling

The data were collected from 38 experts who have at least 5 years of experience in the adoption of high-intelligence digital technologies for improving logistics processes in a company. We used the form (as presented in Figure 4) to obtain knowledge from experts, first on the frequency of adoption of high-intelligent digital technologies and then on the importance of market trends for them. The Likert scale was used. In order to obtain a comprehensive survey for our generic model, experts represented different types of enterprises, namely: manufacturing, retailing (e-tailing), logistics services, and combinations thereof.

Indicate the frequency of use of IT tools in your company's logistics processes:						
	0 not used	1 Very rarely used	2 Rarely used	3 Sometimes used	4 Often used	5 Very often used
Blockchain DLT solution						
Intelligent Transport Systems (ITS)						
Robotic Processes Automation (RPA)						
IoT						
Big Data Analytics						
Cloud &API's						
Indicate the importance of market trends to your company:						
	0 n/a	1 Very low impor tance	2 Low importance	3 Fairly important	4 Important	5 Very important
Sharing economy						
Speed-oriented customer behavior						
E-Commerce						
Sustainability						

Figure 4. Survey form for data collection.

To analyze the results from the experts' survey, we applied the Bayesian framework for the model's specification and estimation. This method applies model ordinal predictors as manifest variables, which do not explicitly consider the potential measurement error in these predictors.

The Bayesian framework was expressed in terms of Bayes' Theorem, which states that the posterior distribution $p(\theta \mid y)$ of the model parameters θ given the data y can be expressed in terms of the product of the likelihood $p(y \mid \theta)$ and prior distribution $p(\theta)$, as well as a normalizing constant $p(y)$ in Equation (2):

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} \tag{2}$$

The Bayesian framework allows monotonic effects to be included in a large class of regression models without the need to develop model-specific estimators. To include information that does not come directly from the data in the form of the likelihood contribution, the priors for b and ζ were chosen. Priors with a normal distribution for b were derived based on the a priori expectation regarding the average difference between adjacent categories. Individual differences between adjacent categories were fully handled by the simplex parameter ζ. The Dirichlet distribution, a multivariate generalization of the beta distribution [92], was chosen for the simplex parameters. The Dirichlet prior has a single parameter vector α with the same length as ζ. Its density was defined according to Equation (3):

$$f(\zeta|\alpha) = \frac{1}{B(\alpha)} \prod_{i=1}^{D} \zeta_i^{\alpha_i - 1} \tag{3}$$

where $B(\alpha)$ was a normalizing constant [93].

A reasonable default prior for ζ would certainly be one that assumes that all differences between adjacent categories are equal, on average, while this expectation is subject to considerable uncertainty. Such a prior implies a linear trend, on average, but with enough uncertainty to account for all other possible monotonic trends. The Dirichlet prior with a constant $\alpha = 1$ put the same probability on all valid simplexes and was understood as the multivariate generalization of the uniform prior to simplexes. Since we have $wi = 1/D$, this prior centers ζ around a linear trend with large uncertainty and therefore seems to be a good standard prior when there is no problem-specific information.

The larger differences between adjacent categories in a Bayesian framework were penalized by means of priors on b and ζ. A constant vector α of Dirichlet prior on ζ implied a linear trend in expectation. Assuming constant α, the prior means of all changes ζi between adjacent categories are the same. Based on knowledge about the outcome scale, it is unlikely that a one-point change in a specific predictor will imply a change in the degree of the digital maturity of logistics processes. In the next section, the detailed results are presented.

4. Results

The results were analyzed following the research methodology presented in Figure 2. First, the data on the frequency of the application of digital technologies were calculated and presented in Figure 5. The most frequently adopted high-intelligence technology for improving the logistics processes was Cloud & API's—an average of 3.5 on a 5-point rating scale, followed by Big Data Analytics. The Blockchain DLT solutions were used the most rarely or not at all—a mean of 1.1. The results were consistent with the conclusions from the literature review (see Section 2).

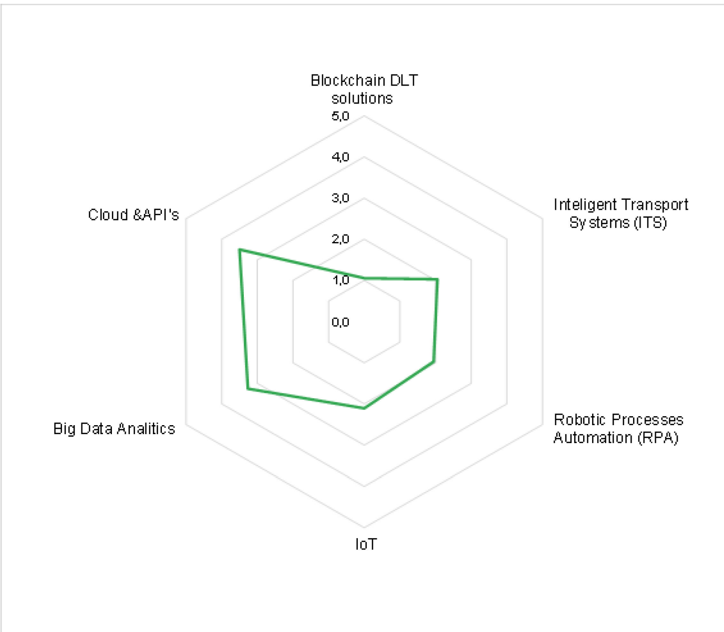

Figure 5. Average rating of the frequency of use of IT tools in surveyed companies, N = 38.

The next step focused on assessing the level of digital maturity of the logistics processes in the companies surveyed, based on the DITILOGPRO maturity model. We used Equation (1) for the results calculation; the obtained results are presented in Figure 6.

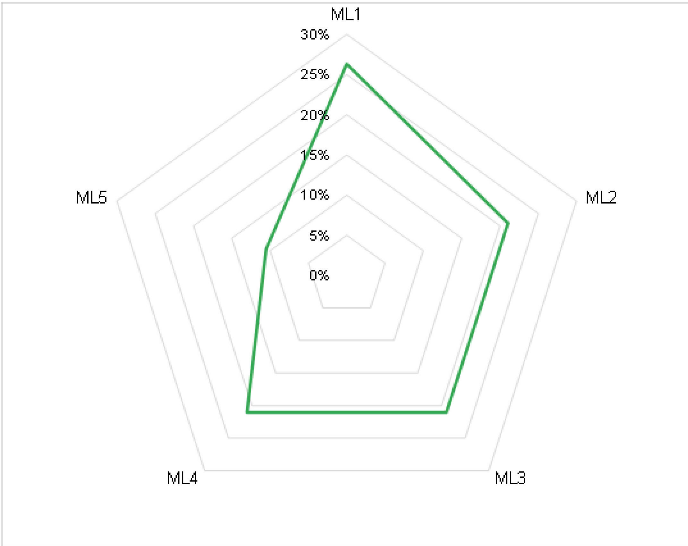

Figure 6. Digital maturity of logistics processes in analyzed companies, N = 38.

According to our analysis, companies mainly achieved the digital maturity of logistics processes in ML1—26%. Maturity levels ML2, ML3, and ML4 were reached by the same number of enterprises, and only 11% were assessed at the highest maturity level, ML5. There was one enterprise in the surveyed population that was assessed as immature, as DITILOGPRO Maturity Index = 0%, which means that the enterprise does not use the analyzed digital technologies with high intelligence, although this enterprise declared implementing some IT solutions to optimize logistics processes.

Following the research methodology in Figure 2, the H1–H4 were tested in order to investigate the impact of the market drivers on the level of implementation of high-intelligence digital technologies. Analyses were performed with Bayesian models using the R Statistical language [94–96] (version 4.2.1; R Core Team, 2022) on Windows 10 64 bit using the packages Rcpp (version 1.0.9), sjPlot (version 2.8.10), report (version 0.5.1), and brms (version 2.17.0)

The four predictors were measured on the Likert scale with a range of 0–5, which reflected the market drivers. The dependent variable was the maturity level measured by the value of the DITILOGPRO Maturity Index (0–100%). We expected the digital maturity level to increase with an increase in each individual predictor (monotonic effect) [96]. The distribution of the values of the DITILOGPRO Maturity Index is presented in the histogram in Figure 7.

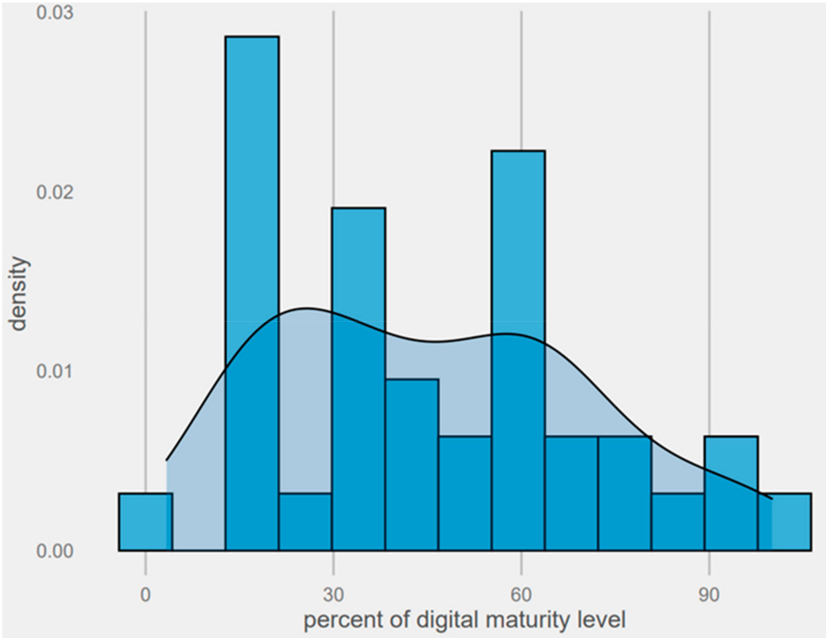

Figure 7. Combined histogram and density plot of the digital maturity level, N = 38.

The DITILOGPRO Maturity Index of the analyzed companies was predominantly between the local peaks of 30% and 60%, with M = 46.4 (25.25).

We tested the first hypothesis H1: The level of importance of e-commerce for a company influences the level of digital maturity of its logistics processes.

The results are presented in Table 2.

Table 2. Summary of parameter estimates for the impact of the importance of e-commerce on the level of digital maturity (MLx) of the company's logistics processes.

Predictors	Estimates	CI (95%)
Intercept	0.44	0.19–0.65
slope_E-commerce growth	0.01	−0.05–0.07
Monolithic effects		
simo_E-commerce [ML1]	0.19	0.01–0.69
simo_E-commerce [ML2]	0.15	0.01–0.60
simo_E-commerce [ML3]	0.14	0.00–0.60
simo_E-commerce [ML4]	0.14	0.01–0.509
simo_E-commerce [ML5]	0.15	0.01–0.58

Note: simo = simplex parameter of the monotonic effect; Estimate = posterior mean; CI = credible interval based on quantiles.

The maximum estimate of simplex [ML1] = 0.19 means that 19% of the total change in the digital maturity level of the company's logistics processes due to the e-commerce growth predictor falls between the first and second predictor categories. In addition, the estimating slope = 0.01 means that the digital maturity of the company's logistics processes increases by 0.01 (1%), on average, for each category with an increase in the importance of the e-commerce predictor. The companies with a higher importance of e-commerce are characterized by a slightly higher level of the digital maturity of the company's logistics processes. Since the confidence interval for the slope [−0.05–0.07] contains 0, no significant effect of the tested predictor on the dependent variable can be demonstrated.

The second hypothesis was focused on the impact of the Sharing Economy as a driver for digitalizing the logistics processes. H2 was stated as: The level of importance of the Sharing Economy for a company influences the level of digital maturity of logistics processes. The results are presented in Table 3.

Table 3. Summary of parameter estimates for the impact of the importance of the Sharing Economy on the level of digital maturity (MLx) of the company's logistics processes.

Predictors	Estimates	CI (95%)
Intercept	0.41	0.21–0.60
slope_Development of the sharing economy	0.02	−0.04–0.07
Monolithic effects		
simo_importance of Sharing Economy [ML1]	0.16	0.01–0.61
simo_importance of Sharing Economy [ML2]	0.17	0.01–0.61
simo_importance of Sharing Economy [ML3]	0.15	0.01–0.58
simo_importance of Sharing Economy [ML4]	0.14	0.01–0.57
simo_importance of Sharing Economy [ML5]	0.18	0.01–0.60

The mean value of the DITILOGPRO Maturity Index for companies that rated the Sharing Economy as not at all important was 0.41.

The estimating slope = 0.02 means that the DITILOGPRO Maturity Index increases by 0.02 (2%), on average, with each increase in the importance of the Sharing Economy predictor. The companies that show a higher importance of the sharing economy are characterized by a higher degree of digital maturity of the company's logistics processes.

Since the confidence interval for the slope [−0.04–0.07] contains 0, no significant effect of the tested predictor on the dependent variable can be demonstrated.

Analogically, we tested the next hypothesis about the impact of the importance of speed-oriented customers' behavior. H3 was stated as: "the level of importance of speed-oriented customers' behaviors influences the level of digital maturity of logistics processes". The results of the statistical tests are presented in Table 4.

Table 4. Summary of parameter estimates for the impact of the importance of speed-oriented customer behaviors on the level of the digital maturity (MLx) of the company's logistics processes.

Predictors	Estimates	CI (95%)
Intercept	0.33	0.11–0.52
Slope_Customers' behavior	0.05	−0.01–0.11
simo_Customers' behavior [ML1]	0.27	0.01–0.74
simo_Customers' behavior [ML2]	0.27	0.01–0.74
simo_Customers' behavior [ML3]	0.24	0.01–0.72
simo_Customers' behavior [ML4]	0.19	0.01–0.67
simo_Customers' behavior [ML5]	0.15	0.01–0.59

The mean value of the DITILOGPRO Maturity Index for companies that rated the speed-oriented changes in customers' behavior as not important was 0.33 (33%).

The estimating slope = 0.05 means that the digital maturity of the company's logistics processes increases, on average, by 0.05 (5%) for each category with an increase in the predictor (speed-oriented changes in customers' behavior). For example, if the predictor importance changes from "low importance" (value 2 on the Likert scale) to "fairly important" (value 3 on the Likert scale), then, on average, the DITILOGPRO Maturity Index will increase by 5%. Companies that perceived higher speed-oriented changes in customers' behavior are characterized by a higher level of digital maturity of the company's logistics processes.

Since the confidence interval for the slope [−0.01–0.11] contains 0, no significant effect of the tested predictor on the dependent variable can be demonstrated.

Finally, the fourth hypothesis was tested. H4 was stated as: The level of importance of the sustainability focus for a company influences the level of digital maturity of logistics processes. The results are presented in Table 5.

Table 5. Summary of parameter estimates for the impact of the importance of environmental sustainability on the level of digital maturity (MLx) of the company's logistics processes.

Predictors	Estimates	CI (95%)
Intercept	0.34	0.03–0.61
Slope_Environmental sustainability	0.03	−0.04–0.10
Monolithic effects		
simo_Environmental sustainability [ML1]	0.20	0.01–0.66
simo_Environmental sustainability [ML2]	0.12	0.01–0.54
simo_Environmental sustainability [ML3]	0.12	0.00–0.52
simo_Environmental sustainability [ML4]	0.18	0.01–0.61
simo_Environmental sustainability [ML5]	0.19	0.01–0.61

The mean value of the DITILOGPRO Maturity Index for companies that rated the environmental sustainability as "not important" was 0.34 (34%).

The maximum estimated value for the simplex was 0.20, which means that 20% of the total change in the digital maturity of the company's logistics processes due to environmental sustainability occurs between the first and second predictor categories. The estimated slope = 0.03 means that, on average, the digital DITILOGPRO Maturity Index increases by 0.03 (3%) for each increase in the importance assessment on the Likert scale for the predictor "environmental sustainability". The companies that place more importance on environmental sustainability are characterized by a higher level of digital maturity of the company's logistics processes. Since the confidence interval for the slope [−0.04–0.10] contains 0, no significant effect of the tested predictor on the dependent variable can be demonstrated. The discussion on the results is presented in the next section.

5. Discussion

In this paper, we combine qualitative and quantitative approaches to assess the digital maturity of logistic processes in a company. We applied the maturity model theory to provide a generic framework for the assessment of different partners in supply chains (suppliers, manufacturers, retailers, e-tailers, logistics service providers) in a homogeneous way. Our approach is consistent with previous studies on the maturity models in the context of Logistics 4.0 [14,83,86,91,97], where the authors have used the descriptive approach and defined four to five maturity levels. In our maturity model, DITILOGPRO, we propose five levels (Avoiding, Discovering, Adopting, Improving, Excelling) for measuring the frequency of the application of digital technologies with high intelligence in the domain of logistics processes. We applied the purposeful sampling to select a group of 38 experts (decision makers for the digitalization of logistics processes) to test our maturity model. The experts, on the Likert scale from 0–5 (not used–very often used), assessed the adoption of digital technologies with high intelligence in their logistics processes. Qualitative experts' knowledge was translated into the generic DITILOGPRO Maturity Index to allow for positioning the companies on the DITILOGPRO maturity model. The distribution of the companies across the defined maturity level ML1–Ml4 was relatively even (from 21 to 26%); the highest level was the most difficult to obtain (11% of companies). These results are consistent with those of previous studies—for example, [86].

In the second part of this study, we follow up on the research gap by linking the reason for implementing the digital technologies (why) with the level of their adoption (what). Previous studies in this area are rather fragmented. There is proof of a positive link between environmental sustainability and selected technologies such as Big Data Analytics [62] or digital manufacturing technologies [63]. Studies on E-Commerce and digitalization also confirm the link between them [56] in the context of logistics processes. The sharing economy is a relatively new market driver which impacts the digitalization of logistics processes [66,77,79,98]. The pressure for quick deliveries from customers requires better trace and tracing digital technologies and extended data exchange between different partners and customers in a supply chain [99].

Our results contribute to the existing body of knowledge through exploratory results on testing the evolutionary character of the adoption of digital technologies (maturity level) and the external drivers at a strategic level (market trends). The drivers did not show a significant impact, but a positive relation was identified; therefore, the way in which the company perceives the importance of the selected market drivers influences the adoption of digital technology with high intelligence.

This study also has managerial implications, as the proposed maturity model can be used by managers in a supply chain to position their companies and for benchmarking. Managers can use the proposed descriptive maturity levels for the self-assessment of their current position in a simple linguistic way. Thanks to the DITILOGPRO Maturity Index, the linguistics assessment can be translated into generic and comparable assessment with other companies in the sector or in the same supply chain. Thus, such knowledge can be used to make a decision about the need to implement high-intelligence digital tools to support the management of logistics processes.

6. Conclusions

In this paper, we investigate how to measure the level of adoption of high-intelligence digital technologies in logistics processes in a simple and actionable way (RQ1). Furthermore, we link the reasons for implementing digital technologies (why) with the level of their adoption (what). We assess how the importance of selected market trends for a company affects the level of digital maturity of its logistics processes (RQ2).

To answer the first question, we have proposed a novel descriptive maturity model for measuring the level of digital maturity of logistics processes with the application DITILOGPRO Maturity Index. We focus on the digital solutions with high intelligence, which are typical for the Logistics 4.0 approach. We applied the maturity model theory to provide a generic framework for the assessment of different partners in supply chains (suppliers, manufacturers, retailers, e-tailers, logistics service providers) in a homogeneous way.

The benefit of the proposed maturity model is its simplicity and flexibility, as the catalog of the technologies that are taken into consideration can be extended/substituted with other technologies. The model is generic in its design, so it can be applied for the assessment of different partners in a supply chain.

To answer the second research question, we applied Bayesian statistics to test the level of the relationship between the digitalization of logistics processes and four market trends, namely, sustainability, e-commerce, the sharing economy, and the speed-orientation of customers. The results show that all the trends tested moderately and positively influence the digital maturity of logistics processes.

The limitation of this research is related to the data collection process, as we rely on the knowledge of experts. To reduce the impact of this limitation, we triangulated the empirical data with the findings of the critical literature review. Moreover, we applied a limited catalog of market trends. Due to the characteristics of the dataset, this study can be treated as preliminary research only. Therefore, further research will include extended studies on the drivers for the digitalization of logistics processes, with a focus on the larger dataset, which is not country-specific. In the future research, we will apply the multi-criteria decision-making methods (e.g., grey decision-making method, multicriteria fuzzy decision-making methods) in order to provide a ranking of the external drivers for the adoption of digital technologies in a supply chain. Multi-criteria decision-making methods will allow for creating the weighting system for drivers in order to make the adoption of them more actionable for participants in a supply chain.

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