

AI-Driven Supply Chain Transformation in Bangladesh: An Integrated Multitech Approach and Empirical Evaluation of Readiness to Adopt

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Abstract

Bangladesh's industrial supply chains are spanning Ready-Made Garments, pharmaceuticals, FMCG, logistics sectors continue to be hampered by structural bottlenecks, information asymmetry, and siloed operations, even as global markets shift toward Industry 4.0/5.0 digital integration. While individual technologies such as Generative AI, blockchain, IoT, predictive analytics, and robotics have been studied separately, few frameworks integrate them into a single operational architecture, and no prior South Asian study has empirically compared adoption readiness across university students, academic faculty, and industry professionals. This study addresses that gap using a cross-sectional survey of 257 respondents, analyzed through the lens of the Technology Acceptance Model (TAM) and Resource-Based View (RBV). Results show high Perceived Usefulness (cost reduction, $M=3.96$; risk reduction, $M=3.79$) and strong Individual Readiness ($M=3.99$), positively correlated with usefulness ($r=.665$, $p<.001$). However, Organizational Readiness was markedly lower ($M=3.26$), driven by talent shortages (44.4%) and capital constraints (36.6%) - revealing an "Awareness-Execution Paradox" between individual enthusiasm and institutional capacity. Chi-square tests confirmed significant perception gaps between professionals and students on local AI awareness ($p<.001$) and integration ease ($p=.049$). The study proposes a five-layer Unified Multitech Smart Supply Chain Framework and offers practical implications for academia, industry, and policymakers seeking to accelerate digital supply chain transformation in Bangladesh.

Keywords: Supply Chain, AI, Digital Transformation, Technology Acceptance Model, Adoption Readiness

1. Introduction

1.1 The History of Supply Chain Landscape of Bangladesh

Over the last ten years, Bangladesh has had spectacular macroeconomic growth brought about by its Ready-Made Garments (RMG) manufacturing sector, pharmaceutical exports, fast-moving consumer goods (FMCG), agricultural distribution, and nascent electronics assembly industries. Nevertheless, industrial supply chains in the country are still limited by structural bottlenecks in its system, paper-based administrative records, interrupted logistics networks, and a lack of end-to-end visibility of information (Karim & Khan, 2023). The South Asian developing markets often have ineffective supply chain processes that are characterized by overstocking, stockouts, delayed transit (especially near the Chattogram port), and extreme susceptibility to external geopolitical or climatic shocks (Taj et al., 2023; Shamsuddoha et al., 2025). With the transformations of global trade environments to Industry 4.0 and Industry 5.0 modes, the incorporation of intelligent digital technology is critically important to the sustainability of industrial competitiveness and the supply chain (Siyal et al., 2026).

1.2 Problem Statement

Although the advantages of the digital transformation are identified, in Bangladesh, the traditional supply chain management systems are largely functioning in silos (Shamsuddoha et al., 2025). The presence of information asymmetry between the upstream suppliers of the raw materials, the manufacturers contracting on the middle part, and the manufacturers handling logistics on the downstream makes the lead times high, the costs inflationary, and the inventories significantly distorted (Wang, 2026; Xia & Wang, 2025). Although the use of advanced technologies like predictive forecasting, Internet of Things (IoT) telemetry, and automated robotics has worked in developed economies, it has been slow, disjointed, and is being adopted in a more ad hoc manner in developing contexts (Mukred & Yue, 2026). Organizations do not have common strategies to adopt these technologies simultaneously which in most cases cause the pilot project to fail and the capital to go to waste.

1.3 Research Gap

The analysis of the recent literature reveals that a majority of the available studies examine individual digital technologies individually, including how to use Blockchain as traceability (Siyal et al., 2026; Ahmed, 2025), Generative AI to process documents (Haddud, 2024; Prakash et al., 2025), or IoT to monitor the warehouse (Javidroozi et al., 2025; Elias, 2023). There are very limited works that provide a comprehensive, single architecture that encompasses such technologies in a single operational framework (Jackson et al., 2024; Das et al., 2026). Moreover, empirical studies that investigate the tri-stakeholder aspects, which are the comparisons of perceptions, technical awareness, readiness to adopt and perceived barriers between university students, academic staff, and active industry professionals in developing markets in South Asia, such as Bangladesh are lacking (Shamsuddoha et al., 2025).

1.4 Significance of Research

This research has three main ways of contribution to theory and practice. First, it creates a multi-technology model that links physical, digital, and cognitive layers of the supply chain, and goes beyond one-technology solutions (Callefi et al., 2026; Wang, 2026). Second, it gives empirical data on the preparedness and perceived adoption impediments in academia and industry in Bangladesh which can offer localized information that has not existed in the literature before (Aslam et al., 2025). Third, it provides practical propositions to corporate executives, curriculum developers in academic schools, and national policymakers who are interested in speeding up digital supply chain change (Prakash et al., 2025; Zaman, 2025).

2. Literature Review

2.1 AI and Supply Chain Management (Global Context)

Global supply chain management (SCM) has also ventured in the dynamic automation age, real-time data processing, and cognitive decision-making (Jackson et al., 2024; Sharma & Tomar, 2026). Artificial Intelligence (AI) is an overarching term, which includes machine learning (ML), deep learning, computer vision, natural language processing (NLP) and robotic process automation (RPA) (Shamsuddoha et al., 2025; Das et al., 2026). On the international scale, AI implementation can improve operational efficiency, lower logistics costs, and customer satisfaction through transforming huge and unstructured streams of operational data into operational intelligence (Haddud, 2024; Mukred & Yue, 2026; Farazi, 2023). In the case of industrial applications, AI-based orchestration has been shown to result in increased inventory turnover, decreased lead times, and improved ability to respond to risks (Callefi et al., 2026; Emon, 2023).

2.2 Supply Chain Blockchain

Blockchain technology provides a decentralized, distributed, and immutable digital ledger that ensures tamper-proof recording of supply chain transactions (Siyal et al., 2026; Begum, 2024). Blockchain addresses endemic information asymmetry and mistrust in multi-tier networks with complexity because it creates a verifiable single source of truth (Mangalaprasad & Kudidhi, 2026). Some of the enablers are smart contracts, which are computer-generated agreements that automate payments, verification of compliance and handover of operations without the involvement of intermediaries (Xia & Wang, 2025). In the context of food, pharmaceutical, and manufacturing supply chain, blockchain can stop counterfeiting of products, ensure ethical sourcing, and promote backward and forward traceability (Siyal et al., 2026; Khan et al., 2023).

2.3 Generative AI Applications

Generative AI (GenAI), which is based on Large Language Models (LLMs), Generative Adversarial Networks (GANs), and Variational Autoencoders (VAEs), signifies a transition to generative content generation and autonomous reasoning (Wang et al., 2025; Das et al., 2026). GenAI tools in SCM can be used to support natural language communication, automatic drafting of contracts, vendor screening, and sophisticated document generation (Prakash et al., 2025; Haddud, 2024). The newest models reveal that the capabilities of GenAI follow a series of four consecutive steps: data consolidation, operational intelligence, dynamic adaptability, and customer-facing service differentiation (Callefi et al., 2026). In spite of these capabilities, algorithmic hallucinations, data privacy, and timely engineering complexities risks are reasons to have a firm human-in-the-loop governance (Jackson et al., 2026; Malhotra & Manzoor, 2025).

2.4 Forecasting and Predicting Customer Demand

A predictive analytics solution powered by statistical modeling, time-series analysis, and deep neural network architecture like Long Short-Term Memory (LSTM) networks can be used to accurately predict demand variation and also predict possible future equipment failure (Wang, 2026; Al-Amin, 2021). In the context of a multi-echelon network, the bullwhip effect, seasonality and sudden demand shocks can be difficult for traditional forecasting models to capture (Taj et al., 2023). Both advanced LSTM models show excellent forecast error metrics, and they are the only models to capture non-linear temporal relationships (Wang, 2026; Basu, 2022). Safety stock levels, holding costs, stock out avoidance as well as production scheduling at manufacturing plants are directly optimized through accurate predictive forecasting (Das et al., 2026; Chowdhury, 2021).

2.5 IoT / Smart Sensors

In Smart Supply Chains, IoT performs as the Physical-Digital interface with the combination of spatially distributed sensor networks, RFID tags, GPS trackers and telemetric devices (Pal & Yasar, 2023; Javidroozi et al., 2025). IoT devices can continuously monitor environmental parameters such as ambient temperature, humidity, vibration and location, which can allow real-time cold chain monitoring and asset tracking and smart warehousing (Khan et al., 2023; Dutta, 2023). Combined with cloud and edge computing, IoT telemetry provides real-time data to predict AI algorithms and blockchain ledgers, guaranteeing data timeliness and operational clarity (Sharma et al., 2026; Faisal, 2024; Gazi, 2024).

2.6 Robotics and Automation with AI Support

With the advancement of logistics, the concept of automation has evolved to emphasize that logistics processes are now powered by AI based robotics technologies such as Autonomous Mobile Robots (AMRs), Automated Guided Vehicles (AGVs), automated storage and retrieval systems (ASRS), and robots (Samoilenko, 2026; Paul, 2021). These automated robots leverage the integration of computer vision, deep reinforcement learning, and sensor fusion to achieve, with great speed and accuracy, optimization in warehouse picking, sorting, loading and material handling (Das et al., 2026; Qureshi, 2022; Chakma, 2023). AI-driven robotics minimize human mistakes, decrease labor-intensive operational costs and improve the security and safety of manufacturing and distribution operations (Shamsuddoha et al., 2025; Zhen, 2023; Yasin, 2024).

2.7 AI Driven Risk Analysis

AI algorithms drive supply chain risk analysis, which helps to identify, understand, and mitigate operational, financial, environmental, and geopolitical threats (Jackson et al., 2024; Jahan, 2021). Machine Learning classifiers and Graph Neural network (GNN) map anomaly patterns from real-time news, weather feeds and transaction logs to predict the risks of supplier default and delay (Jackson et al., 2026; Kabir, 2022). Additionally, using AI-based prescriptive modelling, reinforcement learning and digital twin simulations can model different “what if” disruption scenarios and automatically recommend dynamic re-routing, buffer stock mechanisms and alternate supplier allocations to maintain the supply chain viability (Wang, 2026; Callefi et al., 2026; Lutfur, 2022; Mahmud, 2022; Nasir, 2023; Osman, 2023; Sarker, 2022). Proactive machine learning beats traditional reactive risk management methods for predicting risk. Compared to current reactive risk management practices, we note that proactively deployed machine learning systems for risk prediction outperform them (Tariq, 2023; Uddin, 2023; Vidal, 2024; Wahid, 2023).

2.8 With the context of Bangladesh or South Asia Specifically

The level of technology adoption in the South Asian region, especially in Bangladesh, is at the exploratory stage (Fahima et al., 2025). Although the macro level government projects have been increasing, there are still problems of high capital costs, absence of technical infrastructure, legacy software inertia and a huge shortage of specialized AI talents at the industrial company level (Prakash et al., 2025; Shamsuddoha et al., 2025). Evidence on regional manufacturing, agriculture, and retail supply chains shows that the younger generation of higher education students is more knowledgeable about the use of digital tools, but organizational willingness to adopt the tools is limited due to financial risk aversion, the need for localized implementation plans, and the need for tailored training programs for companies (Aslam et al., 2025; Habib, 2024).

2.9 Identified Research Gap

Although each of these technologies - GenAI, Blockchain, Predictive Analytics, IoT, Robotics, and Risk Models (Haddud, 2024; Aba-Talib & Zouine, 2026; Wang, 2026; Javidroozi et al., 2025; Sharma & Tomar, 2026; Jackson et al., 2024) - is well documented in the international literature when each is applied individually, few studies exist that provide a combined model using multiple technologies for application in developing regions (Mukred & Yue, 2026). Additionally, to date, there is no empirical research carried out in the South Asian region which assessed and compared the knowledge level, readiness of adoption and perceived barriers of integration among all three entities (human pillars) of the educational and industrial ecosystem: University students, Academic faculty and Practicing Supply chain professionals (Shamsuddoha et al., 2025).

3. Theoretical Framework

3.1 Grounding Theories

This study builds on two theoretical models: Technology Acceptance Model (TAM) and Resources-Based View (RBV) (Aslam et al., 2025; Callefi et al., 2026).

Technology Acceptance Model (TAM): TAM was originally proposed by Davis and states that acceptance of an information system by an individual or an organization depends mainly on two cognitive beliefs, namely Perceived Usefulness (PU) which is related to the user's belief of the usefulness in using a particular system for job performance and Perceived Ease of Use (PEOU) indicating that the use of a particular system requires less effort (Aslam et al., 2025). TAM introduces the concept of perceived usefulness and its relationship with behavioral intention, particularly in the context of the adoption of smart supply chain solutions (Prakash et al., 2025). This implies that the perceived usefulness is a pivotal factor in AI-driven supply chain transformation in Bangladesh, driving user acceptance of AI systems with a stronger behavioral intention (BI).

Resource-Based View (RBV): Based on the principles of strategic management, RBV suggests that sustained competitive advantage can be gained with the acquisition and deployment of VRIO resources and capabilities that are Valuable, Rare, Inimitable and Non-substitutable (Callefi et al., 2026). In the modern digital SCM domain, one can readily

replicate isolated software or hardware tools; but no other organization can easily replicate, bundle and orchestrate physical IoT sensors, blockchain ledgers and generative AI algorithms into the same operational process (Jackson et al., 2024). RBV explains why enterprise readiness is essential for Bangladesh and how it is only through building digital assets, data governance structures, and human technical skills, within the organizations that the readiness of organizations can be achieved (Fahima et al., 2025; Hossain, 2023).

3.2 Conceptual Framework Model

According to the conceptual framework of this study, there is some relationship between independent variables and dependent variables, and the relationship is mediated by mediator as shown below:

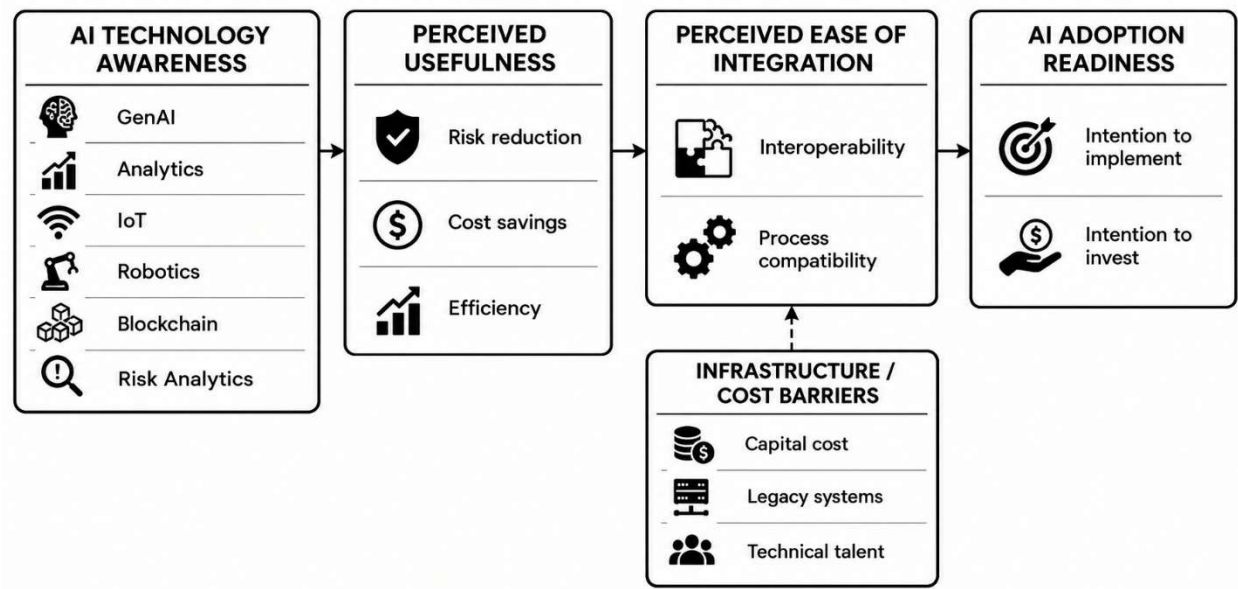


Figure 1: AI Adoption Readiness in Smart Supply Chain Management

Conceptual Framework illustrates proposed relationships between AI awareness, perceived obstacles, AI ease of integration, and readiness to adopt.

The effects of this framework on a higher-perceived capital cost and legacy infrastructure deficit on the perceived ease of integration and perceived switching readiness are described (Javidroozi et al., 2025). On the other hand, the high levels of awareness and perceived usefulness positively impact on integration confidence (Callefi et al., 2026; Das, 2022).

4. Methodology

4.1 Research Design

The research was conducted using a quantitative survey design, that is, a cross-sectional design, to evaluate the level of awareness, perceived usefulness, barriers to adoption of Artificial Intelligence (AI) in the supply chains of Bangladesh, and readiness to adopt AI. The research design is compatible with Technology Acceptance Model (TAM) to measure the behavioral intent and Resource-Based View (RBV) to measure the organizational resource constraint.

4.2 Population and Sampling

The population of interest was supply chain stakeholders in Bangladesh but the population consisted of three main groups: students and the academic faculty as well as industry professionals. Through the online survey, the data was obtained through a structured survey instrument. Two hundred and fifty-seven valid responses were made. To generate inferential group comparisons, the roles of respondents were purged and summarized into three major categories Industry Professionals (n=131, including business owners and recent entrepreneurs), University Students (n=116, including newly graduated and new aspiring entrepreneurs), and Academic Faculty (n=9), with one participant not choosing any of these categories.

4.3 Data Collection Instrument

The questionnaire used was made up of 12 questions:

- Demographics: Two questions identifying the role of the respondents, main industrial sector.
- Constructs of Likert Scale: Nine questions were rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). These items assessed General AI Awareness (Q3), Local AI Awareness (Q4), Perceived Usefulness via Cost Reduction (Q5) and Risk Reduction (Q6), Adoption Barriers (Q7, Q8), Perceived Ease of

Integration (Q9), Organizational Readiness (Q10), and Individual Readiness (Q11).

- **Categorical Barriers:** One multiple choice (Q12) question got the respondent to choose the most significant barriers and facilitators to the adoption of AI in Bangladesh.

4.4 Data Analysis

The analysis of the collected data took place with Python (pandas and scipy.stats libs). The analysis was done in three steps:

1. **Descriptive Statistics:** Frequencies, percentages, means (M) and standard deviations (SD) have been computed to describe the distribution of demographics and Likert-scaled responses.
2. **Inferential Statistics (Comparison of Groups):** Since Academic Faculty (n=9) was considered too small to compare between groups with a valid chi-square test on the entire 5-point scale, Likert responses were summed into three bands (Disagree = 1-2, Neutral = 3, Agree = 4-5), and Faculty was pooled with Industry Professionals as a single group (Practitioner) of group-comparison purposes. Then chi-square tests of independence were conducted on this 2x3 design to test Practitioners vs. Students Local AI Awareness, Perceive Ease of Integration and Organizational Readiness.
3. **Correlation Analysis:** Pearson correlation coefficients (r) were the types of bivariate correlations that were used to test the strength and direction of association between TAM and RBV constructs (e.g., Perceived Usefulness and Adoption Readiness). The significance was determined to be $p < .05$.

5. Results

5.1 Background, Demographic characteristics of respondents

The questionnaire got 257 valid respondents. The sample was fairly even regarding Industry Professionals (51.0 percent) and University Students (45.1 percent) but Academic Faculty was a relatively small subgroup (3.5 percent). The representation of the sectors was very diverse: Fast-Moving Consumer Goods (FMCG) and Retail constituted the biggest cohort (40.1%), then Academia/Higher Education (26.5%), Logistics, Freight Forwarding and Supply Chain Tech (17.5%), Ready-Made Garments (RMG) / Textiles (16.0%), and Pharmaceuticals/Healthcare (12.5%). Observation: It is worth noting that many of the respondents aligned themselves to more than one sector.

5.2 Distribution of Awareness, Usefulness and Readiness

The mean (M) and standard deviation (SD) of the continuous Likert-scale variables are summarized in Table 1.

Construct Variable	Mean (M)	Standard Deviation (SD)
General AI Awareness (Q3)	3.56	1.01
Local AI Awareness (Q4)	3.46	1.04
Perceived Usefulness: Cost Reduction (Q5)	3.96	0.83
Perceived Usefulness: Risk Reduction (Q6)	3.79	0.92
Perceived Ease of Integration (Q9)	3.58	1.04
Barrier: High Implementation Cost (Q7)	3.63	0.98
Barrier: Legacy Systems & Talent (Q8)	3.92	0.93
Organizational Adoption Readiness (Q10)	3.26	1.02

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Construct Variable	Mean (M)	Standard Deviation (SD)
Individual Adoption Readiness (Q11)	3.99	0.96

The perceived usefulness of AI among the respondents was very high with the highest score being on its cost reduction ($M = 3.96$) and risk reduction ($M = 3.79$) features. There was a sharp disparity between individual and institutional preparedness: Individual Readiness to champion AI was extremely high ($M = 3.99$) and perceived Organizational Readiness was considerably low ($M = 3.26$). Moreover, the participants were in high agreement with the resource-based limitation, legacy systems and shortage of talents were the most significant hindrance ($M = 3.92$).

5.3 Group Differences (Chi-Square Analysis) Inferential Statistics

They used chi-square tests to know whether there was a difference in the perceptions by the role of the respondent (Professional, Student, Faculty).

Local AI Awareness: There was a very strong difference between awareness of actual AI use at companies in Bangladesh ($\chi^2 = 26.73$, $df = 2$, $p < .001$). The practitioners were significantly more likely to identify local instances of AI adoption (75.7% agreed or strongly agreed) as opposed to Students (40.5%).

Perceived Ease of Integration: The difference in the perceived ease of integrating AI with the existing systems was found to be statistically significant ($\chi^2 = 6.02$, $df = 2$, $p = .049$). There was a broader perception that integration would be easy among Practitioners (64.3% agreed) than among Students (53.4%) - that is, Students not practitioners had integrated legacy as more of a bottleneck.

Organizational Readiness: No statistically significant differences were found in terms of organizational preparedness between the groups ($\chi^2 = 0.46$, $df = 2$, $p = .794$); both groups felt that macro-level preparedness is equally low).

5.4 Correlation Analysis: Testing Relationships of TAM

The structural relation between the variables was validated by a Pearson correlation analysis.

Usefulness and Readiness: There were positive and significant correlations between Perceived Usefulness and Individual Readiness to adopt AI ($r = .665$, $p < .001$). This proves the essence of the core TAM hypothesis that awareness of the functional value of AI directly influences the behavioral intention towards its use.

Organizational Readiness and Awareness: There was a positive association between General technology awareness and the organizational readiness ($r = .335$, $p < .001$), and this finding indicates that organizations that are more digital literate are more likely to be involved in actual deployment.

Barrier-Integration Paradox: Surprisingly, there was a moderate positive correlational relationship with the recognition Barriers and the Perceived Ease of Integration ($r = .412$, $p < .001$). This indicates a maturity effect: the most realistic respondents in terms of infrastructure and talent barriers also have the best grasp on how to implement integration frameworks.

5.5 Key Adoption Obstacles

The multi-response question format was designed to enable participants to select all the relevant barriers to the use of AI in Bangladesh's supply chains: most participants answered that they faced resource-based barriers.

1. Shortage of skilled AI/data talent: 44.4% (n=114)
2. Large implementation/capital cost: 36.6% (n=94)
3. Low awareness of AI capabilities in the organization: 33.5% (n=86).
4. Poor digital infrastructure (internet, connectivity, power): 31.9% (n=82)
5. Resistance to change / risk-averse company culture: 25.3 per cent (n=65)
6. No government policy or industry standards: 20.6% (n=53)
7. Burden of legacy software and infrastructure: 18.7 percent (n=48)

6. Discussion

6.1 The Unified Multitech Five-layer Supply Chain Model

In the light of the study research focus and identified research gap, to synthesize the study findings, literature and empirical data, the following Unified Multitech Smart Supply Chain Framework has been proposed for Bangladesh (Jackson et al., 2024; Wang, 2026; Callefi et al., 2026). It is a framework in which there are five interlinked levels:

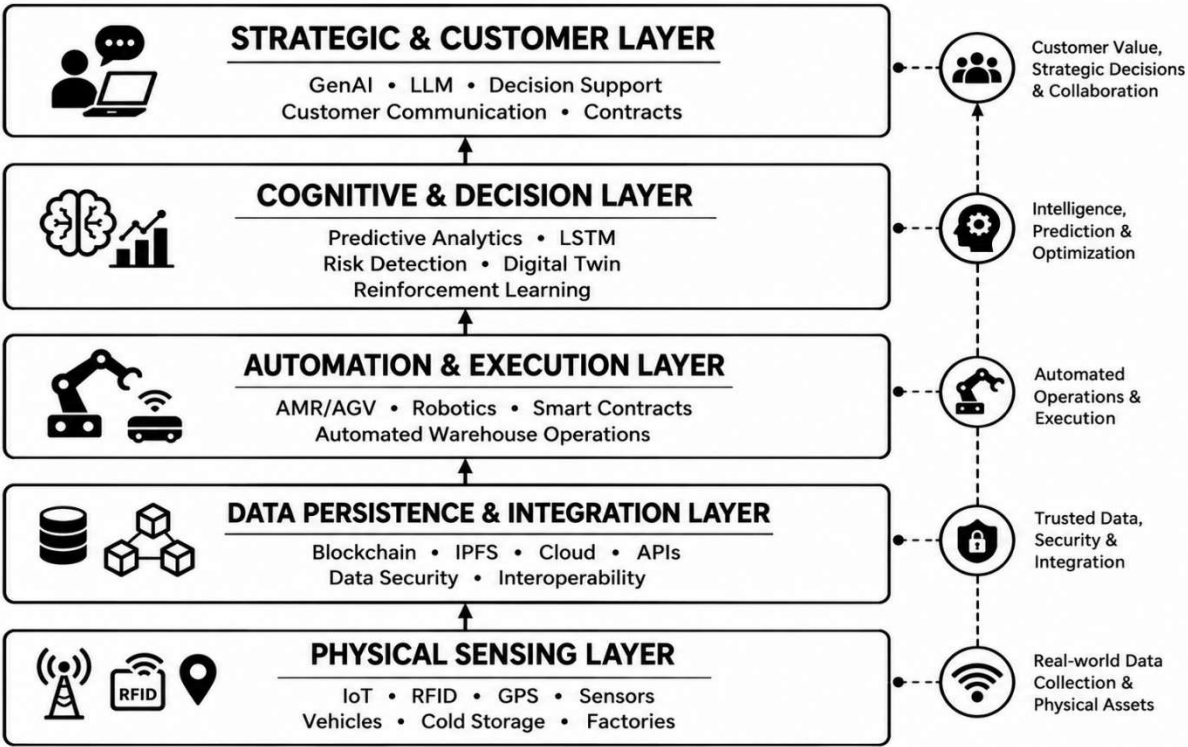


Figure 2: Unified Multitech Five-layer Supply Chain Model

- **Physical Sensing Layer:** Technology that creates an IoT layer across steering and tractor units, cold storage units and manufacturing plants, continually collecting information on environmental and operational conditions.
- **Data Persistence & Integration Layer:** Data immutably recorded on Blockchain smart ledgers and decentralized storage (IPFS) together with data integrity, security and semantic interoperability.
- **Automation & Execution Layer:** integrates AI warehouse robotics (AMRs/AGVs) and blockchain smart contracts for automated physical sorting, verification of quality standards, and automated financial negotiations.
- **Cognitive & Decision Layer:** Inserts predictive forecasted model of LSTM networks and reinforcement learning agents, in order to predict logistics routing optimizations, anomaly detections and digital twin scenario simulations.
- **Strategic & Customer Layer:** Automates contract generation, offers natural language executive decision support and provides custom customer notifications, using Generative AI LLM interfaces.

6.2 Findings Interpretation using TAM and RBV

The empirical findings of the current study offer a detailed insight into the transformation of the supply chain in Bangladesh spurred by AI. The data, taken in the perspective of the Technology Acceptance Model (TAM) proves a high level of Perceived Usefulness (PU). The supply chain stakeholders in Bangladesh are well aware of the benefits of AI, predictive analytics and IoT in the context of reducing lead time, achieving lower operational costs and risk reduction. This elevated PU will directly translate into the high individual behavioral intention, as not only the individual readiness score (M=3.99) is high, but it is as well correlated with usefulness (r=.665).

But the phase between personal passion and company application is extremely bottlenecked by limitations that are underscored by the Resource-Based View (RBV). According to RBV, competitive advantage is based on valuable and rare resources. The statistical information about the survey clearly points out that Bangladeshi supply chains are crippled by a lack of these important resources. The highest barriers to operations as identified by the list include skilled AI talent (44.4%), which is a deficiency of AI/data skills, and capital costs (36.6%) that demonstrate that merely wanting to acquire technology is not sufficient. Organizations cannot deploy without the human capital to create and train algorithms and without financial capital to tear down old infrastructure. Therefore, there were significantly lower organization readiness scores (M=3.26) than personal readiness proving the point that the enterprise infrastructure is willing, as opposed to workforce.

6.3 Awareness-Execution Paradox in South Asian Supply Chains

One interesting result of the data is the Awareness-Execution Paradox. Although industry actors are experiencing very strong awareness of local AI implementations (75.7% have observed actual applications), a significant number of the entire sample (33.5%), nevertheless identify low organizational awareness as a key barrier. This signifies a critical disheartenment between mid-level professional consciousness and the executive level, strategic implementation. Although supply chain managers may know the value of AI, the risk-averse culture of the C-suite (mentioned by 25.3%) and the low level of technological infrastructure of the country (31.9%) stands in the way of successful rollout of multi-tech AI systems.

In addition, the huge distance between the students and the professionals in terms of local knowledge ($\chi^2=26.73$, $df=2$, $p < .001$) speaks of an educational detachment. Students have theoretical understanding but no exposure to actual localized industry implementation and thus tend to be over pessimistic about the simplicity of integration as compared to practitioners involved.

6.4 Practical Implications

In the case of Academia (Bridging the Talent Gap): Since a shortage of talent was the biggest obstacle (44.4%), the Bangladesh universities cannot afford to continue delivering a more theoretical-oriented computer science curriculum anymore, but to invest in more applied, domain-focused data engineering. Students of supply chains and business need to learn to apply Python, predictive analytics, and IoT telemetry to real-life applications in logistics.

Businesses: Companies need to cease thinking of AI as ready-to-install software. The statistics create indications that it is not practical because of legacy systems and broken data. Before trying to implement advanced AI or robotics, businesses have to invest in cloud infrastructure and data standardization.

To the Policymakers: This is because more than 20 percent of those surveyed stated that they believed a government policy was an obstacle, and 31.9 percent said the poor digital infrastructure was an obstacle. The Bangladesh government needs to encourage its digital transformation with subsidized cloud infrastructure, tax breaks on AI research and development in logistics, and nationwide data standardization frameworks.

6.5 Limitations and Future Research

Although this research gives a strong background data (N=257), it utilizes the perceptions as self-reported. The large number of FMCG respondents (40.1) could have a slight skew to the results towards retail-focused supply chains, thus not fully capturing the special bottlenecks in heavy manufacturing. Incorporating Structural Equation modeling (SEM) into future studies should enable the statistical mapping of the highest direct mediating effects of a talent deficiency on variables of TAM. Also, longitudinal case studies tracking in actual Return on Investment (ROI) of AI adoption in Bangladeshi RMG and pharmaceutical supply chains must shift real data perception-based data to empirical financial performance measurements.

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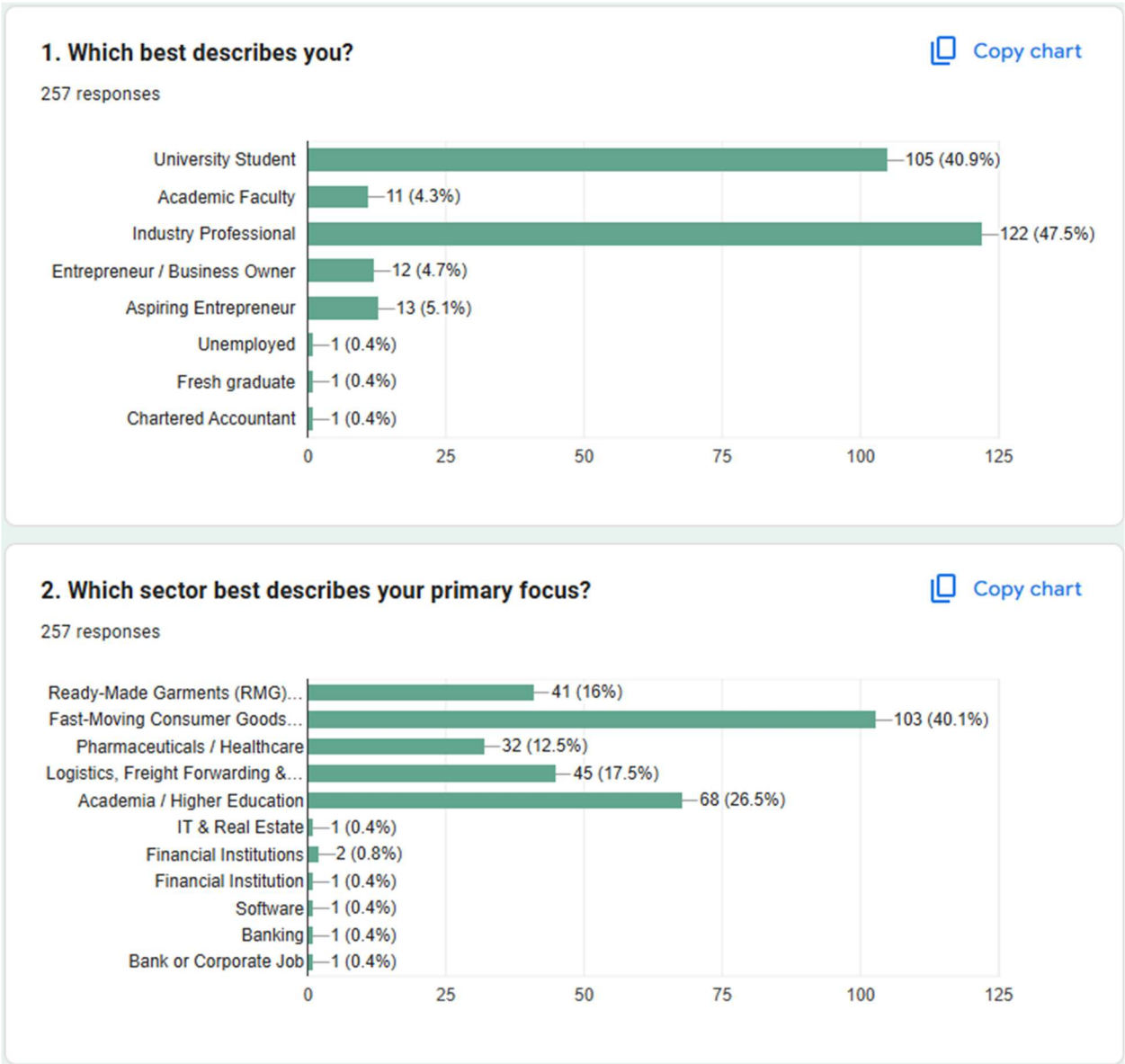
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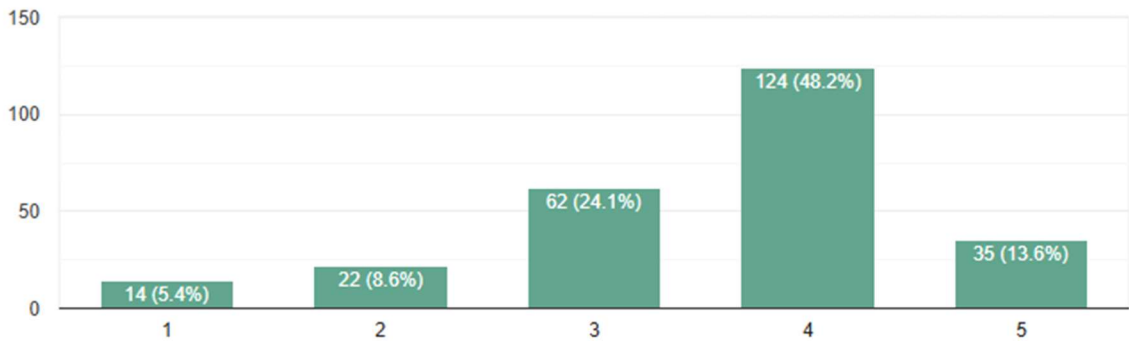
Appendix



3. I am familiar with how AI technologies (GenAI, predictive analytics, IoT, robotics, blockchain) can be applied in supply chain operations.

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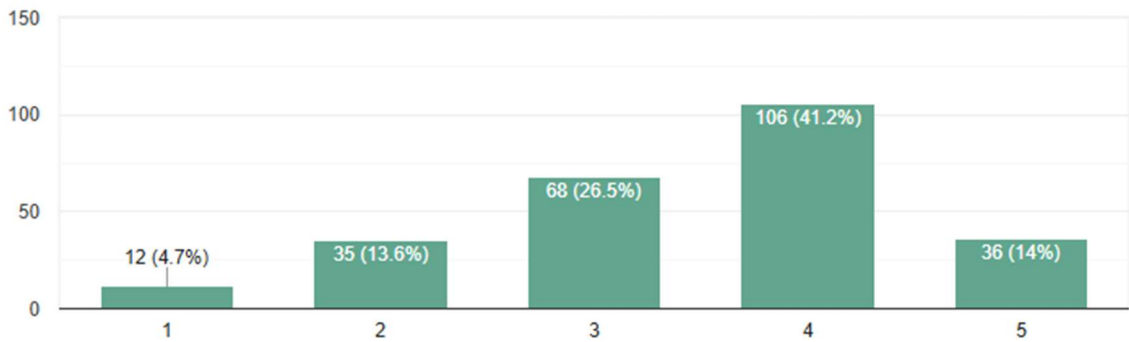
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4. I have seen or heard of real examples of these technologies being used in Bangladeshi companies.

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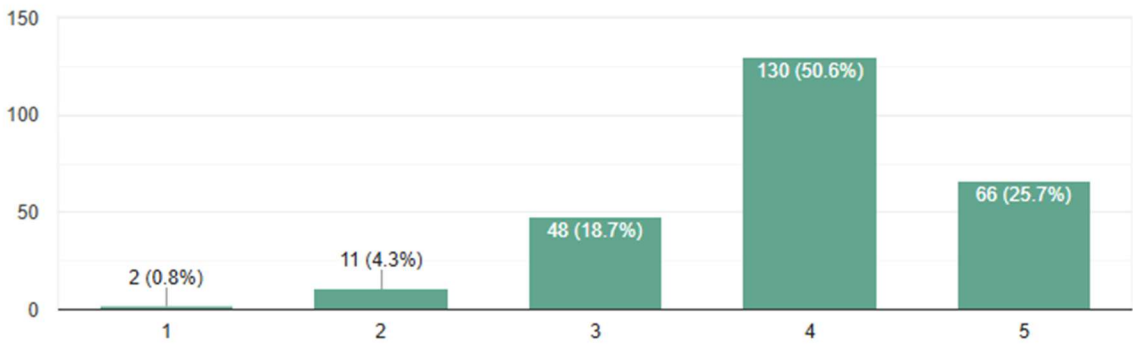
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5. I believe AI-driven tools can meaningfully reduce operational costs and lead times in supply chains.

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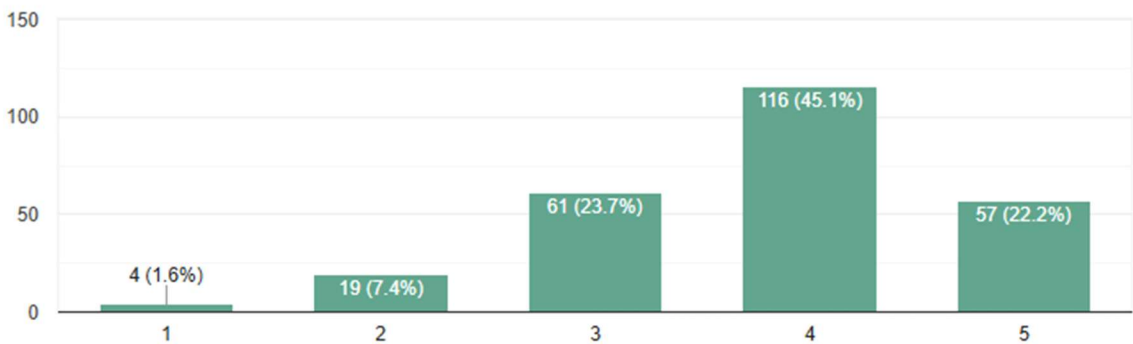
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6. I believe AI adoption would reduce risk (e.g., disruptions, stockouts, fraud) in supply chain operations.

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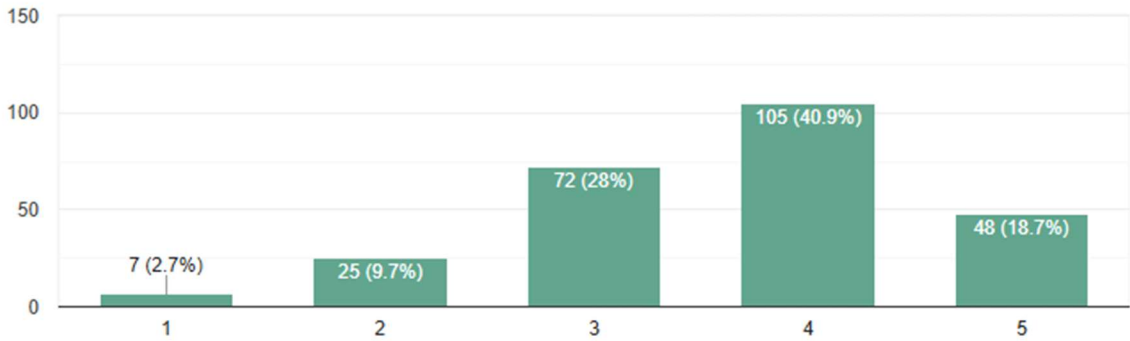
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7. High implementation cost is a major barrier to AI adoption in my organization/field of study.

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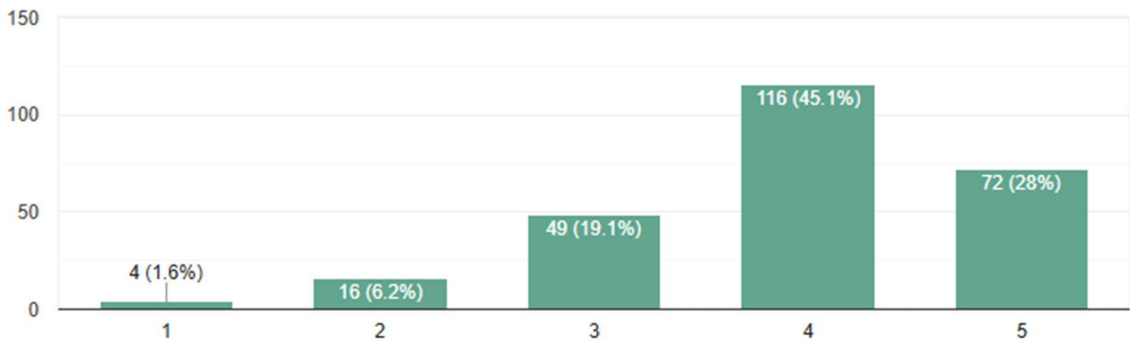
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8. Legacy systems, lack of technical talent, or lack of training are major barriers to AI adoption.

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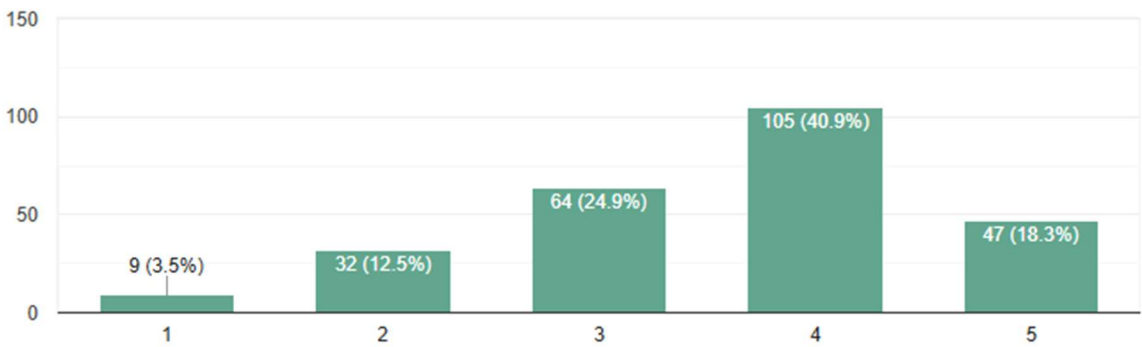
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9. I believe AI technologies can be integrated smoothly with existing systems and processes without major disruption.

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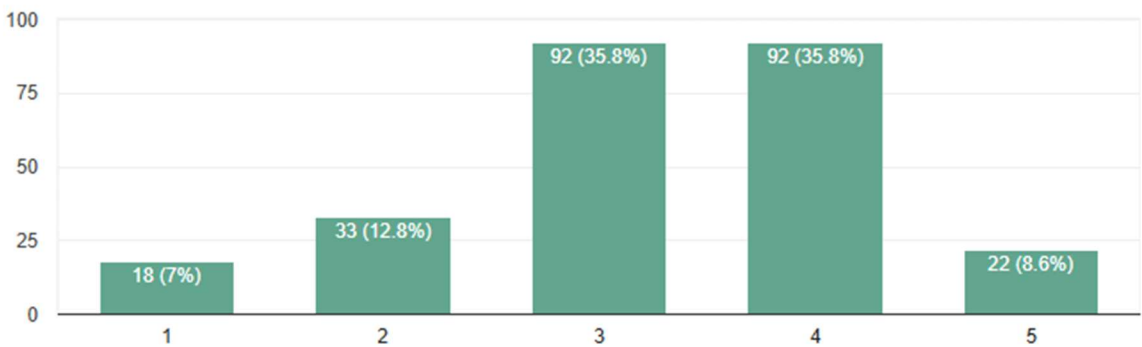
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10. My organization (or the industry I plan to enter) is ready to invest in and implement AI-driven supply chain solutions in the near future.

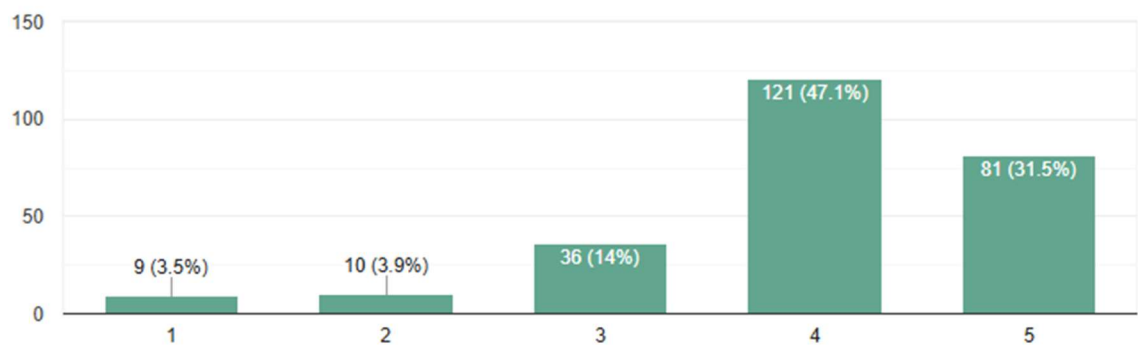
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11. I would personally support or recommend AI adoption initiatives if given the opportunity. [Copy chart](#)

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12. What do you see as the single biggest barrier or enabler to AI adoption in Bangladesh's supply chains? [Copy chart](#)

257 responses

