



The Role of Technology in Modern Logistics and Supply Chain Management

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Abstract

Technology has become a factor in logistics and supply chain management because it manages the movement, coordination and control of goods, information and resources. The purpose of this paper is to study the role of technology in logistics and supply chain management focusing on information technology, Internet of Things, cloud computing, big data analytics, Block chain, automation, robotics and digital systems. Using a questionnaire-based dataset of 100 responses the paper measures how respondents see the three dimensions of technology benefits and the perceived challenges of technology adoption. It also looks at the present and the future using statistical methods such as descriptive statistics (mean median standard deviation) Cronbach's alpha, chi-square, one-way analysis of variance and linear regression. Perceptions of technology were generally positive. The average scores for the three dimensions of benefits ranged from 4.02 to 4.12 out of 5 while the perceived challenges of technology adoption had a score of 3.82. Perception level showed an association with occupation: $(3) = 9.50, p = .023$. The mean perceived benefit also varied by occupation, $F(3, 96) = 3.57, p = .017$ with business respondents reporting the values. No significant differences were seen for gender, age, education or income. In regression perceived operational benefits did not predict future technology potential ($\beta = .18, p = .069, R = .033$). Internal consistency, among item groups was low. 97 Of 100 records were identified as synthetic. These findings should be considered illustrative based on the dataset.

Keywords: logistics technology, supply chain management, information technology, Internet of Things, automation, operational efficiency.

Introduction

Logistics and Supply Chain Management are significant processes to ensure the effective flow, coordination and control of materials, information and resources between suppliers and customers. Organizations are more and more turning to technology to enhance their logistics and supply chain functions to be more efficient, accurate, and responsive in the modern business environment.

Logistics and supply chain functions are being increasingly executed with technologies like Information Technology (IT), Internet of Things (IoT), cloud computing, big data analytics, blockchain, automation, robotics and other digital systems. They help organisations to keep an eye on

processes, track products, manage stock, control supply chain partners and make quicker and informed decisions.

Digital technologies in Logistics and Supply Chain Management (SCM) are even more relevant in the context of Industry 4.0 and Supply Chain 4.0. Better coordination and integration between various activities of the supply chain can be achieved with the help of connected devices, smart systems, data analytics and automated processes.

There are also issues related to the adoption of technology, including the cost of implementing it, its complexity, a lack of skilled personnel, cybersecurity, and data privacy concerns. In this context, the present study is about the use of technology in today's logistics and supply chain management.

Review of Literature

Technology plays a key role in the logistics and supply chain management of all areas, in the exchange of information, coordination, visibility and decision making. The other body of studies has focused on the technological side, such as information technology, integration of supply chains, Internet of Things, automation (Industry 4.0), digitalization and performance of the supply chain. What follows research studies provide useful information about the role and contribution of technology in today's logistics and supply chain management.

2.1 Oliveira-Dias, Moyano-Fuentes and Maqueira-Marn (2022)

Oliveira-Dias, Moyano-Fuentes, and Maqueira-Marn (2022), in "Understanding the Relationships between Information Technology and Lean and Agile Supply Chain Strategies: A Systematic Literature Review," looked at information technology and lean and agile supply chain strategies. The study found a positive correlation between the use of IT and these supply chain strategies and proposed that this correlation would lead to better business results.

2.2 Sun, Yu, Solvang, Wang, and Wang (2022)

Sun, Yu, Solvang, Wang and Wang (2022) have conducted a Systematic Literature Review (SLR) (2012-2020) to explore future research opportunities in the field of application of Industry 4.0 technologies in sustainable logistics. The study identified potential gains in economic efficiency, environmental performance and social impacts, and challenges of technology maturity and implementation.

2.3 Rebelo, Pereira, and Queiroz (2022)

Rebelo, Pereira, and Queiroz (2022), entitled "The Interplay between the Internet of Things and Supply Chain Management: Challenges and Opportunities Based on a Systematic Literature Review", a study, which looked at the impacts of IoT technology on supply chain management performance. The paper identified the IoT applications in supply chains and outlined the opportunities and challenges of connected technologies based on the Internet of Things for managing supply chain processes.

2.4 Naseem and Yang (2021)

Naseem and Yang (2021) examined in their article "Role of Industry 4.0 in Supply Chains Sustainability: A Systematic Literature Review" the impact of Industry 4.0 technologies on supply chain sustainability. The article highlighted the contribution of Industry 4.0 innovations to making the

supply chain sustainable and suggested a pyramid of the impact of these innovations on the activities of supply chains.

2.5 Abdirad and Krishnan (2021)

Abdirad and Krishnan (2021) studied the research on Industry 4.0 Technologies in Logistics and Supply Chain Management in their Systematic Literature Review titled, "Industry 4.0 in Logistics and Supply Chain Management. The research also revealed the importance of the themes related to technology and suggested the need for further research on the implementation, problems and outcomes of Industry 4.0 in the supply chain.

2.6 Efthymiou and Ponis (2021)

In the paper "Industry 4.0 Technologies and Their Impact in Contemporary Logistics: A Systematic Literature Review" (Efthymiou and Ponis, 2021), 65 pieces of literature were studied about Industry 4.0 and its impact on logistics. Different technologies, such as Internet of Things, cyber-physical systems, big data and smart systems were all introduced in the context of their influence on Industry 4.0, as well as recognizing barriers and opportunities.

2.7 Rad Oghazi Palmi Chirumalla, Pashkevich, Patel, and Sattari (2022).

In the SLR titled 'Industry 4.0 and Supply Chain Performance: A Systematic Literature Review of the Benefits, Challenges, and Critical Success Factors of 11 Core Technologies', Oghazi Palmi Chirumalla et al., 2022, analyzed 221 publications on eleven Industry 4.0 technologies. The benefits such as integration and tuning were.

Research Problem Statement

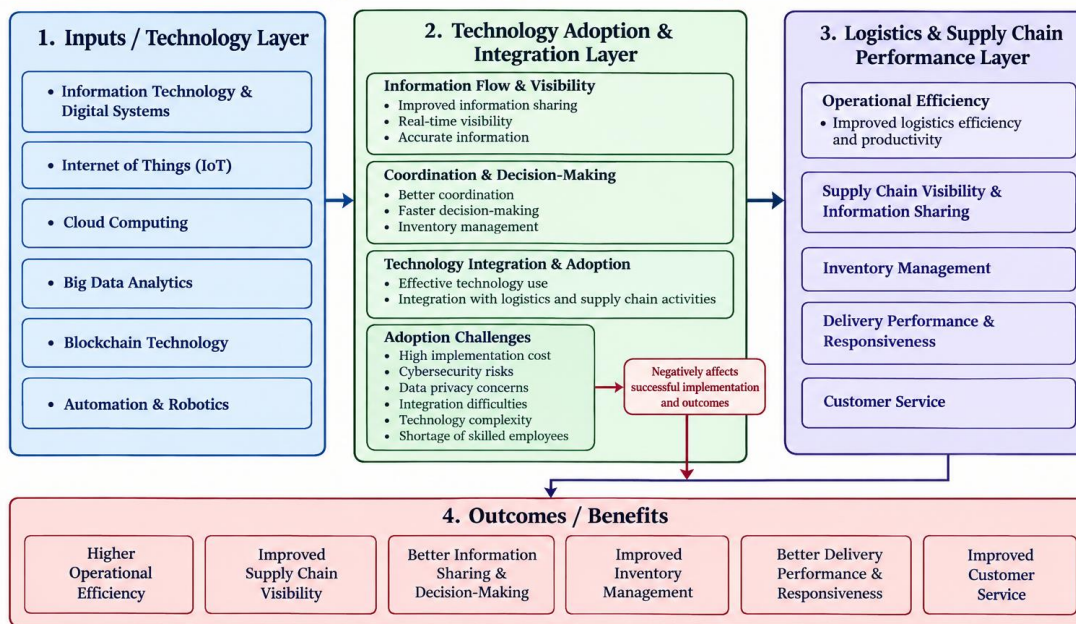
Technologies are being increasingly adopted and implemented to improve logistics and supply chain (LCS) operations, and their effectiveness relies upon how they are implemented and integrated. One must pay attention to how people perceive their ability to increase speed in doing something, managing inventory (moving goods) and what they see happening with the supply chain in the future, and what the large problems are for using these technologies.

Research Gap

By reading the articles reviewed it has been noted that technology has become an integral part of today's logistics and supply chain management which aids in the sharing of information and provides a real-time picture of what is happening, links different parts of the chain together, automates tasks, enables decision-making and optimizes operations. Research for most part focuses on one technology or one aspect of logistics. In this study, the researchers examine technology-based applications in aggregate and technology applications and describe the advantages that people believe they are getting in solving their problems and what could be done in the future in logistics and supply chain management.

Conceptual framework

Conceptual Framework: The Role of Technology in Modern Logistics and Supply Chain Management



Objectives of the Study

1. To explore the role of technology in the modern logistics and supply chain management.
2. To examine the effects of technological applications on logistics and operational efficiency of supply chain.
3. Assess how technology impacts supply chain transparency, information sharing and decision making.
4. To find out the key barriers that organizations face in technology implementation in logistics and supply chain management.
5. To assess the contribution of technology to improved logistics and supply chain performance, responsiveness and customer service.
6. To test statistically whether perceptions of technology differ across respondent groups and whether perceived operational benefits predict expectations of future technology potential.

Research Question and Hypotheses

Research question: What is the perceived role of technology in improving logistics and supply chain performance among the respondents?

H₀₁: There is no significant relationship between the use of technology and logistics and supply chain performance.

H₁₁: There is a significant relationship between the use of technology and logistics and supply chain performance.

Because the questionnaire does not record actual technology use, H₀₁ is operationalised as the relationship between respondents' perceived technology-related operational benefits (Items 1–12) and

their expectation of future technology-driven efficiency (Items 17–20), and is tested with Pearson correlation and linear regression.

H₀₂: There is no significant association between the respondents' demographic characteristics (gender, age, occupation, education and monthly income) and their level of perceived technology benefits (moderate or high). H₁₂: There is a significant association between at least one of these characteristics and the level of perceived technology benefits.

H₀₃: There is no significant difference in mean perceived technology benefits (Items 1–12) across the categories of gender, age, occupation, education and monthly income. H₁₃: The mean perceived technology benefits differ significantly across the categories of at least one of these characteristics.

H₀₄: Perceived operational efficiency, inventory and warehouse management, transportation and delivery, and technology-adoption challenges do not significantly predict future technology potential.

H₁₄: At least one of these four dimensions significantly predicts future technology potential.

Research Methodology

Research Design

The study is of quantitative type with descriptive and cross sectional design with analytical approach. Frequencies, percentages, means, medians and standard deviations are used to summarize responses to the questionnaires. The analytical component involves the use of chi-square test of independence, one-way analysis of variance (ANOVA) and linear regression to test the hypotheses. Correlation and regression show association but NOT causation.

Population and Sample

There are 100 records of responses to the dataset. According to the Data Note in the workbook, the user provided three responses and the other 97 records were synthetic/simulated to achieve 100 records. The results should therefore be taken as an example of how to analyze data from a set of 100 actual respondents. There is no sampling frame defined for the data.

Instrument and Measures

The structured questionnaire includes demographic items and 20 five-point Likert-scale items (1 = Strongly disagree; 5 = Strongly agree). Operational efficiency, Movement of Goods, Delays, Coordination, Inventory accuracy, Warehouse automation, Inventory errors, Real-time tracking, GPS and delivery routes, Transportation costs, Technology-adoption challenges, Artificial Intelligence, Automation, IOT and Efficiency in the future. The items were broken down into five dimension scores, which were respectively calculated as the mean of the items in each dimension: Operational Efficiency (Items 1–4), Inventory and Warehouse Management (Items 5–8), Transportation and Delivery (Items 9–12), Technology-Adoption Challenges (Items 13–16), and Future Technology Potential (Items 17–20). A Perceived Technology Benefits score was determined by averaging the items 1-12 and an overall score by averaging all 20 items. The respondents with a Perceived Technology Benefits score equal to or higher than 4.00 were considered to have a high perception level with all others having a moderate perception level (none had a score below 3.33).

Procedure and Ethics

In order to conduct a true empirical study, participants should be told the aim of the study, they should be encouraged to take part, they should not have to give up any identifying information they do not wish to share and the data should be kept in a secure place. Since the workbook provided

explicitly states that 97 records are synthetic, the present analysis does not state that those records are the actual individuals surveyed. The coded data do not include names or timestamps.

Data Analysis Procedures

The coded responses were typed into a spreadsheet and analysed at a 5% significance level ($\alpha = .05$). For each item and dimension score, descriptive statistics (mean, median, SD, minimum and maximum scores) were computed. Cronbach's alpha was used to determine internal consistency. Each demographic variable was tested for association with level of perception using the chi-square test of independence (Pearson without continuity correction) with the effect size measure of Cramer's V; ages over 30 years were grouped together and government employees and private employees were merged into one category (salaried employees). A Monte Carlo permutation p-value was also calculated for expected counts less than 5, as a check. One-way ANOVA compared mean Perceived Technology Benefits among the demographic groups, using eta squared (η^2) as effect size, Levene's test for homogeneity of variance, Tukey's HSD for post hoc comparisons and the Kruskal-Wallis test as a non-parametric test. Pearson correlations were computed among the dimension scores. Simple linear regression (Future Technology Potential on Perceived Technology Benefits) and multiple linear regression (Future Technology Potential on the four dimension scores), were estimated by ordinary least squares and produced standardized coefficients (β), 95% confidence intervals, variance inflation factors (VIF), and the Durbin-Watson statistic and the Shapiro-Wilk test on residuals. All calculations were done using Python (NumPy and SciPy), and the procedures are the ones that are provided in SPSS and the Excel Data Analysis ToolPak; the procedures given in the Excel workbook are the same as the descriptive statistics that are presented, using Excel spreadsheet formulas.

Results

These are the results for a 100 row dataset supplied. These statistics should be interpreted in the context of the dataset note.

Respondent Profile

Table 1:

Respondent Profile (N = 100)

Characteristic	Category	n	%
Gender	Male	61	61.0
Gender	Female	39	39.0
Age	20–30 years	60	60.0
Age	18–20 years	24	24.0
Age	31–40 years	12	12.0
Age	41–50 years	4	4.0
Occupation	Student	46	46.0
Occupation	Private Employee	22	22.0
Occupation	Business	12	12.0
Occupation	Self-employed	16	16.0
Occupation	Government Employee	4	4.0
Education	Undergraduate	49	49.0

Characteristic	Category	n	%
Education	Postgraduate	23	23.0
Education	Graduate	21	21.0
Education	Diploma	7	7.0
Monthly Income	Below ₹20,000	51	51.0
Monthly Income	₹20,000–₹40,000	29	29.0
Monthly Income	₹40,001–₹60,000	12	12.0
Monthly Income	Above ₹60,000	8	8.0

Note. Counts and percentages are calculated from the supplied 100-row dataset; the workbook notes that 97 records are synthetic simulated.

Males account for 61% of the dataset and females 39%. The largest age group is 20–30 years (60%), students form the largest occupation category (46%), undergraduates account for 49% of respondents and 51% report a monthly income below ₹20,000. The sample is therefore young, student-dominated and low-income, which limits generalization to experienced logistics professionals.

Descriptive Statistics and Reliability

Table 2

Descriptive Statistics and Reliability of Dimension Scores (N = 100)

Dimension	Items	Mean	Median	SD	Min	Max	α
Operational efficiency	1–4	4.02	4.00	0.49	2.75	5.00	.02
Inventory & warehouse management	5–8	4.12	4.00	0.43	3.25	5.00	–.39
Transportation & delivery	9–12	4.11	4.25	0.51	2.75	5.00	.17
Technology-adoption challenges	13–16	3.82	3.75	0.51	2.75	5.00	–.15
Future technology potential	17–20	4.09	4.12	0.48	2.75	5.00	.00
Perceived technology benefits	1–12	4.08	4.08	0.30	3.33	5.00	.15
Overall (all items)	1–20	4.03	4.05	0.25	3.55	5.00	.22

Note. Like coding: 1 = Strongly disagree and 5 = Strongly agree. Each score is the mean of its items; SD is the standard deviation of respondents' scores. α = Cronbach's alpha.

All three benefit dimensions record means above 4.00, with medians of 4.00 or higher: Operational Efficiency (M = 4.02, MDN = 4.00, SD = 0.49), Inventory and Warehouse Management (M = 4.12, MDN = 4.00, SD = 0.43) and Transportation and Delivery (M = 4.11, MDN = 4.25, SD = 0.51). Future Technology Potential is similarly high (M = 4.09, SD = 0.48). Technology-adoption challenges have the lowest mean (M = 3.82, SD = 0.51), yet it remains above the neutral point of 3, so respondents also recognize implementation barriers. Medians show that the typical respondent agrees with every individual statement (MDN = 4 for all 20 items).

Cronbach's alpha values are very low ($\alpha = -.39$ to $.17$ for the five dimensions; $\alpha = .22$ for all 20 items). The items within each group therefore do not vary together across respondents, and the dimension scores should be read as descriptive groupings of related statements rather than as reliable, unidimensional scales. This is a limitation for the inferential tests that follow, and it is consistent with the dataset note that most records were simulated.

Item-wise Response Distribution

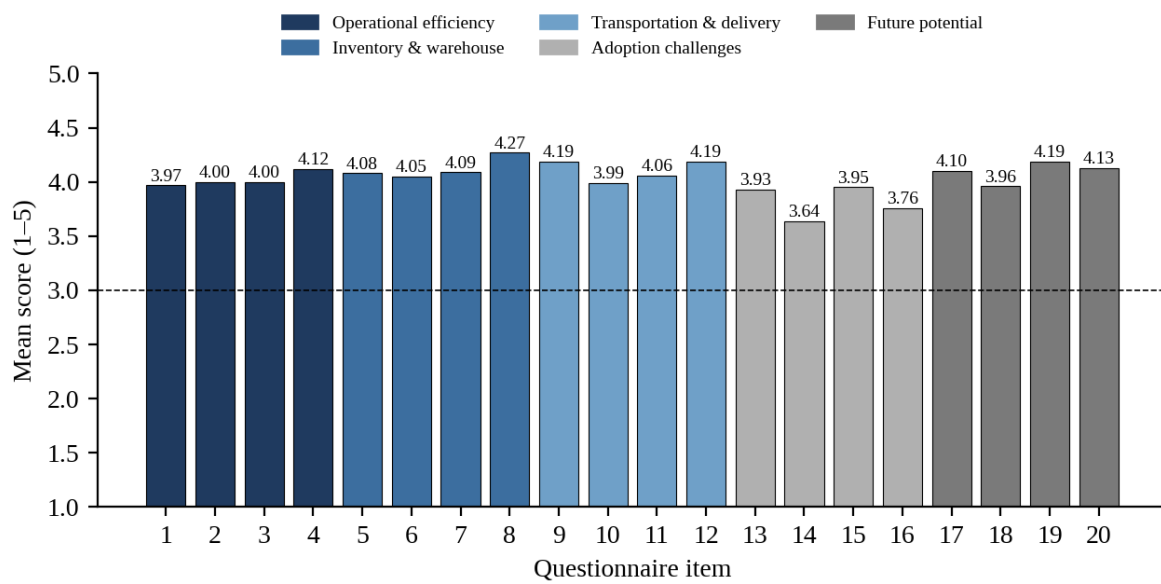
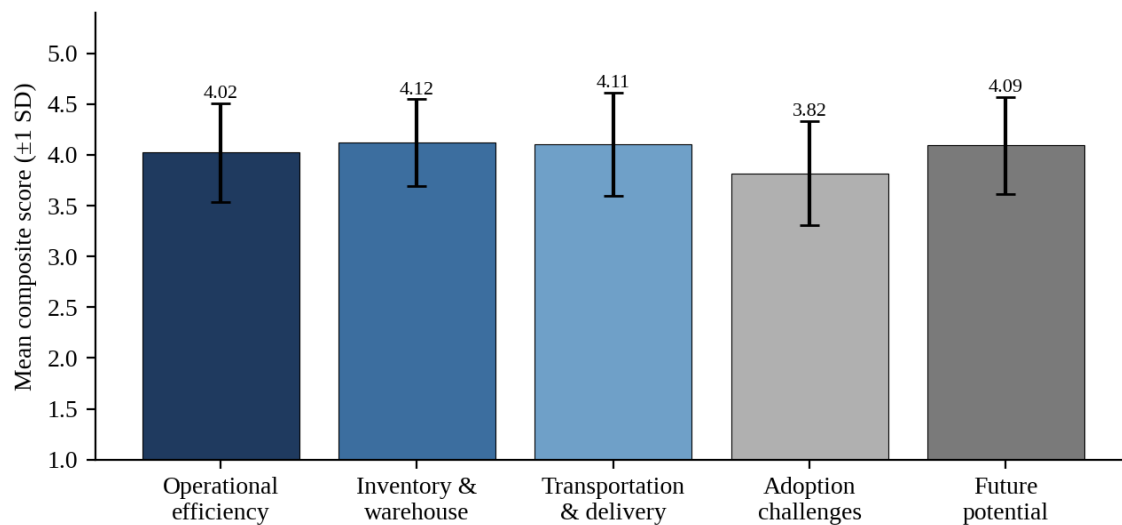
Table 3

Response Distribution by Questionnaire Item (n)

Item	SD	D	N	A	SA	Mean	MDN	SD	% A+SA
1	2	7	19	36	36	3.97	4	1.01	72
2	4	7	11	41	37	4.00	4	1.06	78
3	2	7	10	51	30	4.00	4	0.93	81
4	2	2	13	48	35	4.12	4	0.86	83
5	2	5	17	35	41	4.08	4	0.98	76
6	1	7	19	32	41	4.05	4	0.99	73
7	4	7	9	36	44	4.09	4	1.08	80
8	0	3	12	40	45	4.27	4	0.79	85
9	1	5	11	40	43	4.19	4	0.90	83
10	2	7	15	42	34	3.99	4	0.98	76
11	2	5	15	41	37	4.06	4	0.95	78
12	1	7	12	32	48	4.19	4	0.97	80
13	1	9	19	38	33	3.93	4	0.99	71
14	5	12	25	30	28	3.64	4	1.16	58
15	5	5	17	36	37	3.95	4	1.10	73
16	3	12	19	38	28	3.76	4	1.08	66
17	0	7	17	35	41	4.10	4	0.93	76
18	3	9	11	43	34	3.96	4	1.04	77
19	1	7	7	42	43	4.19	4	0.92	85
20	1	5	15	38	41	4.13	4	0.92	79

Note. SD = Strongly disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly agree; MDN = median; the SD column after MDN is the standard deviation. % A+SA is the percentage choosing Agree or Strongly agree.

Item 8 (real-time inventory tracking improves decision-making) has the highest mean ($M = 4.27$; 85% agreement), followed by Items 9 and 12 and Item 19 (IOT improves real-time visibility; $M = 4.19$). Item 14 (lack of skilled employees as an adoption barrier) has the lowest mean ($M = 3.64$; 58% agreement) and the greatest spread ($SD = 1.16$), indicating the least consensus. Between 58% and 85% of respondents agreed or strongly agreed with each statement.

Figure 1**Mean Score by Questionnaire Item****Figure 2****Mean Dimension Scores**

Chi-Square Tests of Association (H_{02})**Table 4****Chi-Square Tests: Respondent Characteristics and Perception Level of Technology Benefits**

Characteristic	χ^2	df	p	Monte Carlo p	Cramer's V	Cells with expected count < 5	Decision ($\alpha = .05$)
Gender	0.858	1	.354	.387	.093	0 of 4	Fail to reject
Age (3 groups)	0.051	2	.975	1.000	.023	1 of 6	Fail to reject
Occupation (4 groups)	9.499	3	.023*	.020	.308	2 of 8	Reject H_{02}
Education	3.415	3	.332	.344	.185	2 of 8	Fail to reject
Monthly income	5.623	3	.131	.148	.237	2 of 8	Fail to reject

Note. Perception level: high = Perceived Technology Benefits score ≥ 4.00 ($n = 69$); moderate below 4.00 ($n = 31$). * $p < .05$. Monte Carlo p-values are based on 4,000 random permutations.

Table 5**Cross-Tabulation: Occupation and Perception Level of Technology Benefits**

Occupation	Moderate perception	High perception	Total	% High
Student	10	36	46	78.3%
Salaried employee	6	20	26	76.9%
Self-employed	8	8	16	50.0%
Business	7	5	12	41.7%
Total	31	69	100	69.0%

Note. Salaried employee combines private ($n = 22$) and government ($n = 4$) employees.

Perception level was not significantly associated with gender, $\chi^2(1) = 0.858$, $p = .354$, age, $\chi^2(2) = 0.051$, $p = .975$, education, $\chi^2(3) = 3.415$, $p = .332$, or monthly income, $\chi^2(3) = 5.623$, $p = .131$; H_{02} is not rejected for these characteristics. For education and income, two of eight cells had expected counts below five, so these two results should be read with caution (the Monte Carlo p-values lead to the same conclusion).

Occupation showed a statistically significant association with perception level, $\chi^2(3) = 9.499$, $p = .023$, Cramer's $V = .308$, a medium effect, so H_{02} is rejected for occupation. High perception is most common among students (78.3%) and salaried employees (76.9%) and least common among business respondents (41.7%) and the self-employed (50.0%). Two of the eight cells had expected counts below five (minimum = 3.72), but the Monte Carlo permutation p-value ($p = .020$) supports the same conclusion.

One-Way ANOVA (H_{03})**Table 6****One-Way ANOVA: Perceived Technology Benefits (Items 1–12) by Respondent Characteristic**

Factor	F	df	p	η^2	Levene p	Kruskal–Wallis p	Decision ($\alpha = .05$)
Gender	0.791	1, 98	.376	.008	.047	.304	Fail to reject
Age (3 groups)	1.651	2, 97	.197	.033	.987	.333	Fail to reject
Occupation (4 groups)	3.568	3, 96	.017*	.100	.874	.032	Reject H_{03}
Education	2.198	3, 96	.093	.064	.872	.110	Fail to reject
Monthly income	0.871	3, 96	.459	.027	.140	.283	Fail to reject

Note. * $p < .05$. Gender has two groups, so its F equals the square of an independent-samples t statistic. Levene's test was marginally significant for gender ($p = .047$); the Kruskal–Wallis result agrees with the ANOVA.

Table 7**Group Means of Perceived Technology Benefits**

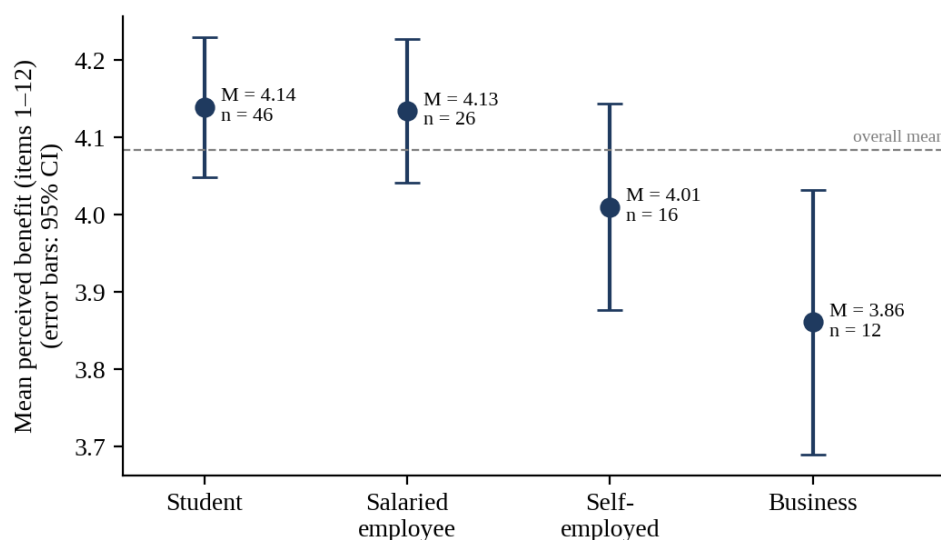
Factor	Group	n	Mean	SD
Gender	Female	39	4.118	0.221
Gender	Male	61	4.063	0.340
Age (3 groups)	18–20 years	24	3.997	0.301
Age (3 groups)	20–30 years	60	4.099	0.304
Age (3 groups)	31 years and above	16	4.161	0.264
Occupation (4 groups)	Student	46	4.139	0.313
Occupation (4 groups)	Salaried employee	26	4.135	0.240
Occupation (4 groups)	Self-employed	16	4.010	0.274
Occupation (4 groups)	Business	12	3.861	0.302
Education	Undergraduate	49	4.156	0.308
Education	Graduate	21	3.988	0.287
Education	Postgraduate	23	4.054	0.285
Education	Diploma	7	3.964	0.235
Monthly income	Below ₹20,000	51	4.103	0.343
Monthly income	₹20,000–₹40,000	29	4.040	0.260
Monthly income	₹40,001–₹60,000	12	4.028	0.267
Monthly income	Above ₹60,000	8	4.208	0.109

Mean perceived technology benefits differed significantly across occupation groups, $F(3, 96) = 3.568$, $p = .017$, $\eta^2 = .100$ (a medium effect), so H_{03} is rejected for occupation. Tukey's HSD showed that business respondents ($M = 3.86$) scored significantly lower than students ($M = 4.14$, $p = .019$) and salaried employees ($M = 4.13$, $p = .039$); no other pairwise difference was significant. The Kruskal–Wallis test agreed, $H(3) = 8.807$, $p = .032$.

No significant differences were found by gender, $F(1, 98) = 0.791$, $p = .376$, age, $F(2, 97) = 1.651$, $p = .197$, education, $F(3, 96) = 2.198$, $p = .093$, or monthly income, $F(3, 96) = 0.871$, $p = .459$; H_{03} is not rejected for these factors. The education result is close to the 10% level, with undergraduates scoring highest and diploma and graduate respondents lowest, but this is not significant at 5%. Because ten significance tests were run in total (five chi-square and five ANOVA), the occupation findings would not survive a strict Bonferroni correction ($\alpha = .005$) and should be treated as exploratory.

Figure 3

Mean Perceived Technology Benefits by Occupation



Correlation and Linear Regression (H_{01} and H_{04})

Table 8

Pearson Correlations Among Dimension Scores (N = 100)

Variable	1	2	3	4	5	6
1. Operational efficiency	—					
2. Inventory & warehouse	.13	—				
3. Transportation & delivery	.13	.03	—			
4. Adoption challenges	.09	-.05	-.04	—		
5. Future potential	.21*	.08	.05	.15	—	
6. Perceived benefits (1–12)	.68***	.56***	.65***	.00	.18	—

Note. * $p < .05$; *** $p < .001$. Correlations of Perceived Benefits with its three component dimensions are part-whole correlations and are expected to be high.

The correlation between Perceived Technology Benefits and Future Technology Potential is weak and positive but not significant at the 5% level, $r = .18$, $p = .069$. Among the individual dimensions, only Operational Efficiency correlates significantly with Future Technology Potential, $r = .21$, $p = .035$; the correlations of Future Technology Potential with Inventory and Warehouse Management, Transportation and Delivery and Adoption Challenges are not significant. The three benefit dimensions are largely uncorrelated with one another ($r = .03$ to $.13$), which agrees with the low alpha values reported earlier.

Table 9**Simple Linear Regression: Future Technology Potential on Perceived Technology Benefits**

Section	Statistic	Value	Statistic	Value
Model summary	R	.182	R ²	.033
	Adjusted R ²	.023	Std. error of estimate	0.471
ANOVA	Source	SS / df	MS	F (p)
	Regression	0.747 / 1	0.747	3.369 (p = .069)
	Residual	21.726 / 98	0.222	
	Total	22.473 / 99		

Table 10**Simple Linear Regression Coefficients**

Predictor	B	SE	β	t	p	95% CI for B
Constant	2.911	0.647	—	4.499	< .001	[1.627, 4.195]
Perceived technology benefits	0.290	0.158	.182	1.835	.069	[-0.024, 0.603]

Note. Dependent variable: Future Technology Potential (Items 17–20). Durbin–Watson = 1.63; Shapiro–Wilk test on residuals $p = .163$, so the normality assumption is not rejected.

The simple linear regression model was not statistically significant at the 5% level, $F(1, 98) = 3.369$, $p = .069$, and explained only 3.3% of the variance in Future Technology Potential ($R^2 = .033$, adjusted $R^2 = .023$). The fitted equation is Future Potential = $2.911 + 0.290 \times$ Perceived Benefits. A one-point increase in perceived benefits is associated with a 0.29-point increase in future potential, but the 95% confidence interval for the slope $[-0.024, 0.603]$ includes zero. H_{01} is therefore not rejected at the 5% level; the relationship is significant only at the 10% level.

Linear Regression of Future Technology Potential on Perceived Technology Benefits

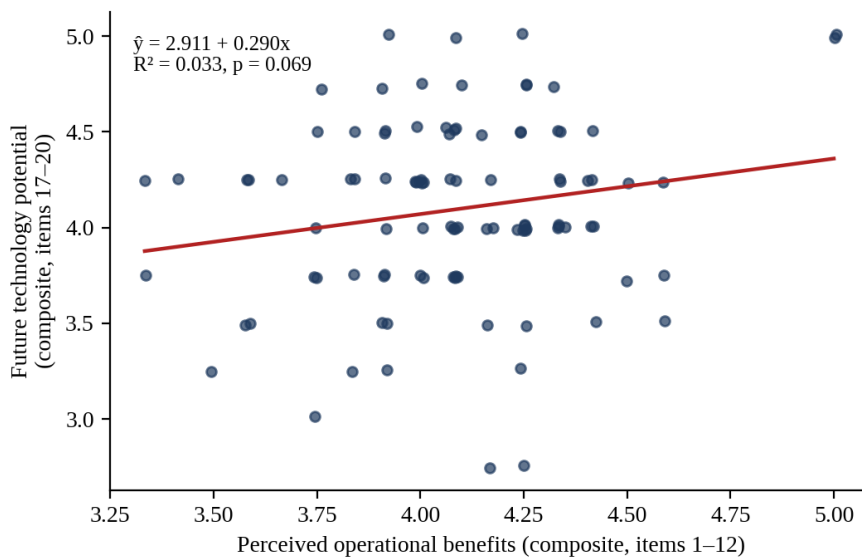


Table 11

Multiple Linear Regression: Future Technology Potential on the Four Dimension Scores

Predictor	B	SE	β	t	p	95% CI for B	VIF
Constant	2.462	0.749	—	3.288	.001	[0.976, 3.949]	—
Operational efficiency	0.182	0.099	.186	1.838	.069	[-0.015, 0.379]	1.05
Inventory & warehouse	0.071	0.112	.064	0.638	.525	[-0.151, 0.294]	1.02
Transportation & delivery	0.028	0.094	.030	0.302	.763	[-0.158, 0.215]	1.02
Adoption challenges	0.128	0.093	.138	1.383	.170	[-0.056, 0.312]	1.01

Note. $R = .259$, $R^2 = .067$, adjusted $R^2 = .028$, $F(4, 95) = 1.702$, $p = .156$; Durbin–Watson = 1.71; Shapiro–Wilk test on residuals $p = .189$. The multiple regression model with the four dimension scores as predictors was not significant, $F(4, 95) = 1.702$, $p = .156$, with $R^2 = .067$ (adjusted $R^2 = .028$). No individual predictor reached significance at the 5% level: Operational Efficiency was the strongest ($\beta = .186$, $p = .069$), followed by Adoption Challenges ($\beta = .138$, $p = .170$). Variance inflation factors were close to 1 (1.01–1.05), so multi co-linearity is not a concern, and the residual diagnostics raise no assumption problems. H_{04} is not rejected. A separate simple regression of Future Technology Potential on Operational Efficiency alone was significant ($B = 0.206$, $\beta = .211$, $p = .035$, $R^2 = .044$), but this was one of several possible predictors examined and it is not significant once the other dimensions are included, so it is treated as suggestive only.

Summary of Hypothesis Testing

Table 12: Summary of Hypothesis Tests ($\alpha = .05$)

Hypothesis	Statement (null)	Test	Result	Decision
H ₀₁	No relationship between technology use (perceived benefits) and performance (future potential)	Pearson r / simple regression	$r = .18, p = .069$	Not rejected
H ₀₂	No association between demographics and perception level	Chi-square	Occupation: $p = .023$; others $p > .05$	Rejected for occupation only
H ₀₃	No difference in mean perceived benefits across demographic groups	One-way ANOVA	Occupation: $p = .017$; others $p > .05$	Rejected for occupation only
H ₀₄	The four dimensions do not predict future potential	Multiple regression	$F(4, 95) = 1.70, p = .156$	Not rejected

Discussion

Logistics and Supply Chain Management are significant processes to ensure the effective flow, coordination and control of materials, information and resources between suppliers and customers. Organizations are more and more turning to technology to enhance their logistics and supply chain functions to be more efficient, accurate, and responsive in the modern business environment.

Logistics and supply chain functions are being increasingly executed with technologies like Information Technology (IT), Internet of Things (IoT), cloud computing, big data analytics, blockchain, automation, robotics and other digital systems. They help organisations to keep an eye on processes, track products, manage stock, control supply chain partners and make quicker and informed decisions.

Digital technologies in Logistics and Supply Chain Management (SCM) are even more relevant in the context of Industry 4.0 and Supply Chain 4.0. Better coordination and integration between various activities of the supply chain can be achieved with the help of connected devices, smart systems, data analytics and automated processes.

There are also issues related to the adoption of technology, including the cost of implementing it, its complexity, a lack of skilled personnel, cybersecurity, and data privacy concerns. In this context, the present study is about the use of technology in today's logistics and supply chain management.

Conclusion

The study analyzed the role of technology in the modern logistics and supply chain management system with regard to perceived effects on operational efficiency, inventory and warehouse management, transportation and delivery, challenges in technology adoption and future potential technology. Overall, the perceptions of technology and awareness of adoption challenges are generally positive. However, statistical testing leads to limited conclusions: perceived operational

benefits were not statistically significantly related to future technology potential and the only significant difference between the groups was in terms of occupation (business respondents were the least favorable). The findings cannot be considered as empirical findings from 100 actual respondents, because 97 out of the 100 records are synthetic and because the sample is overrepresented with students and the internal consistency of the item groups is low.

Limitations

The user provided responses and synthetic responses were created for 97 records. Other constraints are the cross sectional research design, perceptions which are self-reported, absence of a probability sampling frame, low income sample, and low Cronbach's alpha scores for the item groups in the tests that limit the validity of dimension scores. Multiple comparisons tests were not performed on the same data; some cells were small in some chi-square tables; Likert items were analyzed as interval data for means, ANOVA and regression. Correlation and regression does not prove causation. The questionnaire also features a marital status question but marital status is not included in The principal limitation is the composition of the supplied dataset: The supplied coded dataset is not analyzed because only three.

Recommendations and Future Research

Future research should gather and analyze authentic data from a well-defined target group (logistics and supply chain workers) and, if possible, apply an adequate sampling method, test the questionnaire beforehand, and retest the items to ensure that the reliability ($\alpha \geq .70$) for each dimension is acceptable. Structural equation modeling and tests of mediating and moderating effects of firm size, industry and technology type would be possible with larger and more balanced samples. In future studies, specific technologies (IOT, AI, automation, Block chain, cloud computing) can be investigated in isolation and compared to each other on the basis of objective performance indicators as well as perceptions, in relation to the various logistics functions.

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