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Navigating Success: How Decision–Making Transforms Software Performance into Business Performance in the Logistics Industry from an Emerging Country

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Background/Purpose: This study investigates the mediating role of decision–making performance in the link between software performance and overall business performance in the logistics sector of an emerging economy. As logistics companies increasingly rely on digital infrastructures, understanding how advanced systems contribute to strategic outcomes is critical for sustaining competitiveness.
Methods: A conceptual framework was developed integrating ERP systems, big data analytics, and IoT applications. In this model, software performance is positioned as the independent variable, decision–making performance as the mediator, and business performance as the dependent variable. Data were collected from medium- and large–scale logistics firms and analyzed using regression and bootstrapping methods through SPSS and the PROCESS Macro.
Results: The findings reveal that software performance significantly improves decision–making performance ($\beta = 0.552$, $p < 0.01$), which in turn has a strong positive effect on business performance ($\beta = 0.817$, $p < 0.01$). The mediation analysis confirms that decision–making performance mediates the effect of software performance on business outcomes.
Conclusion: The results highlight the strategic importance of aligning digital capabilities with organizational decision processes. By demonstrating the mediating role of decision–making, the study highlights that the effective use of advanced analytical tools is crucial for optimizing performance and achieving a sustainable competitive advantage in logistics.

Keywords: *Software performance, Decision–making performance, Business performance, TMS systems, Logistics industry, Emerging economy*

1 Introduction

In today’s highly competitive business environment, it is recognized that sustainable growth and competitive advantage depend not only on financial resources but also on effective, timely decision–making at both strategic and operational levels to respond to environmental uncertainties, competitive pressure, and technological changes. Un-

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der uncertain and volatile market conditions, the capacity to make accurate, fast, and flexible decisions is considered a decisive factor for both daily operations and long–term strategic positioning (James & Mark, 1996; Chatterjee et al., 2023). Decision–making performance is closely linked to a business's ability to respond to environmental uncertainties, competitive pressures, and technological disruptions, thereby driving organizational agility, sustainable competitive advantage, and overall business performance (Grover et al., 2018; Wang et al., 2016; Baum & Wally, 2003).

The decision–making process is operationalized as involving problem identification, data collection, evaluation of alternatives, decision execution, and feedback mechanisms (Sauter, 2014). Its effectiveness is dependent upon decision–makers' analytical capabilities, real–time access to quality data, and the supporting technological infrastructure. Business systems – including ERP, Decision Support Systems (DSS), and Business Intelligence (BI) – are employed to integrate vast amounts of structured and unstructured data, thereby enhancing analytical capacity and decision accuracy (Hopkins & Hawking, 2018; HassabElnaby et al., 2011).

A shift is observed from intuition–based decision models to data–driven, predictive analytics–driven approaches, which substantially improve both decision quality and business performance (Chatterjee et al., 2023; McAfee & Brynjolfsson, 2017). Central to this transformation are ERP systems that integrate data across departments, providing decision–makers with real–time insights, predictive analytics, and scenario–based forecasting tools (Carton & Adam, 2010; Ouiddad et al., 2020).

Within the logistics industry, ERP and Transportation Management Systems (TMS) are utilized to optimize decision–making for supply chain coordination, fleet management, and order fulfillment (Wang et al., 2016; Mishra et al., 2023). Given the complex and dynamic nature of logistics operations, fast and accurate decision–making is deemed essential for ensuring on–time deliveries, reducing costs, and maintaining customer satisfaction (Dubey et al., 2021a). TMS is further enhanced by the integration of AI, IoT, and geospatial analytics, which facilitate real–time tracking, demand forecasting, automated routing, personalized service offerings, and predictive maintenance (Hopkins & Hawking, 2018; Goswami et al., 2025).

It is argued by Carton and Adam (2010) that while real–time data processing via ERP and TMS improves decision speed, the overall effectiveness depends on the quality of data integration and system responsiveness. Similarly, Ouiddad et al. (2020) and HassabElnaby et al. (2011) report that ERP systems significantly enhance decision-making accuracy. However, they may yield mixed effects on decision speed, particularly when manual data processing or offline data warehouses are involved.

The integration of DSS with ERP and TMS is implemented as a strategic response to these limitations, enabling the generation of customized reports, AI–driven recommendations, and scenario analysis to optimize both the speed and accuracy of strategic decision–making (Alake et al., 2025; Chatterjee et al., 2023). Moreover, the emergence of Big Data analytics and Machine Learning is employed to enhance decision–making performance through predictive modeling and prescriptive analytics, thereby allowing businesses to anticipate disruptions and make proactive adjustments (Wang et al., 2016).

While prior studies have confirmed the operational and financial benefits of ERP and TMS (Akkermans et al., 2003; Gattiker & Goodhue, 2005; Hendricks et al., 2007), the underlying mechanisms through which these systems create business value remain ambiguous. Scholars have increasingly emphasized that enterprise systems do not automatically lead to superior business performance; instead, their value is realized through organizational capabilities that mediate this relationship (Wade & Hulland, 2004; Mithas et al., 2011). Within such mediators, decision-making performance is recognized as a critical channel that translates technological capabilities into strategic and operational success by improving decision speed, accuracy, and flexibility. However, empirical evidence on this mediating effect remains limited, particularly in the logistics industry, where digital adoption is uneven and businesses often struggle with operational inefficiencies (Gunasekaran et al., 2017; Dubey et al., 2021b). This gap is significant because logistics operations are highly dynamic and vulnerable to fluctuations in demand, cost pressures, and disruptions, making effective decision-making a crucial element in competitiveness. By examining the mediating role of decision-making performance, this study aims to enhance our understanding of how TMS impacts business performance. In doing so, it not only provides theoretical contributions to the literature on enterprise systems and performance alignment but also offers practical insights for managers in emerging economies who must maximize returns from digital investments under conditions of uncertainty (Tallon, 2008; Liang et al., 2010).

Despite these advancements, it is acknowledged that the effectiveness of decision–making performance in driving improved operational efficiency, enhanced decision-making capabilities as well as business success is contingent upon several contextual factors, including organizational alignment, user training, system customization (Nicolaou, 2004), rigid system structures, resistance to change, managerial support, process reengineering, cultural adaptation (Bahrami & Jordan, 2009), business data literacy, system interoperability, and leadership adaptability (Grover et al., 2018). The enhanced decision accuracy and real–time analytics provided by ERP and TMS are realized only when decision–makers are equipped to leverage these insights effectively.

This study examines the multifaceted effects of TMS software on decision–making performance in logistics, investigating how decision speed, accuracy, and flexibility influence overall business performance. It is anticipated that the findings will contribute to an improved understanding of how digital decision–making frameworks translate into competitive advantage, particularly in emerging economies where logistics inefficiencies persist.

2 Literature Review

Enterprise Resource Planning (ERP) systems have been integral to organizational decision–making processes for the past two decades. Existing literature highlights their significant role in improving decision accuracy and enhancing decision–making speed, as presented in Table 1. However, empirical findings on these performance dimensions are inconsistent and sometimes contradictory. While some studies suggest that ERP systems facilitate faster and more accurate decision–making by integrating real–time data and streamlining information flow, others indicate that complex system architecture, data integration challenges, and issues related to user adaptability may hinder decision efficiency. This divergence in findings highlights the need for a more nuanced examination of how ERP systems impact decision–making performance across various business contexts. Consequently, the subsequent subsections delve deeper into the various components of decision–making.

Table 1: The Effects of ERP Systems on Decision–Making Performance

Theme	Findings	Impact Area	Supporting Studies
Information Quality	ERP systems enhance information accuracy and completeness, improving decision–making accuracy.	Decision Accuracy	HassabElnaby et al. (2011); Ouiddad et al. (2020)
System Quality	ERP system design and user-friendliness improve decision–making quality.	Decision Accuracy	Ouiddad et al. (2020)
Integration Challenges	Poor integration of ERP with other systems may negatively affect both decision accuracy and speed.	Decision Accuracy and Speed	Carton & Adam (2010)
Reality Distortion	ERP may sometimes distort organizational reality, leading to inaccurate decisions.	Decision Accuracy	Carton & Adam (2010)
Real–Time Data Access	ERP aims to increase decision speed through real–time data access, though this is not always achieved.	Decision Speed	Carton & Adam (2010)
Manual Data Integration	The need for manual data gathering from non–ERP systems may slow down decision–making.	Decision Speed	Carton & Adam (2010)
Strategic Fit	ERP contributes positively to decision–making and financial performance when aligned with prospector strategies.	Strategic Decision Performance	HassabElnaby et al. (2011)
Organizational Capabilities	ERP enhances organizational capabilities, improving the quality of decision-making and flexibility.	Strategic Decision Performance	HassabElnaby et al. (2011)
Financial Performance	ERP indirectly enhances financial performance through improved decision quality and organizational capabilities.	Outcome (Indirect Effect)	Wier et al. (2007)
BI (Business Intelligence) Integration	Integrating ERP with BI systems further enhances decision–making accuracy and speed.	Decision Accuracy and Speed	Hou & Papamichail (2010); Ouiddad et al. (2018)
ERP's Role in Logistics Decision–Making	ERP systems support logistics decision–making by integrating real–time data; however, system complexity may slow response times.	Decision Speed and Accuracy	Alake et al. (2025); Carton & Adam (2010)
Advanced Analytics & Big Data	The integration of ERP with big data analytics enhances decision–making performance by improving predictive capabilities.	Decision Accuracy and Strategic Impact	Chatterjee et al. (2023); Wang et al. (2016)
Process Optimization & Digitalization	ERP enables process transparency, facilitating better data–driven decision-making in logistics.	Decision Quality and Speed	Hopkins & Hawking (2018)

Source: Authors' work

3 Impact on Decision Accuracy

Several studies emphasize that ERP systems significantly enhance decision–making accuracy. It is demonstrated that information systems play a critical role in improving both analytical capacity and decision quality (Pilepić & Šimunić, 2009) and the integrated, high–quality information infrastructure provided by ERP systems enables decision–makers to access more complete, accurate, and up–to–date information, thereby improving both strategic and tactical decision accuracy (HassabElnaby et al., 2011; Ouiddad et al., 2020). HassabElnaby et al. (2011) show that ERP systems enhance organizational capabilities, indirectly improving business performance, while Ouiddad et al. (2020) find that information and system quality directly contribute -by providing decision-makers with real-time, reliable, and comprehensive data, establishing a strong link between internal processes and strategic objectives (Kumar & Van Hillegersberg, 2000)- to decision quality. Bernroider and Koch (1999) reveal that ERP systems broaden the scope and consistency of decision evaluations.

Recent advancements in Big Data analytics are also shown to enhance decision accuracy within ERP systems. Big Data analytics enables decision–makers to process vast amounts of data from multiple sources, thereby improving forecasting and strategic decision–making (Chatterjee et al., 2023). Moreover, the integration of ERP with Decision Support Systems (DSS) further improves decision quality by providing real–time insights and predictive analytics (Alake et al., 2025). In addition, IoT–enabled logistics are found to further enhance decision accuracy by offering real–time visibility into supply chain and operational performance, thereby enabling timely and precise decisions (Goswami et al., 2025; Mishra et al., 2023).

4 Impact on Decision–Making Speed

The impact of ERP systems on decision–making speed remains a debated topic. Some studies argue that ERP systems accelerate decision–making through real–time data access (Carton & Adam, 2010), whereas others report that this effect is context–dependent and sometimes limited by integration challenges. Carton and Adam (2010) find that despite the promise of faster decisions, delays may occur due to offline data warehouses, manual data integration, and system complexity. Furthermore, excessive data availability may increase the cognitive load on decision–makers, potentially leading to decision paralysis (Carton & Adam, 2010). In the logistics industry, where dynamic, fast–paced environments demand instant yet accurate decisions, the integration of AI–driven analytics and IoT–enabled data streams with ERP is proposed to mitigate delays by automating routine decisions and prioritizing high–impact areas (Hopkins & Hawking, 2018). Grover et al. (2018) further indicate that Big Data analytics enables proactive strategy adjustments based on real–time insights, while AI–driven decision support minimizes human biases and accelerates decision–making (Wang et al., 2016).

5 ERP and Organizational Capabilities

It is suggested that the impact of ERP systems on decision–making performance is not solely technical but is significantly influenced by organizational capabilities. HassabElnaby et al. (2011) emphasize that ERP systems indirectly improve decision quality by enhancing organizational capabilities, especially in businesses pursuing innovative and agile strategies. Conversely, businesses that do not adapt their business processes to ERP functionalities may experience suboptimal decision performance. Wier et al. (2007) report that ERP systems indirectly affect financial performance through improved decision–making efficiency and strategic agility, highlighting the need for complementary managerial competencies, a data–driven culture, and continuous system optimization.

6 ERP and Decision Support Systems (DSS)

Decision Support Systems (DSS) are shown to play an integral role in enhancing the decision–making capabilities of ERP systems. Alake et al. (2025) note that when DSS are integrated with ERP systems, decision accuracy and speed are substantially improved through the provision of customized, real–time reports that facilitate rapid, informed decisions. In logistics, DSS helps managers prioritize tasks, allocate resources efficiently, and optimize delivery routes for maximum efficiency. Moreover, the combination of Big Data analytics and DSS within ERP frameworks has considerable potential for enabling data–driven decision-making in supply chain management, allowing for more informed and timely decisions in volatile market environments (Dubey et al., 2021a).

7 ERP–Business Intelligence (BI) Integration and Supporting Systems

Another critical element in enhancing decision–making is the integration of ERP with Business Intelligence (BI) systems. ERP systems alone may not suffice; when integrated with BI tools, decision–making performance is further enhanced by enabling advanced data analysis and visualization (Hou & Papamichail, 2010). Ouiddad et al. (2018) emphasize that ERP–BI integration has become increasingly important for improving decision quality by leveraging historical data, identifying patterns, and generating actionable insights. BI–driven ERP systems are also found to improve decision speed by automating routine analyses, reducing reliance on manual data processing, and providing real–time dashboards for executives. In logistics, ERP–BI integration is demonstrated to optimize fleet management, route planning, and supply chain coordination, ultimately enhancing decision efficiency and operational resilience (Chatterjee et al., 2023; Wang et al., 2016). As businesses in emerging economies navigate infrastructural and logistical complexities, leveraging ERP–BI analytics is considered a strategic differentiator for decision–making effectiveness.

8 Research Model and Hypotheses

The primary objective of this study is to investigate whether the impact of software performance on business performance is mediated by decision–making performance. In this research, software performance is conceptualized as the independent variable (X), decision–making performance as the mediating variable (M), and business performance as the dependent variable (Y). The research model is grounded in a conceptual framework widely adopted in the literature, emphasizing the relationship between decision–making capabilities and business performance (Lee et al., 2011; Rosemann & de Bruin, 2004; Tallon, 2008). Furthermore, the model posits that, in addition to the direct effect of software performance on business performance, there exists an indirect effect mediated by decision–making performance.

The research model of this study is presented in Figure 1. Within this framework, the following hypotheses are tested:

H1: Software performance has a positive and significant effect on decision–making performance.

H2: Decision-making performance has a positive and significant effect on business performance.

H3: Software performance has a direct positive and significant effect on business performance.

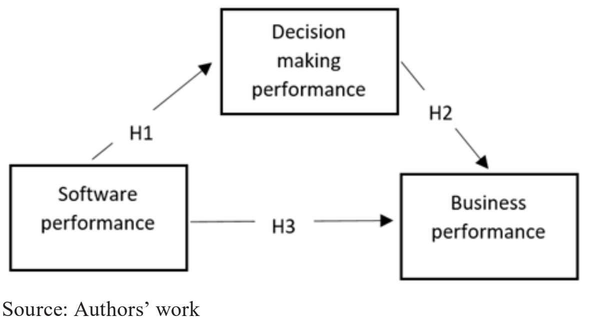
H4: The effect of software performance on business performance is significant through decision-making performance indirectly.

9 Research Population and Sample

The population of this study comprises medium- and large–scale logistics companies operating in Turkey. Data are collected using a convenience sampling method from businesses that actively utilize the Transportation Management System (TMS) software. To identify the sampling frame, a survey is conducted among middle and senior managers working in the logistics, operations management, and information systems departments. Out of 182 distributed surveys, 124 valid responses are obtained, yielding a response rate of 68,1%.

As part of the research, questionnaire forms are distributed to employees working in logistics companies. A total of 126 completed questionnaires are included in the analysis, after adjusting for both positive and negative statements, ensuring no data deficiencies. Only two responses do not provide answers to the questions concerning the business for which they work.

The descriptive statistics presented in Table 2 reveal that many participants (49.2%) are employed in medium–sized businesses, with nearly half (54.8%) working in businesses with an annual financial balance exceeding 100 million TL. The participants are predominantly in the 26–35 (35,7%) and 36–45 (30,2%) age brackets. Most participants hold at least a bachelor's degree (62,7%), while 18,3% have completed postgraduate education. In terms of professional background, a substantial proportion of participants have significant experience, with 42,1% possessing over 12 years of industry–specific experience and 40.5% having more than 12 years of professional experience. Overall, the sample is characterized by a predominance of experienced professionals working in medium to large–scale businesses.



Source: Authors' work

Figure 1: Proposed Research Model

Table 2: Demographic and Organizational Profile of the Respondents

Variable	Categories	Frequency	Percentage (%)
Business Size	Micro	11	8,7
	Small	15	11,9
	Medium	62	49,2
	Large	17	13,5
	Very Large	21	16,7
Annual Financial Balance	< 10 million TL	15	11,9
	10–100 million TL	27	21,4
	100–500 million TL	36	28,6
	> 500 million TL	33	26,2
Age	18–25	22	17,5
	26–35	45	35,7
	36–45	38	30,2
	46–55	20	15,9
	56+	1	0,8
Education Level	Associate	24	19,0
	Bachelor	79	62,7
	Master	21	16,7
	Doctorate	2	1,6
Industrial Experience	< 3 years	24	19,0
	3–6 years	23	18,3
	6–9 years	14	11,1
	9–12 years	12	9,5
	>12 years	53	42,1
Professional Experience	< 3 years	22	17,5
	3–6 years	25	19,8
	6–9 years	15	11,9
	9–12 years	13	10,3
	>12 years	51	40,5

Source: Authors' work

10 Measurement Instruments and Variables

The measurement scales used in this study are developed based on established literature and adapted into Turkish. Each construct is operationalized as a multidimensional conceptual structure and measured using a five–point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree in accordance with the following explanations:

a) Software Performance: Measured through 5 factors comprising 16 items, covering service, technological competence, functionality, software vendor performance, and cost (Doğaner Duman & Altuntaş, 2024).

b) Decision–Making Performance: Measured through several dimensions, including coherence of case analysis, strategic planning, decision effectiveness, analysis capability, rapid decision making, access to information, rapid identification of problems and opportunities, and coordination between units (Gable, Sedera, & Chan, 2008; Huber, 1990; McLaren et al., 2011; Mithas et al., 2011; Tippins & Sohi, 2003; Aydıner, 2016).

c) Business Performance: Measured through indicators such as return on investment, employee productivity, customer complaint response time, market share, sales volume, customer satisfaction, growth rate, profitability, service/product cost, and number of customers (Vickery, 1993; King & Zeithaml, 2001; Rosenzweig, 2003).

11 Validity and Reliability

The test of normality is conducted using skewness and kurtosis values as benchmarks. The fact that the skewness and kurtosis values for the scales remain within ±1,5 (Tabachnick & Fidell, 2013) or ±2,0 (George & Mallery, 2010) indicates that the data are normally distributed. Given that the skewness coefficients for the model's dimensions ranged from -1.439 to -0.941, and the kurtosis values ranged from 0.907 to 1.375, both falling within the acceptable thresholds, parametric tests can be appropriately applied in the subsequent analyses of these dimensions.

The dataset's suitability for factor analysis is assessed using the Kaiser–Meyer–Olkin (KMO) Test and Bartlett's Test of Sphericity. KMO values above 0,50 and statistically significant Bartlett's Test results ($p < 0,01$) are required for adequacy (Altuntaş et al., 2020). As presented in Table 3, all scales demonstrate superb sampling adequacy (KMO > 0,90), and Bartlett's Test confirms significant intercorrelations ($p < 0,01$), validating the dataset's suitability for factor analysis.

The exploratory factor analysis reveals a three–factor structure of the latent construct, as presented in Table 4. The first factor predominantly includes indicators related to software performance, the second factor aggregates metrics reflecting process performance, and the third factor encompasses variables related to business performance. A significant proportion of standardized factor loadings ($\lambda \geq 0,50$) exceeds conventional psychometric thresholds, indicating strong item–construct alignment. This empirical configuration supports the triadic measurement model proposed by existing theoretical frameworks. In addition, inter–factor correlations remain within acceptable psychometric limits ($\Delta\lambda < 0,30$), confirming discriminant validity across the latent constructs. Convergent validity is verified through average variance extracted (AVE) values greater than 0,50, and discriminant validity is further validated using the Fornell–Larcker criterion (Hair et al., 2019). The Confirmatory Factor Analysis (CFA) confirms that the model has a three–factor structure, with fit indices under acceptable thresholds ($\chi 2$ / df = 2.36, CFI = 0.94, TLI = 0.92, RMSEA = 0.062, and SRMR = 0.048).

Reliability is crucial for ensuring the validity of measurements. The internal consistency of the scales used to measure software, process, and business performance is assessed using both Composite Reliability (CR) and Cronbach's alpha coefficients, as shown in Table 4. All dimensions demonstrate exceptional reliability, with CR and Cronbach's alpha values exceeding 0.90 and 0.95, respectively, for all sub-dimensions. These values exceed the threshold for internal consistency as outlined by Nunnally and Bernstein (1994) and surpass the acceptable limits set by George and Mallery (2003), where values below 0.50 are considered inadequate. Therefore, the scales are deemed reliable and retained for further analysis.

Table 3: KMO and Bartlett's Test Results

Variable	KMO Value	Chi–Square	Bartlett's Test (p)
Software Performance	0,903	1138,49	Significant (p < 0.01)
Decision–Making Performance	0,924	1218,94	Significant (p < 0.01)
Business Performance	0,934	1285,57	Significant (p < 0.01)

Source: Authors' work

Table 4: Standardized Factor Loadings and Cronbach's Alpha, AVE, and CR Values of Factors

No.	Construct	Item	Standardized Factor Loadings	Cronbach's Alpha	Average Variance Explained (AVE)	Composite Reliability (CR)
1	**Software Performance**			0,964	0,659	0,892
		SoftPerf3	0,860			
		SoftPerf5	0,790			
		SoftPerf2	0,780			
		SoftPerf1	0,770			
		SoftPerf4	0,749			
2	**Decision–Making Performance**			0,967	0,568	0,913
		DMPerf6	0,801			
		DMPerf7	0,800			
		DMPerf8	0,787			
		DMPerf3	0,754			
		DMPerf2	0,746			
		DMPerf1	0,740			
		DMPerf5	0,731			
		DMPerf4	0,660			
3	**Business Performance**			0,952	0,656	0,927
		BusPerf5	0,842			
		BusPerf2	0,826			
		BusPerf4	0,765			
		BusPerf12	0,762			
		BusPerf6	0,734			
		BusPerf8	0,693			
		BusPerf7	0,689			
		BusPerf3	0,683			
		BusPerf2	0,672			
		BusPerf9	0,603			
		BusPerf10	0,598			
		BusPerf11	0,497			

Source: Authors' work

12 Data Analysis Method

Hypothesis testing and mediation analysis are performed using SPSS 28 and the PROCESS Macro v4.0 (Hayes, 2022), a robust statistical tool designed for path analysis and mediation modeling. Model 4 of the PROCESS Macro is applied to simultaneously test the direct effect of software performance on business performance, as well as the indirect effect mediated by decision–making performance. This methodology aligns with current best practices for examining complex interrelationships in business research (Zhao et al., 2023).

13 Findings

Before mediation modeling, a Pearson correlation analysis is done, as presented in Table 5. The results reveal statistically significant and positive relationships ($p < 0.01$) between all variables. A strong positive correlation is observed between software performance and decision–making performance ($r = 0.800$, $p < 0.01$), as well as between decision–making performance and business performance ($r = 0.654$, $p < 0.01$). These findings suggest that decision–making performance is significantly related to overall business success. In addition, the correlation coefficient between software performance and business performance ($r = 0.722$, $p < 0,01$) is relatively stronger, indicating that the impact of software performance on business performance may be mediated indirectly through decision–making performance.

Following Pearson correlation, to assess the mediation effect, the bias-corrected bootstrap method is employed using 5,000 resamples and 95% confidence intervals (CIs), incorporating the lower limit confidence interval (LLCI) and upper limit confidence interval (ULCI). This non-parametric approach is favored over conventional techniques, such as the causal steps method proposed by Baron and Kenny (1986) and the Sobel test, as it relaxes the assumption of normality and enhances statistical power, particularly in studies with small to moderate sample sizes (Gürbüz, 2019a; Gürbüz, 2019b; Hayes, 2022). The bootstrap method is especially beneficial in the context of emerging economies – such as Türkiye's logistics industry – where diverse business practices and infrastructural limitations may lead to deviations from normal data distributions.

A regression analysis is conducted to test the hypotheses of the mediation model based on Model 4 – Simple Mediation Model, as outlined by Hayes (2022). This model incorporates a mediator variable, examining both direct and indirect effects. To examine the mediation relationships in this study, a regression analysis using the bootstrap method is employed (Gürbüz, 2019a; Gürbüz, 2019b). All analyses are performed using Hayes' (2022) PROCESS Macro, with the bootstrap technique applied using 5.000 resamples. For statistical significance, the obtained 95% confidence intervals should not include zero (0) (Gürbüz, 2019a; Gürbüz, 2019b).

For the analysis model presented in Table 6, the effect of software performance on decision–making performance (path a) is found to be statistically significant and positive ($\beta = 0.0552$, 95% CI = [0.7095, 0.9281], $p < 0.00$). Software performance accounts for approximately 63% of the variance in decision–making performance. Similarly, the results indicate that decision–making performance has a statistically significant and positive effect on overall business performance (path b) ($ß = 0,817$, 95% CI = [0,2811, 0.6047], $p < 0,00$).

Table 5: Pearson Correlation Analysis Results

No.	Variable	Arithmetic Mean	Standard Deviation	1	2	3
1	**Software Performance**	3,771	1,080	1,00		
2	**Decision–Making Performance**	3,859	1,508	0,800*	1,00	
3	**Business Performance**	3,514	0,886	0,654*	0,722*	1,00

Source: Authors' work

Table 6: Results of the Mediation Model between Variables

Variable				
	Decision-Making Performance (Mediator)		**Business Performance**	
		%95 CI		**%95 CI**
Model	**ß / SE**	**LLCI/ULCI**	**ß / SE**	**LLCI/ULCI**
Software Performance	0,0552	0,7095 / 0,9281	0,0837	0,0078 / 0,3392
Decision-Making Performance (Mediator)	–	–	0,817	0,2811 / 0,6047
Constant	0,2166	0,3415 / 1,1988	0,2069	0,7471 / 1,5609
Model Summary	*$R^2 = 0,6394$*		*$R^2 = 0,5378$*	
	F = 219,8737	*p = 0,000*	*F = 71,5659*	*p=0,000*

Source: Authors' work

Table 7: Mediation Effect Results of Decision–Making Performance

Direct Effect								
			Effect	***S. H.***	***LLCI***	***ULCI***	***t***	***p***
Software Performance	**Business Performance**		0,1735	0,0837	0,0078	0,3392	2,0727	0,00
Indirect Effect								
Software Performance	**Process Performance**	**Business Performance**	0,3626	0,0841	0,1591	0,4970		
Total Effect			0,5361	0,557	0,4259	0,6464	9,6229	0,00

The analysis results reveal that the effect of TMS software performance on overall business performance is mediated by decision–making performance. The bootstrap analysis, conducted to assess whether decision–making performance mediates the relationship between software performance and overall business performance, indicated a significant mediation effect. Since the 95% confidence interval obtained through the bootstrap method does not include zero (0), it is concluded that decision–making performance plays a significant mediating role in the relationship between software performance and overall business performance.

The mediation analysis results, as presented in Table 7, indicate that the direct effect of software performance on overall business performance (β = 0.1735, 95% CI [0.0078, 0.3392]) is positive and statistically significant ($p < 0.01$). Furthermore, the indirect effect of software performance on overall business performance, mediated through decision–making performance (β = 0.3626, 95% CI [0.1591, 0.4970]), is also positive and statistically significant ($p < 0.01$). The total effect of software performance on overall business performance, combining both direct and indirect effects (β = 0.536, 95% CI [0.4259, 0.6464]), is likewise positive and statistically significant ($p < 0.01$). These findings suggest that enhancing the effectiveness of TMS systems software results in a more substantial impact on overall business performance by improving decision–making processes.

14 Conclusion, Limitations, Future Research Directions, and Recommendations

This study examines the impact of software performance on decision–making performance and overall business performance in logistics companies, with a particular focus on the mediating role of decision–making performance. The findings demonstrate that software performance has a significant influence on business performance through both direct and indirect pathways. A robust positive relationship is observed between software performance and decision–making performance (β = 0.0552, 95% CI = [0.7095, 0.9281], $p < 0.01$), with software performance enhancing the quality, accuracy, and speed of the decision–making process. This supports the view that systems such as ERP and TMS facilitate faster and more accurate decisions by providing integrated information, real–time data access, and advanced analytical capabilities (Hou & Papamichail, 2010; HassabElnaby et al., 2011). Furthermore, the integration of big data analytics strengthens these outcomes by improving forecasting and decision accuracy (Chatterjee et al., 2023; Wang et al., 2016).

A key finding is that decision–making performance significantly mediates the effect of software performance on overall business performance. This aligns with the findings of Carton and Adam (2010) and Ouiddad et al. (2020), who emphasize that software systems, such as ERP, primarily contribute to business performance through their impact on decision–making processes. The identified indirect effect suggests that the influence of software performance on overall business performance is more pronounced when mediated by decision–making performance. Given the dynamic and complex structure of the logistics industry, these findings underscore the crucial role of effective decision–making processes in achieving business success. IoT–enabled analytics in logistics (Hopkins & Hawking, 2018) further reinforce the capacity for real–time decision–making and operational agility.

Further analysis reveals that decision–making performance has a substantial and statistically significant impact on business performance (β = 0.817, 95% CI = [0.2811, 0.6047], $p < 0.00$). This indicates that, particularly in decision–intensive areas such as order management, transportation planning, fleet optimization, and customer service, the effectiveness of decision–making processes directly affects performance indicators, including cost efficiency, customer satisfaction, and operational effectiveness (Alake et al., 2025).

Overall, the study supports existing literature by confirming that software performance enhances business performance through decision–making processes, particularly within the logistics industry. It validates the frequently discussed notion that ERP and similar systems function not only as technical tools but also as integral components of organizational decision–making frameworks (Tallon, 2008; Hou & Papamichail, 2010). Moreover, by integrating big data analytics, businesses can better forecast trends and mitigate risks, ultimately strengthening their competitive position (Chatterjee et al., 2023; Wang et al., 2016).

The findings suggest that logistics companies should not focus solely on improving software performance but also ensure that software systems are effectively integrated with decision–making processes. Managers should structure systems, such as ERP and TMS, to support and enhance decision–making capabilities. Furthermore, integrating complementary tools – such as Decision Support Systems (DSS) and Business Intelligence (BI) – with ERP can further enhance both the quality and speed of decision-making.

The results indicate that the contribution of enterprise software to business performance should be understood primarily through the lens of decision-making performance rather than as a direct and unconditional outcome of system use. This finding is consistent with the broader enterprise systems literature, which has long emphasized that information systems yield business value through organizational capabilities and contextual mechanisms rather than in isolation (Wade & Hulland, 2004; Mithas et al., 2011). By empirically demonstrating the mediating role of decision-making performance, the study advances this stream of research. It provides robust evidence that decision quality, accuracy, and speed are the primary channels through which software investments in the logistics industry translate into measurable improvements in business performance. These insights reinforce the relevance of theoretical perspectives such as the resource-based view and the dynamic capabilities framework, which argue that organizational performance stems not from technology itself but from the business's ability to reconfigure and integrate technology into core processes (Tallon, 2008; Liang et al., 2010).

From a practical standpoint, the findings highlight that logistics businesses should not evaluate ERP and TMS projects merely as operational tools but as strategic enablers of organizational agility and competitiveness. Investments in software performance must be complemented by initiatives that enhance decision-making capabilities, such as training programs, data governance structures, and the integration of advanced analytics tools. Furthermore, the results underline that businesses in dynamic and uncertain environments—such as logistics providers—are more likely to achieve sustainable performance gains if they can leverage these systems to shorten decision cycles, increase accuracy, and align operational decisions with strategic objectives. In this sense, software systems should be regarded as integral elements of decision-making frameworks rather than as stand-alone technological artifacts.

The study also contributes to the literature by offering empirical evidence from an emerging economy context, where digital adoption is often uneven and logistics inefficiencies are prevalent. This contextual contribution is important because much of the existing research on ERP and TMS has been conducted in developed economies, and the transferability of those findings to other contexts has been questioned. By confirming that decision-making performance is a key mechanism in this setting as well, the study provides valuable insights for both scholars and practitioners seeking to understand how digital systems can foster competitiveness under resource constraints and institutional challenges.

Improving the software usage skills of decision–makers also emerges as a critical factor. Logistics companies should provide continuous training for employees and develop guided materials to facilitate the effective and efficient use of these systems. Additionally, continuous monitoring and evaluation of software–supported decision-making processes, coupled with regular reporting to management, will help maximize the benefits derived from these systems. Managers should not only focus on the technical performance of software but also strive to simplify and optimize decision–making processes, thereby making the impact of software on decision–making performance more tangible.

For researchers, exploring the relationship between software performance, decision–making performance, and business performance across different industries and various types of software presents an important avenue for future study. Analyses that consider the sub-dimensions of decision–making performance—such as decision speed, decision accuracy, and decision quality—could elucidate which aspects are most influenced by software systems. Moreover, developing comprehensive structural models that examine the impact of ERP and similar systems on decision–making, in conjunction with variables such as organizational learning, agility, and innovation, would significantly advance the literature. Finally, employing qualitative or mixed–method approaches could provide deeper insights into the impact of software use on decision–making processes by capturing decision–makers' perceptions and experiences regarding system usage.

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