



The Role of Generative Artificial Intelligence (GenAI) in Transforming Logistics and Supply Chain Management: Opportunities, Challenges, and Future Business Applications

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ABSTRACT :

This pilot study explores how people perceive the opportunities and challenges of Generative Artificial Intelligence (GenAI) in logistics and supply chain management. Data were collected from 50 respondents through an online questionnaire using convenience sampling. The responses were analysed using descriptive statistics, Cronbach's alpha, correlation, regression, ANOVA and chi-square tests. Respondents showed positive perceptions of GenAI, with scores for operational efficiency ($M = 3.49$), decision-making ($M = 3.55$), cost reduction ($M = 3.48$) and transformation potential ($M = 3.58$), all significantly above the neutral midpoint of 3. Transformation potential explained approximately 61% of the variation in perceived operational efficiency ($\beta = .78, p < .001$). Efficiency differed significantly by age, $F(2, 47) = 6.10, p = .004$, but not by education. Data privacy and security was the most frequently reported barrier (32%). Despite limitations, the findings highlight optimism alongside concerns about security, reliability and employee acceptance.

Keywords: *Generative Artificial Intelligence, logistics & supply chain management, operational efficiency, decision-making; AI adoption, supply chain transformation*

Introduction

Generative Artificial Intelligence (GenAI) has quickly become part of everyday life, helping people write, summarise information, answer questions and support decision-making. In logistics and supply chain management, it offers opportunities to analyse large amounts of data, identify shipment delays, monitor supplier performance, understand customer demand and improve operational efficiency (Dwivedi et al., 2023; Kshetri, 2023). It can also help managers access information more easily, identify potential risks and make faster decisions. Previous studies highlight its benefits in forecasting, communication and supply chain planning, while also raising concerns about inaccurate results, data privacy, security, cost and the need for skilled employees (Frederico, 2023; Fosso Wamba et al., 2024; Haddud, 2024; Alsuwaidi et al., 2022). However, the successful adoption of GenAI depends not only on its capabilities but also on how people understand and accept the technology. Therefore, this pilot study examines the perceptions of 50 respondents with some exposure to logistics and supply chain activities, focusing on GenAI's potential to improve efficiency, reduce costs, support decision-making and transform the sector, while identifying the major barriers to its adoption.

Literature Review

Alsuwaidi, Aydin and Rashid (2022) studied the barriers to AI implementation in logistics. The study identified high costs, lack of skilled employees, poor infrastructure, data quality, privacy and security as major challenges. The findings provide a foundation for understanding barriers to GenAI adoption in logistics.

Frederico (2023) examined the initial applications of ChatGPT in supply chain management. The study highlighted its potential in information processing, communication and decision-making. It also identified the need for further research on practical GenAI applications in supply chains.

Wamba et al. (2023) investigated the benefits and challenges of Generative AI in operations and supply chain management. The study found that GenAI can improve customer satisfaction, reduce costs and increase process efficiency. However, technological, data and organizational challenges may affect its adoption.

Haddud (2024) explored the applications, benefits and challenges of ChatGPT in supply chains. The study identified applications in forecasting, data

analysis and supplier/customer communication. It also highlighted limitations such as inaccurate information and the need for human supervision.

Esaadi, Sarir and Louah(2024) reviewed AI applications in supply chain management, logistics and transportation. The study identified major applications in forecasting, transportation, inventory management and optimisation. It provides a foundation for understanding the development of advanced AI technologies such as GenAI.

Teixeira, Ferreira and Ramos (2025) reviewed AI contributions to intelligent supply chain management. The study highlighted AI's role in resilience, optimization and sustainability while identifying challenges related to data, ethics and implementation. It also emphasised the importance of human-AI collaboration.

El Jaouhari et al. (2025) examined Generative AI applications in green logistics. The study highlighted GenAI's potential in decision-making, risk assessment, scenario planning and sustainable logistics. However, infrastructure limitations, costs, skills and regulatory issues remain major challenges.

Prakash, Shaikh and Mutha (2025) reviewed opportunities, benefits and challenges of GenAI in supply chains. The study identified forecasting, inventory management, risk management and decision-making as major applications. Data quality, workforce skills and responsible implementation were identified as key challenges.

Panja, Zheng and Glock (2026) reviewed GenAI applications in logistics and supply chain management. The study identified applications in forecasting, inventory, warehouse and risk management. It also highlighted the need for more empirical research on practical implementation and long-term impacts.

Bahrour et al. (2026) systematically analysed GenAI for supply chain transformation. The study identified applications in forecasting, risk analysis, supplier screening, logistics visibility and sustainability. It highlighted the limited evidence on long-term performance and the need for responsible GenAI implementation.

3. Research Gaps

Kache and Seuring (2017) and Chan et al. (2024) highlighted how digital technologies and AI-based analytics improve demand forecasting, inventory planning, transportation routing and supplier risk management. By combining data from ERP, WMS, TMS, IoT and external sources, AI helps businesses predict delays, assess risks and make faster decisions. Studies reported improvements in forecasting accuracy, inventory management, delivery performance and logistics costs. Kache and Seuring (2017) reported an approximately 20% reduction in forecasting errors in the automotive industry. However, further research is needed on long-term environmental impacts, data privacy and differences across industries. The Resource-Based View (RBV) and Dynamic Capabilities theories help explain how AI resources and organisational skills can support sustainable supply chain performance.

4. Objectives of the Study

- To examine the role of Generative AI in improving logistics and supply chain operations.
- To identify the major business applications of Generative AI in logistics and supply chain management.
- To evaluate the impact of Generative AI on operational efficiency, cost reduction, and decision-making.
- To identify the key challenges and barriers to adopting Generative AI in logistics and supply chain management.

5. Conceptual Framework of the Study

The conceptual framework is organized from the variables and objectives stated in the study. Generative AI adoption and application are treated as the central technology factor. Its expected effects are examined through operational efficiency, cost reduction, decision-making, and broader supply chain transformation, while challenges such as implementation cost, data privacy, skill gaps, infrastructure, reliability, and resistance to technology are treated as adoption barriers.



6. Hypotheses of the Study

H₀₁: GenAI does not significantly affect operational efficiency.

H₁₁: GenAI significantly affects operational efficiency.

H₀₂: Mean security readiness is similar among organizations with low, medium, and high cybersecurity maturity.

H₁₂: Mean security readiness differs significantly among organizations with low, medium, and high cybersecurity maturity.

7. Research Methodology

7.1 Research Approach

The study takes a quantitative approach to examine the role of Generative AI in transforming logistics and supply chain management. Primary data were collected through a structured questionnaire from respondents involved in, or familiar with, logistics, supply chain and related business activities. Descriptive statistics were used to summarise opportunities, challenges and expectations, and inferential tests were used to examine relationships between the variables.

7.2 Research Design

The study uses a descriptive, cross-sectional research design. It focuses on understanding the opportunities, challenges and future business applications of GenAI as perceived by respondents at one point in time. The paper reports a pilot phase of the research; the instrument and analysis plan are being tried out on a small sample before a larger survey.

7.3 Population of the Study

The population consists of students, employees, professionals and other individuals with knowledge of, or exposure to, logistics and supply chain activities. The study focuses on respondents who are relevant to the use and adoption of AI in these areas.

7.4 Sample of the Study

The pilot sample consists of 50 completed responses. A larger sample of about 300 respondents is planned for the full study. Respondents were selected from individuals who have knowledge or awareness of logistics, supply chain management and Generative AI.

7.5 Sampling Technique

Convenience sampling, a non-probability technique, was used. Respondents who were easily accessible and willing to take part were included. This is practical for a pilot but it limits how far the results can be generalised.

7.6 Sources and Instrument of Data Collection

Primary data were collected through a Google Forms questionnaire covering demographics and 15 questions on GenAI in logistics and supply chain management. Secondary data were obtained from research papers, journals, books, and reports.

7.7 Variables and Measurement

Table 1. Constructs, questionnaire items and reliability

Construct (abbreviation)	Questionnaire items	Scale	Cronbach's α
Operational efficiency (OE)	Q1 ease of day-to-day activities; Q3 help with routine work and information; Q7 faster completion of work	1–5	.48
Decision-making (DM)	Q5 predicting customer demand; Q6 solutions to delays and disruptions; Q9 quicker and better managerial decisions	1–5	.25
Cost reduction (CR)	Q8 reducing unnecessary logistics and supply chain costs	1–5	single item
Transformation potential (TP)	Q13 potential to change how businesses work; Q14 will become common in coming years	1–5	.69
Reliability concern (RC)	Q11 concern about accuracy or reliability of GenAI output	1–5	single item
Employee hesitation (EH)	Q12 employees hesitant because of job worries	1–5	single item
Categorical items	Q2 area of biggest difference; Q4 most helpful business area; Q10 biggest difficulty; Q15 most valuable future benefit	single choice	–
All nine benefit items	Q1, Q3, Q5, Q6, Q7, Q8, Q9, Q13, Q14	1–5	.84

7.8 Statistical Tools used

Data were analysed using Excel and Python, with descriptive statistics, correlation, regression, ANOVA and chi-square tests. Additional tests were used to check reliability, group differences and the validity of results.

7.9 Ethical Considerations

Participation was voluntary, and respondents were told the purpose of the research. The information collected is kept confidential and used only for academic purposes, and respondents' privacy and anonymity are maintained. Names were removed before analysis.

8. Data Analysis and Interpretation

Profile of the Respondents

Table 2 describes the 50 respondents. Seven in ten were women (70.0%). Nearly half were below 20 years of age (48.0%) and another 44.0% were between 21 and 30, so the sample is young. Students made up almost two-thirds of the group (64.0%). The rest were logistics and supply chain professionals (10.0%), employees or executives (8.0%), and managers, business owners and academicians (6.0% each). Most respondents were undergraduates (70.0%), and 48.0% reported that monthly income was not applicable to them, which fits the student-heavy profile. Eighty-four per cent were single. Readers should keep this profile in mind: the findings mostly reflect the views of young, educated people at an early stage of their careers.

Table 2. Demographic profile of respondents (n = 50)

Characteristic	Frequency	Percentage
Gender		
Female	35	70.0%
Male	15	30.0%
Age group		
Below 20 years	24	48.0%
21–30 years	22	44.0%
31–40 years	4	8.0%
Occupation		
Student	32	64.0%
Logistics/supply chain professional	5	10.0%
Employee/executive	4	8.0%
Manager	3	6.0%
Business owner/entrepreneur	3	6.0%
Academician/teacher	3	6.0%
Educational qualification		
Higher secondary	5	10.0%
Undergraduate	35	70.0%
Postgraduate	10	20.0%
Monthly income		
Not applicable	24	48.0%
Below ₹20,000	10	20.0%
₹20,001–₹40,000	5	10.0%
₹40,001–₹60,000	4	8.0%
₹60,001–₹80,000	3	6.0%
Above ₹80,000	4	8.0%
Marital status		
Single	42	84.0%
Married	4	8.0%
Prefer not to say	4	8.0%

Source: Primary data.

Reliability of the measures

Table 1 reports Cronbach's alpha for each composite. The nine benefit items taken together are internally consistent ($\alpha = .84$), which suggests that respondents hold a fairly general favourable or unfavourable attitude towards GenAI's benefits. The shorter sub-scales are weaker: transformation potential reaches $\alpha = .69$, close to the usual .70 benchmark, while operational efficiency ($\alpha = .48$) and decision-making ($\alpha = .25$) fall well below it. This is common when a construct has only two or three items and the sample is small, but it does mean that OE and DM scores should be treated as indicative. The two challenge items (Q11 and Q12) are barely related to each other ($r = -.12, p = .41$), so they were not combined and are examined separately. The reliability of each sub-scale will be revisited, and the weaker ones extended with more items, in the main study.

Descriptive statistics: mean, median and standard deviation

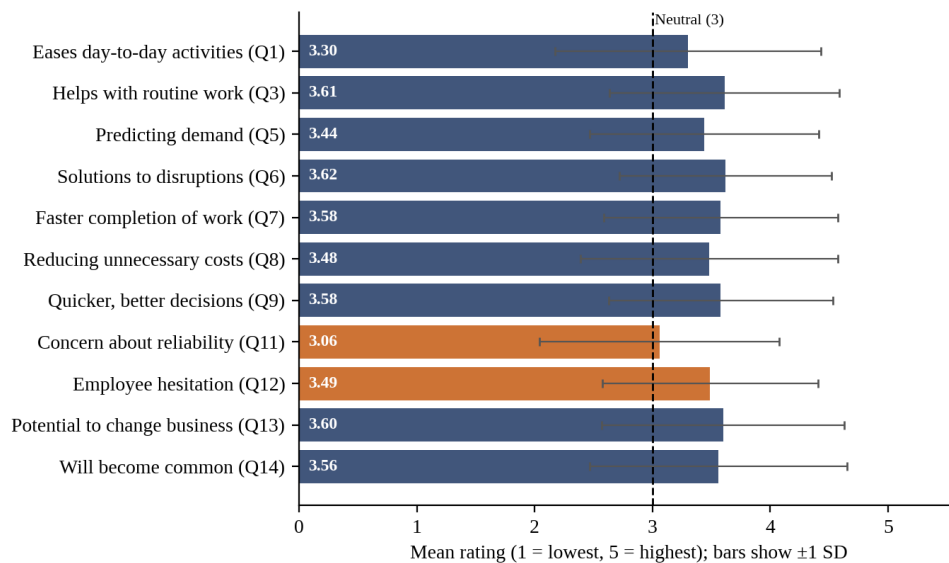
Table 3 gives the mean, median and standard deviation of every rated item and composite, together with a one-sample *t*-test against the neutral midpoint of 3. All benefit items have means between 3.30 and 3.62. The highest are better solutions during disruptions (Q6, $M = 3.62$), help with routine work (Q3, $M = 3.61$) and potential to change the sector (Q13, $M = 3.60$). The lowest is ease of day-to-day activities (Q1, $M = 3.30$), which is the only benefit item that does not differ significantly from neutral, $t(49) = 1.88$, $p = .066$. Medians sit at 3 or 4, so the typical respondent is neutral to positive rather than strongly enthusiastic, and the skewness of every item lies between -0.5 and 0.5 , which means the distributions are close to symmetric.

Table 3. Mean, median and standard deviation of rated items and composite scores

Item / composite	<i>n</i>	Mean	Median	<i>SD</i>	<i>t</i>	<i>p</i>
Individual items						
Q1 Eases day-to-day activities	50	3.30	3.00	1.13	1.88	.066
Q3 Helps with routine work	49	3.61	4.00	0.98	4.40	<.001
Q5 Useful for predicting demand	50	3.44	3.00	0.97	3.20	.002
Q6 Better solutions to disruptions	50	3.62	4.00	0.90	4.87	<.001
Q7 Faster completion of work	50	3.58	4.00	0.99	4.14	<.001
Q8 Reduces unnecessary costs	50	3.48	3.00	1.09	3.11	.003
Q9 Quicker, better decisions	50	3.58	4.00	0.95	4.32	<.001
Q11 Concern about reliability	50	3.06	3.00	1.02	0.42	.679
Q12 Employee hesitation	49	3.49	3.00	0.92	3.74	<.001
Q13 Potential to change business	50	3.60	4.00	1.03	4.12	<.001
Q14 Will become common	50	3.56	4.00	1.09	3.63	<.001
Composite scores						
Operational efficiency (OE)	50	3.49	3.67	0.72	4.79	<.001
Decision-making (DM)	50	3.55	3.67	0.59	6.55	<.001
Cost reduction (CR)	50	3.48	3.00	1.09	3.11	.003
Transformation potential (TP)	50	3.58	3.50	0.94	4.34	<.001

Note. Scale: 1 = lowest, 5 = highest. *t* is a one-sample test against 3 ($df = n - 1$). Q11 and Q12 are concerns, so higher means more concern or more hesitation.

At the composite level the picture is the same. Transformation potential has the highest mean (3.58), but decision-making sits furthest from neutral relative to the spread of answers (Cohen's $d = 0.93$, a large effect) because its scores are tightly clustered ($SD = 0.59$). It is followed by operational efficiency ($d = 0.68$), transformation potential ($d = 0.61$) and cost reduction ($d = 0.44$). All four are significantly above 3. Cost reduction is the most divided score: its standard deviation (1.09) is the largest of the four and its median is exactly neutral. On the concern side, respondents were split on reliability ($M = 3.06$, not different from neutral), with “moderately concerned” the most common answer (46.0%) and 28.0% saying they would be very or extremely concerned. Employee hesitation was rated higher ($M = 3.49$, $p < .001$): 49.0% of those who answered agreed or strongly agreed that staff may resist because they fear for their jobs. Figure 2 shows the item means.

**Figure 2. Mean ratings of the rated items (concern items shown in orange)**

Applications, challenges and future benefits

Table 4 and Figure 3 summarise the four single-choice questions. When asked where GenAI would make the biggest difference (Q2), respondents most often named transportation and delivery (28.0%) and planning and forecasting (26.0%), followed by inventory management (22.0%). A related question about where it would be most helpful in a business (Q4) put demand forecasting first (26.0%) and inventory management second (22.0%). Taken together, forecasting, inventory and transport are the areas that respondents associate most with GenAI, which fits the applications listed in the reviews of Esaadi et al. (2024), Prakash et al. (2025) and Panja et al. (2026). Warehousing was named least often in both questions.

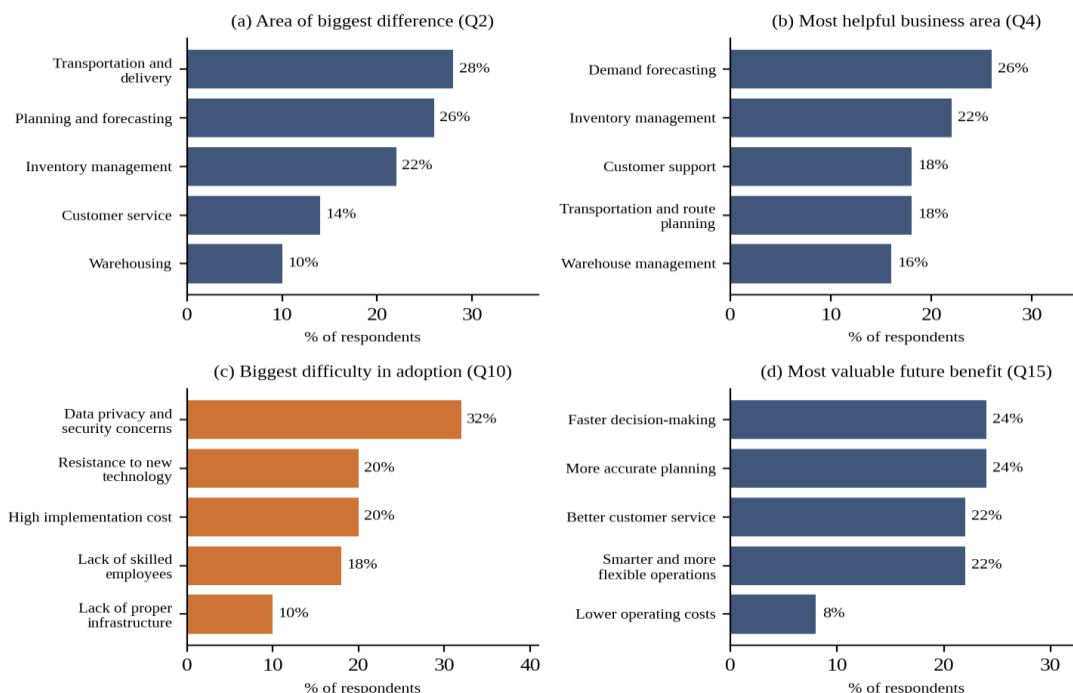
Table 4. Responses to the single-choice questions (n = 50)

Option	Frequency	Percentage
Q2. Area where GenAI could make the biggest difference		
Transportation and delivery	14	28.0%
Planning and forecasting	13	26.0%
Inventory management	11	22.0%
Customer service	7	14.0%
Warehousing	5	10.0%
Q4. Where GenAI would be most helpful in a supply chain business		
Demand forecasting	13	26.0%
Inventory management	11	22.0%
Customer support	9	18.0%
Transportation and route planning	9	18.0%
Warehouse management	8	16.0%
Q10. Biggest difficulty when introducing GenAI		
Data privacy and security concerns	16	32.0%
Resistance to new technology	10	20.0%
High implementation cost	10	20.0%
Lack of skilled employees	9	18.0%
Lack of proper infrastructure	5	10.0%
Q15. Most valuable future benefit		
Faster decision-making	12	24.0%
More accurate planning	12	24.0%
Better customer service	11	22.0%
Smarter and more flexible operations	11	22.0%
Lower operating costs	4	8.0%

Source: Primary data.

On challenges (Q10), data privacy and security concerns were the most common answer by some distance (32.0%), ahead of resistance to new technology and high implementation cost (20.0% each), lack of skilled employees (18.0%) and lack of infrastructure (10.0%). This matches the barriers reported by Alsuwaidi et al. (2022) and Prakash et al. (2025). Looking ahead (Q15), respondents most valued faster decision-making and more accurate planning (24.0% each), followed by better customer service and smarter, more flexible operations (22.0% each). Lower operating costs came last with only 8.0%. That is worth noting: cost reduction is rated positively in Table 3 ($M = 3.48$), but it is not what people most want from GenAI in the long run.

Figure 3. Distribution of responses to the single-choice questions



Correlation analysis

Table 5 shows the Pearson correlations among the composite scores and the two challenge items. The four benefit measures move together strongly. Transformation potential is correlated with operational efficiency ($r = .78$), decision-making ($r = .68$) and cost reduction ($r = .81$), and the three effect measures are also correlated with each other (r between $.59$ and $.70$), all at $p < .001$. By the usual guidelines these are large correlations. Respondents who believe GenAI can change the sector also tend to believe that it will make operations more efficient, decisions better and costs lower.

Table 5. Pearson correlation matrix ($n = 50$; $n = 49$ for correlations with EH)

	OE	DM	CR	TP	RC	EH
OE	1					
DM	.695**	1				
CR	.625**	.587**	1			
TP	.780**	.677**	.813**	1		
RC	.388**	.409**	.487**	.451**	1	
EH	-.317*	.023	-.098	-.261	-.121	1

Note. OE = operational efficiency; DM = decision-making; CR = cost reduction; TP = transformation potential; RC = reliability concern (Q11); EH = employee hesitation (Q12). ** $p < .01$; * $p < .05$ (two-tailed). Spearman rank correlations gave the same pattern (for example, OE–TP $\rho = .79$).

The two challenge items behave differently. Reliability concern is positively correlated with every benefit measure ($r = .39$ to $.49$, $p < .01$). In other words, those who are most positive about GenAI are also the ones who say they are more concerned about the accuracy of what it produces. Employee hesitation goes the other way: it is negatively correlated with operational efficiency ($r = -.32$, $p = .027$) and not significantly related to the other measures. Respondents who think staff will resist GenAI therefore give lower efficiency ratings.

Regression analysis

Simple linear regression (H01). To test whether GenAI's perceived potential affects operational efficiency, OE was regressed on TP (Table 6). The model was significant, $F(1, 48) = 74.50$, $p < .001$, and explained 60.8% of the variance in operational efficiency ($R^2 = .608$, adjusted $R^2 = .600$). The slope was $.598$ ($SE = .069$, 95% CI $[.459, .737]$, $p < .001$): for every one-point rise in transformation potential, perceived operational efficiency rose by about 0.6 of a point. The standardised coefficient ($\beta = .78$) shows a strong relationship. The null hypothesis H01 is therefore rejected. Figure 4 shows the fitted line.

Table 6. Simple linear regression: effect of transformation potential on operational efficiency

Predictor	<i>B</i>	<i>SE</i>	β	<i>t</i>	<i>p</i>	95% CI
Constant	1.349	0.256	–	5.26	<.001	[0.833, 1.864]
Transformation potential (TP)	0.598	0.069	.780	8.63	<.001	[0.459, 0.737]

Note. Dependent variable: OE. $R = .780$, $R^2 = .608$, adjusted $R^2 = .600$, SE of estimate = 0.458, $F(1, 48) = 74.50$, $p < .001$, $n = 50$. Sum of squares: regression 15.62, residual 10.07, total 25.69.

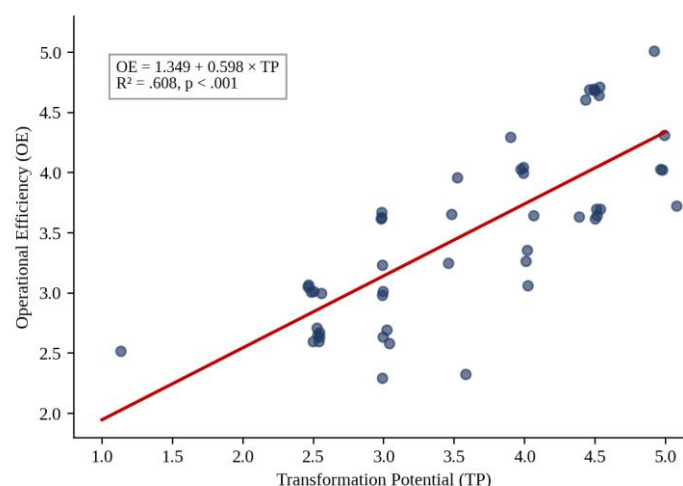


Figure 4. Scatter plot and fitted regression line (small random jitter added so overlapping points are visible)

Two cautions apply. The residuals were slightly non-normal (Shapiro–Wilk $W = .941$, $p = .015$), although with this strong an effect and a rank-based correlation that tells the same story ($\rho = .79$) the conclusion is not in doubt. More importantly, the relationship is not equally strong across the items that make up OE. When each item was regressed on TP separately, TP predicted Q1 ($R^2 = .51$) and Q3 ($R^2 = .50$) strongly, both $p < .001$, but it hardly predicted Q7, faster completion of work ($R^2 = .04$, $p = .164$). Both predictor and outcome come from the same respondents answering the same questionnaire, so part of the link probably reflects a general positive attitude towards GenAI rather than a specific effect on efficiency.

Multiple linear regression (supplementary). To see what else matters, OE was regressed on TP together with DM, CR, RC and EH (Table 7). The model was significant, $F(5, 43) = 19.66$, $p < .001$, and explained 69.6% of the variance (adjusted $R^2 = .660$). Two predictors stood out: transformation potential

($\beta = .46, p = .011$) and decision-making ($\beta = .38, p = .003$), both positive. Employee hesitation had a significant negative effect ($\beta = -.20, p = .034$). Cost reduction and reliability concern added nothing once the others were in the model. Variance inflation factors were all below 5 (highest 4.26 for TP), so multicollinearity is within acceptable limits, but TP and CR are strongly correlated ($r = .81$). The lack of an independent effect for cost reduction should therefore not be read as saying that costs do not matter.

Table 7. Multiple linear regression predicting operational efficiency (n = 49)

Predictor	B	SE	β	t	p	VIF
Constant	1.111	0.449	–	2.47	.017	–
Transformation potential (TP)	0.355	0.133	.464	2.67	.011	4.26
Decision-making (DM)	0.469	0.148	.382	3.16	.003	2.07
Cost reduction (CR)	0.006	0.101	.009	0.06	.953	3.27
Reliability concern (RC)	–0.004	0.070	–.006	–0.06	.954	1.37
Employee hesitation (EH)	–0.163	0.074	–.204	–2.20	.034	1.22

Note. Dependent variable: OE. $R^2 = .696$, adjusted $R^2 = .660$, SE of estimate = 0.426, $F(5, 43) = 19.66, p < .001$. One respondent with a missing Q12 answer is excluded.

Analysis of variance (ANOVA)

One-way ANOVA was used to test whether mean operational efficiency differs between groups (Table 8).

Age group (H02). Younger respondents rated operational efficiency higher. Those below 20 had a mean of 3.78, those aged 21 to 30 had 3.33, and the four respondents aged 31 to 40 had 2.67. The difference was significant, $F(2, 47) = 6.10, p = .004$, with a large effect ($\eta^2 = .21$), so H02 is rejected. Tukey's test showed that the clearest gap was between the youngest and oldest groups (mean difference = 1.11, $p = .008$, 95% CI [0.25, 1.97]). The other two comparisons did not reach significance after adjustment: below 20 versus 21–30 (difference = 0.45, $p = .062$) and 21–30 versus 31–40 (difference = 0.66, $p = .168$). This result needs care. The 31–40 group has only four people, all of whom gave the same average score, so the variances are clearly unequal (Levene's $p = .001$) and the ANOVA assumption is not met. The Kruskal–Wallis test, which does not assume equal variances, points the same way, $H(2) = 9.71, p = .008$. The age effect is therefore probably real in this sample, but its size is uncertain. It is also tangled up with occupation, because most of the youngest respondents are students.

Table 8. One-way ANOVA: operational efficiency by age group and educational level

Grouping	Group	n	Mean	SD	F(df)	p	η^2
Age group	Below 20 years	24	3.78	0.81			
	21–30 years	22	3.33	0.49	6.10 (2, 47)	.004	.206
	31–40 years	4	2.67	0.00			
Education	Higher secondary	5	3.53	0.77			
	Undergraduate	35	3.47	0.73	0.04 (2, 47)	.964	.002
	Postgraduate	10	3.53	0.74			

Note. Age: Levene's $p = .001$ (equal variances not assumed to hold); Kruskal–Wallis $H(2) = 9.71, p = .008$. Education: Levene's $p = .926$; Kruskal–Wallis $H(2) = 0.06, p = .970$.

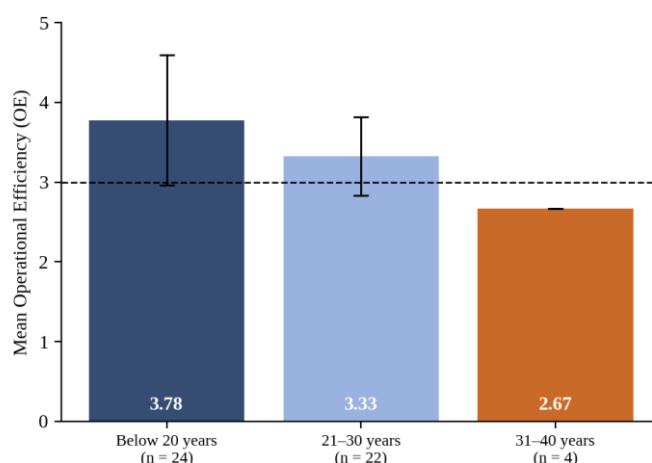


Figure 5. Mean operational efficiency by age group (bars show ± 1 SD; dashed line marks neutral)

Educational level (H03). Educational level made no difference. Higher secondary (3.53), undergraduate (3.47) and postgraduate (3.53) respondents gave almost identical ratings, $F(2, 47) = 0.04, p = .964, \eta^2 = .002$, and the Kruskal–Wallis test agreed ($p = .970$). H03 is not rejected. In this sample, how much formal education a person has says nothing about how efficient they expect GenAI to make logistics work.

Chi-square analysis

Chi-square tests of independence were used to see whether the belief that GenAI will become a common part of logistics and supply chain management (Q14) is linked to respondent characteristics. To keep expected cell counts above five, responses were grouped into “Agree” (agree or strongly agree, 26 respondents, 52.0%) and “Neutral/Disagree” (24 respondents, 48.0%). Occupation was grouped into students (32) and working professionals (18). The results are in Table 9.

Table 9. Chi-square tests of independence

Test	Observed pattern	χ^2 (df)	p	Cramér's V	Exact / alternative p
H04: Occupation group $\times$ outlook	Agree: students 53.1%, professionals 50.0%	0.05 (1)	.832	.03	Fisher 1.000
H05: Gender $\times$ outlook	Agree: women 60.0%, men 33.3%	2.99 (1)	.084	.25	Fisher .124
Exploratory: Age group $\times$ outlook	Agree: below 20, 66.7%; 21 and above, 38.5%	3.98 (1)	.046	.28	Yates .087; Fisher .055
Exploratory: Occupation group $\times$ biggest difficulty (Q10)	Data privacy named by 40.6% of students and 16.7% of professionals	3.73 (4)	.443	.27	Permutation .489

Note. Outlook = response to Q14 (will GenAI become common). In the first three tests all expected counts exceed 5. In the last test, 50% of cells have expected counts below 5 (minimum 1.8), so the Monte Carlo permutation p (20,000 runs) is the more trustworthy figure.

Occupation group is unrelated to the belief that GenAI will become common, $\chi^2(1) = 0.05$, $p = .832$, so H04 is not rejected: students and working professionals are about equally likely to agree. Gender shows a gap, with 60.0% of women and 33.3% of men agreeing, but it is not statistically significant, $\chi^2(1) = 2.99$, $p = .084$ (Fisher's exact $p = .124$), so H05 is not rejected. With only 15 men in the sample, a difference of this size could easily arise by chance.

Of the two exploratory tests, the age result is borderline. The uncorrected chi-square is just under the 5% line, $\chi^2(1) = 3.98$, $p = .046$, but the Yates-corrected ($p = .087$) and Fisher's exact ($p = .055$) tests are not. It fits the age pattern in Section 8.7, since younger respondents were more likely to agree (66.7% against 38.5%), but it should be treated as a lead for the main study and not as a firm result. Occupation group and the biggest adoption difficulty are not significantly associated ($p = .443$; permutation $p = .489$), although students named data privacy more often than working professionals did.

Summary of hypothesis testing

Table 10. Summary of hypothesis tests

Hypothesis	Test	Result	Decision
H01: GenAI potential does not affect operational efficiency	Simple regression	$R^2 = .608$, $\beta = .78$, $p < .001$	Rejected
H02: Efficiency is the same across age groups	One-way ANOVA	$F(2, 47) = 6.10$, $p = .004$	Rejected (interpret with care)
H03: Efficiency is the same across educational levels	One-way ANOVA	$F(2, 47) = 0.04$, $p = .964$	Not rejected
H04: No association between occupation group and outlook	Chi-square	$\chi^2(1) = 0.05$, $p = .832$	Not rejected
H05: No association between gender and outlook	Chi-square	$\chi^2(1) = 2.99$, $p = .084$	Not rejected

Note. Tests were not adjusted for multiple comparisons. With five hypotheses and two exploratory tests, results close to the 5% line should be read cautiously.

9. Major Findings

1. Generative AI can improve operational efficiency and decision-making in logistics and supply chain management.
2. GenAI is useful for demand forecasting, inventory management, logistics planning and customer service.
3. GenAI can help organisations achieve cost reduction and better supply chain visibility.
4. Major challenges include data privacy, security, implementation costs and lack of skilled employees.
5. GenAI has strong future potential in automation, risk management, sustainability and overall supply chain transformation

10. Findings and Suggestions

- **Improve Demand Forecasting:** GenAI can support demand forecasting by analysing historical sales, market trends, and customer preferences. Logistics companies should use reliable data and regularly review forecasts to improve planning and reduce errors.
- **Enhance Inventory Management:** GenAI can help businesses monitor stock levels, identify possible shortages, and reduce excess inventory. Companies should integrate AI tools with inventory management systems to improve stock availability and reduce storage costs.
- **Optimize Transportation and Route Planning:** GenAI can assist in planning delivery routes, preparing transportation schedules, and identifying possible delays. Businesses should combine AI-generated suggestions with real-time traffic and transport information to improve delivery efficiency.

- Improve Warehouse Operations: GenAI can support warehouse activities by assisting with stock tracking, order processing, and operational planning. Companies should train employees to use AI tools effectively and improve warehouse productivity.
- Strengthen Supply Chain Visibility: GenAI can help summarize supply chain information and identify potential disruptions, such as supplier delays and transportation problems. Organizations should maintain accurate, updated data to improve coordination and decision-making.

11. Conclusion

Generative AI has significant potential to transform logistics and supply chain management, and the people surveyed here largely agree. They expect it to improve operational efficiency, support better decisions, help with forecasting and inventory, and reduce costs, and just over half believe it will become a common part of the sector. The strongest statistical finding is that those who see greater transformation potential also expect greater operational efficiency. The optimism is not unconditional, however. Data privacy and security, reliability of AI output, implementation cost, skills and employee acceptance all worry respondents, and the most positive respondents are also among the most concerned about accuracy.

12. Limitations and Scope for Future Research

The study is limited by its sample size, geographical coverage and dependence on respondents' perceptions and awareness of Generative AI, which may not fully represent actual organisational usage. As GenAI is rapidly evolving, its applications and challenges may also change over time. Future research can use larger and more diverse samples and examine the actual impact of GenAI on cost, productivity, forecasting accuracy, sustainability, risk management, data security and overall supply chain performance

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