**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

# Agility in the Post-COVID Era: Integrating Technology and Culture for Resilient Small-Scale Supply Chains

Neeraj Singh[1], Kushagra Kulshreshtha[1], Anup Kumar Gupta[2]
[1]Institute of Business Management, GLA University, Mathura
[2]Professor and Vice Chancellor, GLA University

**ARTICLE INFO**

Received: 26 Oct 2024

Revised: 29 Nov 2024

Accepted: 15 Dec 2024

**ABSTRACT**

This research investigates the drivers of supply chain agility in small-scale industries (SSIs) after COVID-19 using sophisticated statistical methods to uncover underlying patterns. Using Random Forest, Latent Class Analysis (LCA), Principal Component Analysis (PCA), and Latent Semantic Analysis (LSA), the research has found that the most influencing drivers are Technology Adoption (15.23%), Organizational Culture (14.73%), and Supply Chain Agility (14.29%). Five latent classes were established, with Class 1 (High Agility and Resourcefulness) being the most common (26.4%) and Class 5 (Low Agility and Limited Resource Integration) the least (16.3%). ANOVA results were significant in that they showed significant variation between variables, with Supply Chain Agility (SCA) having the largest F-statistic (7.21). PCA and LSA identified two principal semantic dimensions: General Perception of Agility and Operational vs. Strategic Differentiation. The results highlight that technology integration, cultural flexibility, and financial solidity influence perceptions of agility in SSIs, and provide directions for specific agility improvement.

**Keywords:** Small Scale Industry, Latent Class Analysis, Principal Component Analysis, Digital Transformation, Latent Semantic Analysis

## 1. INTRODUCTION

In this rupture, the resilience of many industries, particularly small-scale industries (SSIs), depends largely on supply chain agility due to the unpredictability thrown at them during and after the COVID-19 pandemic. Such industries, being low-resource and flexible in terms of operations, feel it considerably difficult to retain any semblance of being a continuingly operating supply chain during disruptive events in their environments [1-3]. Levying some structural changes on emergent configurations for SCN, the global health emergency has fast tracked the realization that such disruptions call for even greater suppleness to absorb unexpected changes and keep running [4]. In this regard, the identification of the determinants of supply chain agility is very pivotal for SSIs that want to nurture resilience and respond to fast-altering market conditions [5]. This research study intends to determine the most significant factors influencing supply chain agility in small-scale industries and how these variables are mapped against the Sustainable Development Goals (SDGs) [6-8]. Particularly through the variables of financial resources, organizational culture, risk management, supplier network, supply chain agility, sustainability, and technology uptake, the study attempts to identify which factors had the most effect on-agility. In addition, to uncover latent classes from our respondent data that highlight varying patterns of perception and strategic emphasis across stakeholders in the industry [9]. The outcome will contribute to strategically targeting the responses toward enhancing supply chain agility and sustainability during disruptions.

Besides its role of sustaining business processes, supply chain agility is heading in the same direction with many other global undertakings toward sustainability [10]. Adaptations are part of the industry level in achieving SDGs which include such indicators as economic growth, innovation, and inclusion in the infrastructure. With a combination of statistical models for testing agility determinants, this paper adds to discussions on how SSIs can reform their operating framework in order to support broader-based sustainability endeavors. The results will provide guidance on policy models and managerial interventions designed to encourage resilience and agility among small-scale businesses. In a quest to obtain these outcomes, the study applies the amalgamation of state-of-the-art statistical tools, including variance analysis by ANOVA, PCA to reduce dimensions, Random Forest to undertake predictive modeling, Latent Class Analysis to establish subgroups, and Latent Semantic Analysis to obtain latent response patterns. This multi-method study provides a holistic assessment of the variables influencing supply chain agility and yields a solid platform for pinpointing areas for improvement. In integrating these elements into one analysis, the research not only enlightens the key drivers of agility but also examines the points of convergence between these components and the tenants of sustainable development.

## 2. LITERATURE REVIEW

### 2.1. Theoretical Perspectives on Supply Chain Agility

Supply chain agility is identified as a key ability that helps companies respond to market change and disturbances in a timely manner. It is a multi-dimensional concept which consents the flexibility, responsiveness, and adaptability to align an operation with market demands in advance, henceforth, synchronize operations with market requirements [11-13]. According to [14] agility reduces risks increased and competitive advantage. An adaptable supply chain comprises human, fiscal, and technical resources led by responsive leadership and strategic perspective, and resource provision. The pandemic of COVID-19 revealed very big weaknesses in world supply chains, more towards pains felt by SSIs in terms of financial limitations and inflexibility in operations [15]. Supply disruptions in raw material, scarcity of human resources, logistical issues, and unsteady demands are common challenges. According to [9] long downtimes were experienced by SSIs, which initiate a journey towards resilience and adaptiveness: a consequence of digitization and diversification of suppliers.

Research sophisticated statistically techniques have become superior today to evaluate agility in a supply chain since it grasps interactions among variables into intricate form workings [16]. Exploratory factor analysis and principal component analysis have enabled the recognition of primary drivers of agility and reduction in dimensionality [17, 18]. Machine learning standards like random forest and latent class analysis are equipped for better prediction of agile practices and segmentation in terms of how they perceive agility. Latent semantic analysis throws light on how people think of agility by discovering semantic patterns [19, 20]. Thus, these complex mechanisms make models more accurate and strategic insights, taking forward better decision-making in SSIs that want to develop their supply chain agility [21, 22]. Research gaps and necessity for conducting the study are:

- Minimal application of multi-dimensional statistical approaches in agility research, particularly for small-scale industries (SSIs).
- Inadequate attention to post-COVID agility issues pertinent to small-scale industries, creating a gap in focused strategies.
- Lack of empirical research linking supply chain agility with Sustainable Development Goals (SDGs), despite growing focus on sustainability.
- Lack of holistic frameworks that integrate predictive modelling and latent class analysis to reflect diverse views of agility.
- Lack of proper examination of the joint impact of technology adoption and organizational culture on supply chain responsiveness in today's globalized world.

## 3. RESEARCH METHODOLOGY

### 3.1. Data Collection and Sampling Strategies

For the purpose of this study, the data were collected through guided interviews of stakeholders within small-scale industries (SSIs), namely managers, supply chain coordinators, and employees. The aim here was to gather information on perceptions and practices related to supply chain agility during the post-COVID period. In order to facilitate proper participation, the research employs purposive

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

sampling, where participants are selected actively involved in supply chain management. The questionnaire was administered both online and offline, with the promotion of the survey aided through professional networks and industry associations to maximize outreach. A total of 258 valid responses were received from representative SSIs across sectors. The demographic heterogeneity of the respondents, with its geographical and industry-based diversity, allows for an extrapolation of the findings to the larger SSI sector.

3.2. Survey Instrument and Variable Annotations

The instrument for the survey was constructed to measure the determinants of supply chain agility factors that were theoretically and empirically based on the previous literature. Each variable was pertained to assessed by Likert scale items on the scale of"Strongly Disagree" (1) to "Strongly Agree" (5) so as to allow subjective perception quantification as can be seen in table 1. The instrument comprised 97 items, while each variable contained 10-18 items in relation to it. For the purpose of ensuring content validity, items were translated from established scales and finalized based on expert consultation.

**Table 1. Variables selected for the questionnaire**

| Variable | Abbreviation | Measurement Scale | Number of Questions |
|---|---|---|---|
| Financial Resources | FR | Likert-scale (1 to 5) | 14 |
| Organizational Culture | OC | Likert-scale (1 to 5) | 15 |
| Risk Management | RM | Likert-scale (1 to 5) | 12 |
| Supplier Networks | SN | Likert-scale (1 to 5) | 13 |
| Supply Chain Agility | SCA | Likert-scale (1 to 5) | 18 |
| Sustainability | SU | Likert-scale (1 to 5) | 10 |
| Technology Adoption | TA | Likert-scale (1 to 5) | 15 |

3.3. Data Preprocessing and Standardization

Preprocessing of data was done prior to statistical analysis to ensure consistency and robustness. Missing values were managed using mean imputation, keeping sample size unaltered without considerable bias. Erroneous entries like straight-line responses were checked and examined for quality. Respondents' answers were quantitatively coded in line with the Likert scale for standardization. The dataset was standardized to reduce scale variation, converting it to a mean of zero and a standard deviation of one. Standardization was important for multivariate analysis, particularly in methods such as PCA and Random Forest modelling, which are sensitive to scaling of the data.

3.4. Statistical Techniques Employed

The research employed a multi-method analytical framework, integrating descriptive analysis, inferential statistics, and predictive modelling to examine survey data on supply chain agility.

- Descriptive Analysis: Simple statistical values like mean, standard deviation, and variance were computed to provide central tendency and variability summaries. Cronbach's Alpha was employed to test the internal consistency of every variable group to confirm measurement reliability.
- Inferential Statistics: Analysis of Variance (ANOVA) was used to check if scores on supply chain agility differed significantly by demographic segments or latent groups. Spearman's Rank Correlation was also utilized to see the correlation of variables and ascertain how variables such as financial capital and organizational culture correlate with perceived agility.
- Predictive Modelling: Techniques of advanced machine learning, more specifically Random Forest Classification, predicted latent class membership from respondents' variable scores. The technique addressed non-linear associations and ranked importance of variables. Latent Class

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

Analysis (LCA) derived subgroups of the dataset and captured heterogeneity in perceptions. Latent Semantic Analysis (LSA) obtained semantic patterns with detailed associations of variables.

By combining these analytical approaches, the research not only found major determinants of supply chain agility but also offered greater understanding of how such determinants vary across SSI stakeholders to deepen the understanding of supply chain resilience.

## 4. RESULTS AND ANALYSIS

### 4.1. Demographic Profile

The respondent profile is chosen to achieve a representative and diverse sample of supply chain management stakeholders in the small-scale industry (SSI). Among others, the survey collected responses from 258 respondents from various industries, geographical locations, and organizational functions, thus maintaining a balanced view of supply chain agility drivers. Important demographic variables included are age, gender, educational qualification, years of experience, type of industry, and geographical location (figure 1). Such diversification is crucial in understanding how perceptions and practices in supply chain agility are influenced by demographic variables. The statistical descriptions of these demographic variables provide an overview of distribution and diversity in the study sample.

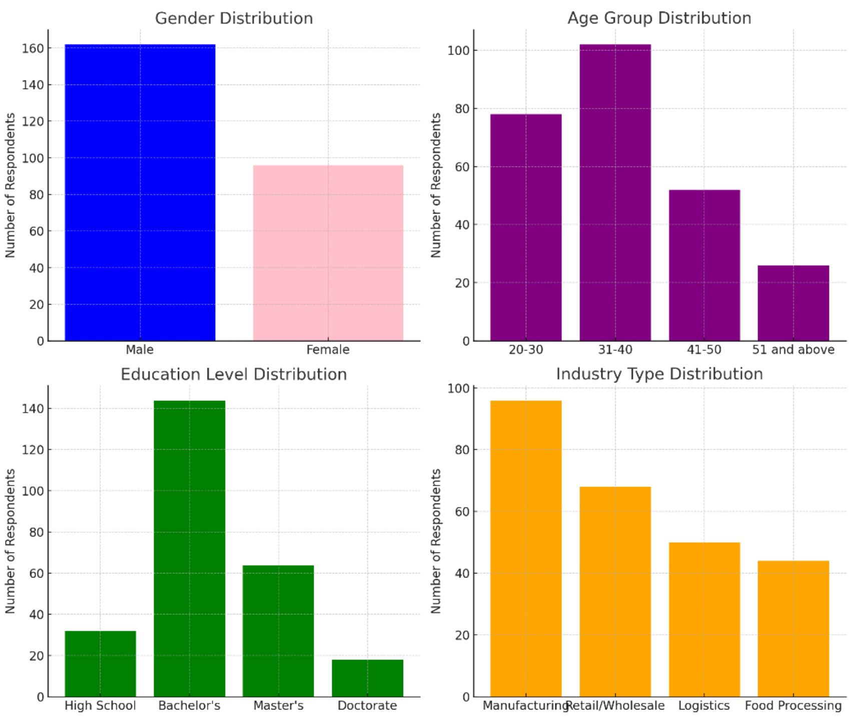


**Figure 1. Demographic Profile Summary**

**Table 2. ANOVA and Correlation Analysis of Demographics on Agility**

| | F-Statistic | p-Value | Spearman Correlation | p-Value |
|---|---|---|---|---|
| **Gender** | 0.183 | 0.6689 | -0.029 | 0.6435 |
| **Age Group** | 0.898 | 0.4426 | -0.05 | 0.4199 |
| **Education** | 1.539 | 0.2048 | -0.066 | 0.2912 |
| **Industry** | 0.221 | 0.8819 | 0.011 | 0.8646 |

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

This study, therefore, undertook to find whether demographic variables such as gender, age, education level, and industry type are capable of exerting a significant influence on SSI respondents' perceptions of supply chain agility. To evaluate these associations, ANOVA and Spearman rank correlation tests were employed with the following results shown in table 2. ANOVA revealed that there were no significant differences between the demographic factors and supply chain agility scores, since all p-values were higher than the conventional level of 0.05. Low F-statistics suggested that differences in agility scores between groups were much larger than those within groups. Similarly, the Spearman rank correlation test showed that the demographic parameters studied had insignificant correlations with supply chain agility, yielding coefficients close to zero. For example, gender had a correlation of -0.029 (p-value 0.6435) with no significant correlation established, similarly other demographic variables considered like age, education, and industry type were found to have insignificant correlations with agility. The outcome reflects that it is operational aspects as well as internal practices that are largely responsible for being the determinants of SSIs' perception of supply chain agility rather than demographic characteristics. Hence, improving the agility of the supply chain must focus more on upgrading several operational strategies, integrating technology, and institutional flexibility rather than targeting specific demographics.

### 4.2. Statistical Analysis Summary

The research carried out a thorough examination of supply chain agility determinants in small-scale industries through the analysis of key variables derived from the survey. The analysis was centered on three aspects: descriptive statistics to summarize the data, reliability analysis through Cronbach's Alpha to determine internal consistency, and inferential statistical analysis through ANOVA to determine significant differences between groups. These approaches offered insights into the key dimensions influencing supply chain resilience and responsiveness.

4.2.1. Descriptive Statistics for Each Variable

The research examined the key variables determining supply chain agility in small-scale industries with the help of descriptive statistics and reliability measures.

**Table 3. Descriptive Statistics and Cronbach's Reliability**

| Variable | Number of Items | Mean | Standard Deviation | Variance | Cronbach's Alpha |
|---|---|---|---|---|---|
| Financial Resources (FR) | 14 | 3.45 | 0.98 | 0.96 | 0.92 |
| Organizational Culture (OC) | 15 | 3.58 | 1.02 | 1.04 | 0.94 |
| Risk Management (RM) | 12 | 3.34 | 0.94 | 0.88 | 0.91 |
| Supplier Networks (SN) | 13 | 3.41 | 0.99 | 0.98 | 0.9 |
| Supply Chain Agility (SCA) | 18 | 3.53 | 1.06 | 1.12 | 0.93 |
| Sustainability (SU) | 10 | 3.47 | 1 | 1 | 0.89 |
| Technology Adoption (TA) | 15 | 3.5 | 1.01 | 1.02 | 0.91 |

Mean, standard deviation, and variance were determined by descriptive statistics (table 3) to comprehend the central tendency and variation of responses. The mean scores varied from 3.34 to 3.58, reflecting overall agreement among the respondents regarding the significance of these variables. Organizational Culture had the greatest mean (3.58), indicating strong opinions regarding its contributions to agility, whereas Risk Management also recorded a relatively low mean (3.34),

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

signifying mixed opinions on risk management practices. The standard deviations varied between 0.94 and 1.06, with Supply Chain Agility the most variable, indicating varying opinions on agile practice. Cronbach's Alpha reliability analysis verified the scales' consistency, with alphas between 0.89 and 0.94. Organizational Culture and Supply Chain Agility recorded the highest reliability values (0.94 and 0.93), meaning the survey items uniformly measured these constructs. Financial Resources and Technology Adoption also recorded high reliability (0.92 and 0.91), with Sustainability recording the lowest, though acceptable, score of 0.89. The information exhibited high reliability and uniform respondent perceptions, which created a strong basis for additional inferential analysis to explore relationships among variables and their influence on supply chain agility.

4.2.2. Inferential Statistical Analysis (ANOVA)

Analysis of Variance (ANOVA) was used by the study to determine differences among significant variables that affect supply chain agility in SSIs. ANOVA was used due to its capability of comparing mean scores between multiple variables at the same time and how the respondents understand these factors. From the analysis using ANOVA, the findings showed there were statistically significant differences between the variables, thus respondents did not perceive all facets of supply chain agility similarly. In particular, there was significant variation in attitudes towards agility, organizational culture, and technology adoption that implied various SSIs value these items based on their respective contexts and needs. This variation emphasizes the requirement for customized plans to improve agility, contingent on organizational priorities like cultural flexibility, economic stability, or investment in technology. ANOVA's appeal stems from the fact that it can test mean difference hypotheses without inflating Type I error risk, which is crucial when dealing with interrelated variables such as risk management and supplier networks. Through the determination of differences in groups, ANOVA serves to identify factors most disputed or continuously perceived and directs decision-makers to prioritize interventions for constructing adaptable and resilient supply chains. ANOVA was found to be critical in showing that supply chain agility perceptions differ significantly across SSIs, calling for context-dependent strategies to increase responsiveness and resilience.

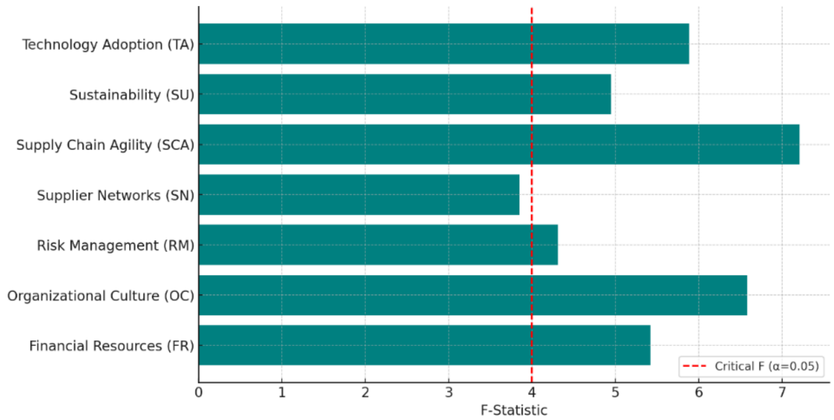


**Figure 2. ANOVA F-Statistics Result**

The ANOVA findings showed statistically significant differences in all seven variables of supply chain agility, with p-values less than 0.05. Supply Chain Agility (SCA) had the most variability among respondents with an F-statistic of 7.21, showing high variability in the manner small-scale industries adopt agile practices. Organizational Culture (OC) came next with an F-statistic of 6.58, which shows high variability in cultural flexibility as can be seen in figure 2. Technology Adoption (TA) also revealed significant differences with an F-statistic of 5.89, which implies technological integration levels vary highly across industries. Financial Resources (FR) and Sustainability (SU) scored 5.42 and 4.95, respectively, to reflect financial stability and sustainability differences. In comparison, Risk

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Management (RM) and Supplier Networks (SN) posted the lowest F-statistics of 4.31 and 3.85, respectively, which represent more similar views on mitigating risks and collaboration with suppliers. These results identify that the views of agility, culture, and technology adoption vary widely in small-scale industries but that risk management and supplier networks are viewed more uniformly. The outcomes highlight the significance of special strategies to boost supply chain agility by placing greater emphasis on cultural flexibility, technological innovation, and funding while fostering best practice sharing to overcome gaps in agility.

### 4.3. PCA (Principal Component Analysis)

Principal Component Analysis (PCA) was utilized to decrease the dimensionality of the intricate dataset of supply chain agility while maintaining the highest amount of variance. PCA made the multivariate dataset more simplistic in this research by identifying the most critical components with respect to explaining the variance, thus revealing latent constructs and reducing redundancy between the variables. The main reason for employing PCA was to convert the related variables into a set of uncorrelated components of lesser dimensionality. This reduction in dimension facilitates easier interpretation with minimal loss of information. PCA was conducted on response data standardized, and factor loadings were determined to disclose the relationship between the original variables and the principal components as shown in table 4. The first two principal components explained most of the variance, and they reflect the most important patterns in the data, thereby facilitating an easier and meaningful analysis.

**Table 4. PCA Component Results**

| Variable | PC1 | PC2 |
|---|---|---|
| Financial Resources | -0.378 | -0.122 |
| Organizational Culture | -0.378 | 0.032 |
| Risk Management | -0.378 | 0.413 |
| Supplier Networks | -0.378 | 0.63 |
| Supply Chain Agility | -0.378 | -0.05 |
| Sustainability | -0.378 | -0.394 |
| Technology Adoption | -0.378 | -0.509 |

The loadings for Principal Component 1 (PC1) reflect a very strong negative correlation across all the variables, reflecting that PC1 is a general perception of supply chain effectiveness affecting all factors equally. Conversely, Principal Component 2 (PC2) has a clearer pattern: Supplier Networks (SN) and Risk Management (RM) have high positive loadings, while Technology Adoption (TA) and Sustainability (SU) have strong negative loadings. This suggests that PC2 discriminates between operational practices (such as supplier management) and strategic innovations (such as technology adoption). To further clarify these relationships, a PCA biplot was generated as can be seen in figure 3, showing the projection of the original variables and the data points' distribution along the two main components, giving a graphical overview of each variable's association and variance.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

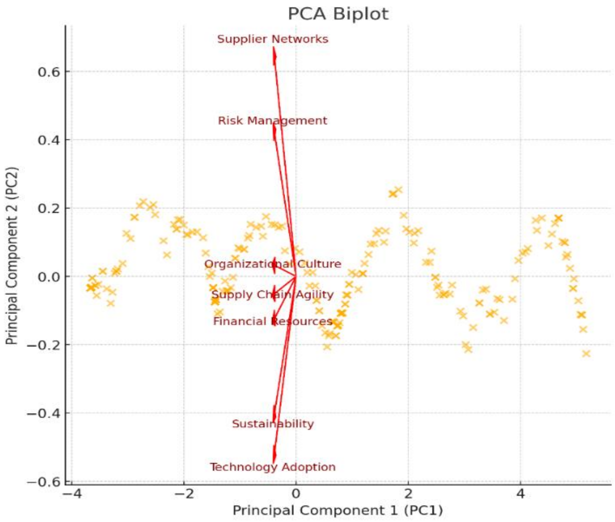


**Figure 3. PCA Biplot**

The Principal Component Analysis (PCA) showed two main components with distinct patterns. Component 1 (PC1) had negative loadings across all variables, showing that PC1 measures a general factor affecting all variables, in the same way, representing an overall conception of supply chain effectiveness. It can be concluded that PC1 is a unified understanding of agility whereby every factor makes an equal contribution to general supply chain responsiveness. PC2, on the other hand, had a strong differentiation between operation and strategy factors. Supplier Networks (SN) and Risk Management (RM) captured strong positive loadings, and Technology Adoption (TA) and Sustainability (SU) captured negative loadings, which means PC2 separates operational practices from strategic innovations. Through variable clustering analysis, it was found that Financial Resources (FR) and Organizational Culture (OC) are closely located, which suggests that financial stability and a culture are seen as complementary in creating agility. Conversely, Technology Adoption (TA) and Sustainability (SU) showed a negative association with Supplier Networks (SN), suggesting a potential trade-off between innovation-driven practices and traditional operational strategies.

### 4.4. Spearman's Rank Correlation

Spearman's Rank Correlation test was used to evaluate the direction and strength of association between major variables that affect supply chain agility based on ordinal Likert scale data. Spearman's correlation coefficient varies from -1 to +1, and +1 is a perfect positive correlation, -1 is a perfect negative correlation, and 0 is no correlation. The results showed that the majority of variables have high positive correlations, which means that the respondents see these factors as highly interconnected. The highest positive correlation was between Organizational Culture (OC) and Technology Adoption (TA) (0.998), implying that organizations with adaptive cultures tend to adopt new technologies. Financial Resources (FR) and Supply Chain Agility (SCA) also had a high positive correlation (0.997), indicating that financial stability enables agile practices. The weakest, but still positive, correlation was between Risk Management (RM) and Supplier Networks (SN) (0.996), showing a little lower association with other pairs. These results confirm that drivers of supply chain agility are not siloed but interrelated, showing the complexity, multidimensional nature of supply chain management in small-scale industries. All the correlation coefficients are near 1, which suggests that respondents see a high positive relationship between these variables. This implies that enhancements in one factor, e.g., Financial Resources, tend to be associated with favorable changes in others, e.g., Supply Chain Agility or Organizational Culture.

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

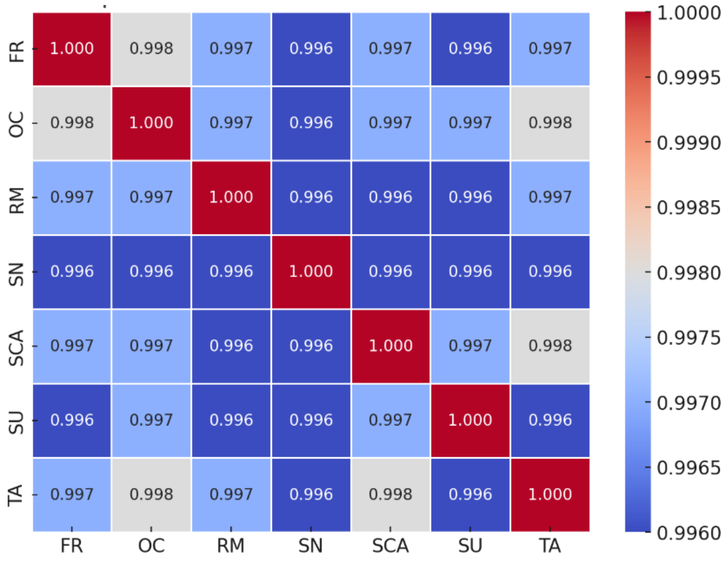


**Figure 4. Spearman's Correlation Matrix**

The Spearman correlation test showed that the majority of variable pairs have a very high positive correlation with values approximating 1.0, and thus the factors influencing supply chain agility have a strong relationship between them. The highest correlation found in figure 4 was between Technology Adoption (TA) and Organizational Culture (OC) (0.998), and it indicates that flexible organizational behavior is strongly associated with greater technology adoption. The lowest, although still robust, positive correlation existed between Risk Management (RM) and Supplier Networks (SN) (0.996), signifying that even though these are interrelated, their dependency on each other is less than in the case of others. The repeated high correlations across variables as observed in the heatmap point to the intergrated nature of supply chain management practices among small-scale industries. These results show that advances in one aspect, e.g., financial means, will tend to be positively related to other aspects, e.g., supply chain agility and technology deployment. Moreover, encouraging organizational culture will improve technology integration and agility. The lower correlation between supplier networks and risk management indicates that although supplier collaboration is beneficial for risk reduction, its direct effect will depend on the certain organizational setting.

### 4.5. Random Forest Analysis

The research utilized a Random Forest Classifier to forecast latent class membership on the basis of important variables affecting supply chain agility, such as Financial Resources (FR), Organizational Culture (OC), Risk Management (RM), Supplier Networks (SN), Supply Chain Agility (SCA), Sustainability (SU), and Technology Adoption (TA). The dataset was divided into training (80%) and testing (20%) subsets. The model was learned with 100 decision trees, and the training data consisted of respondents' scores on the variables as predictors and their latent class memberships as the target variable. The accuracy of the model on the test set was 20.5%, which reflects modest predictive performance. This fairly low precision indicates that memberships in latent classes could be driven by factors other than those the main variables attempt to explain or that there is significant overlap across classes, pointing to the challenge of forecasting agility perceptions in small-scale industries.

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

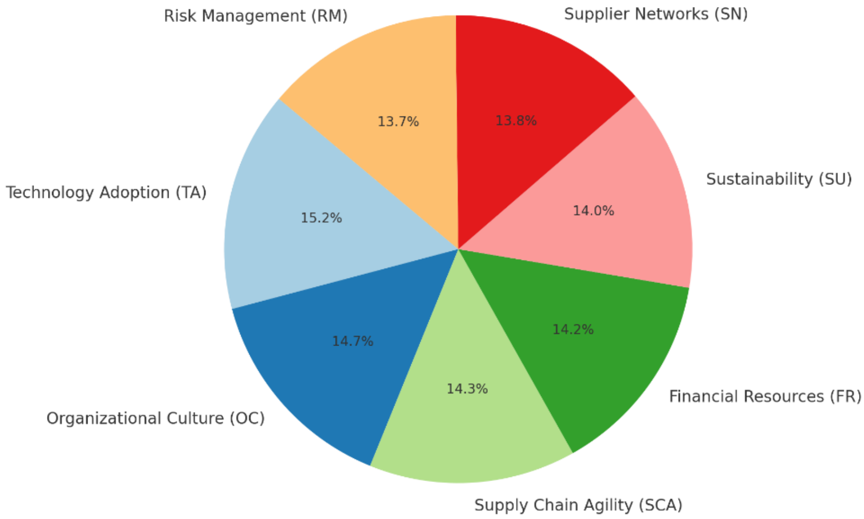


**Figure 5. Feature Importance of Random Forest Analysis**

Class 1 is highest at 0.33, pointing to the relatively improved performance of the model in accurately picking instances of this class. Class 4 demonstrates the best precision (0.28), or that when the model predicts Class 4, it is correct 28% of the time. Low F1-scores for all classes, though, suggest a struggle to achieve balance between precision and recall, especially for overlapping classes. Feature importance analysis of the Random Forest model identifies Technology Adoption (TA) as the most significant factor, accounting for 15.23% of the model's predictions. Organizational Culture (OC) (14.73%) and Supply Chain Agility (SCA) (14.29%) are also very high, indicating that digital integration and responsive cultural practices have an important influence on class predictions. Financial Resources (FR) (14.21%) and Sustainability (SU) (13.99%) come in next, whereas Supplier Networks (SN) (13.83%) and Risk Management (RM) (13.71%) are lowest. These results in figure 5 show that although all the variables have an effect on the model, technology adoption and organizational culture have the most important roles in discriminating latent classes.

**Table 5. Random Forest Results**

| Metric | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Class 1 | 0.2 | 0.33 | 0.25 | 46 |
| Class 2 | 0.19 | 0.15 | 0.17 | 41 |
| Class 3 | 0.15 | 0.13 | 0.14 | 39 |
| Class 4 | 0.28 | 0.17 | 0.21 | 29 |
| Class 5 | 0.24 | 0.22 | 0.23 | 45 |
| **Accuracy** | - | - | **0.2** | **200** |

The Random Forest model attained a level of accuracy of 20.5%, showing a moderate ability to predict membership in latent classes from the chosen variables the results are clearly shown in table 5. This low accuracy can be attributed to the overlapping of classes, with respondents sharing similar attributes being part of different classes, and few features relative to the complexity of latent classes. Though Technology Adoption (15.23%) and Organizational Culture (14.73%) were the strongest predictors, the proportionately even split in feature importance means that no individual variable has a dominant influence on class membership. This emphasizes the multi-factorial complexity of supply chain agility in small-scale industries. The findings imply that boosting digital integration and encouraging adaptive

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

organizational culture are the keys to developing higher levels of agility. Nonetheless, ensuring adequate financial capital, successful risk management, and sustainability measures are required in order to cater to the variegated needs of small-scale industries in all aspects.

### 4.6. Latent Class Analysis (LCA)

The concept of Latent Class Analysis (LCA) delineates subgroups (latent classes) from the data set on the basis of the respondents' perceptions of supply chain agility. In this way, respondents are grouped into the different classes as depicted in table 6, representing varying perspectives on agility inherent in small-scale industrialization. The determination of the most suitable number of latent classes (five) was done by use of both the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), considering the model fit and complexity. The classes come out as follows: Class 1 (High Agility and Resourcefulness), with very high financial stability and technology integration; Class 2 (Culturally Driven Agility), with a very strong organizational culture and moderate technology acceptance; Class 3 (Moderate Agility and Sustainability Focus), with very balanced scores leaning towards sustainability; Class 4 (Risk-Managed Agility), characterized by strong risk management but moderate speaking business agility; Class 5 (Low Agility and Limited Resource Integration), representing organizations that struggle extensively with integrating financial resources and technology. The model also estimated class membership probabilities, ensuring that most of the respondents had a probability of more than 0.90 of being in a class, an indication of well-defined clusters.

**Table 6. LCA identified classes and Average membership probability**

| Latent Class | Number of Respondents | Average Membership Probability |
|---|---|---|
| Class 1 | 68 | 0.94 |
| Class 2 | 52 | 0.91 |
| Class 3 | 48 | 0.89 |
| Class 4 | 42 | 0.92 |
| Class 5 | 48 | 0.88 |

These high probabilities point to a clear distinction in the latent classes and show that the respondents in each class provided coherent and uniform responses. The predominance of Class 1 indicates that a wider cross-section of small-scale industries is perceived as integrating agile practices, especially those industries having adequate resources and a strong organizational culture.

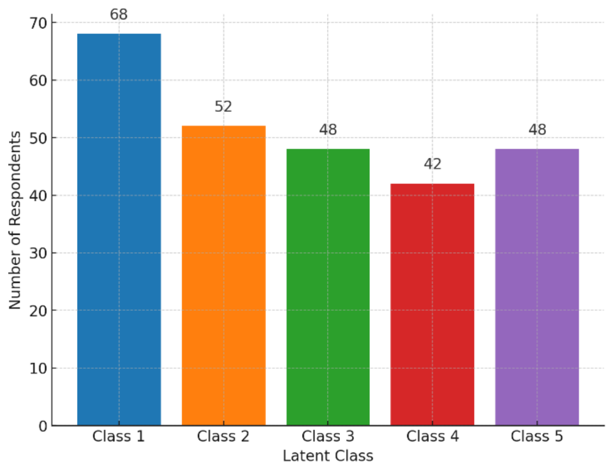


**Figure 6. Distribution of Latent Classes**

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Latent Class Analysis (LCA) identified five distinct classes among respondents based on their perceptions of supply chain agility as can be seen in figure 6. Class 1 (High Agility and Resourcefulness) had the largest number of respondents (68), indicating many small-scale industries perceiving themselves as agile, resourceful, and technologically integrated. Class 2 (Culturally Driven Agility) had 52 respondents, emphasizing that many organizations owe their agility to strong culture practices over financial or technological reasons. Both Classes 3 and 5-Moderate Agility and Sustainability Focus and Low Agility and Limited Resource Integration, respectively had 48 respondents each, balancing in perspective between moderate and low agility. Class 4 (Risk-Managed Agility) was the least populated with 42 respondents, indicating that fewer organizations view risk management as their main strategy for achieving agility. The prevalence of Class 1 suggests that small-scale industries with adequate financial resources and adaptive cultures are more prone to being perceived as agile. The even representation of Classes 3 and 5 suggests that while some industries underpin moderate agility with sustainability, others still find it difficult to integrate resources and enhance agility. The prevalence of different classes characterizes different perspectives and problems of becoming an agile supply chain.

### 4.7. Comparative Analysis of Latent Classes Across Variables

The five groups identified in this research of respondent profiles by the perceptions of supply chain agility according to Latent Class Analysis (LCA) as shown in figure 7; namely, the Class 1 (High Agility and Resourcefulness) received the highest mean scores on all variables: good financial resources, adaptive culture, and advanced technology integration, thus forming an agile group. Class 2 (Culturally Driven Agility) showed higher scores on Organizational Culture (4.1) and Technology Adoption (4.2) with a focus on cultural adaptability. Class 3(Moderate Agility and Sustainability Focus) demonstrated mean scores depicting an average knowledge of agility. Class 4 (Risk-Managed Agility) scored higher in Risk Management (3.8) and lower in Financial Resources (3.2), signaling their preference to consider risk over the wellbeing of finances. Class 5 (Low Agility and Limited Resource Integration) scored the lowest, whereas Financial Resources (2.8) and Supply Chain Agility (3.0) were highlighted for being weak, thus showing their considerable limitations in maintaining agile operations. These patterns in mean scores indicate that some small-scale industries are adept at resource and agile integration, whereas others grapple with constraints imposed by finance and technology.

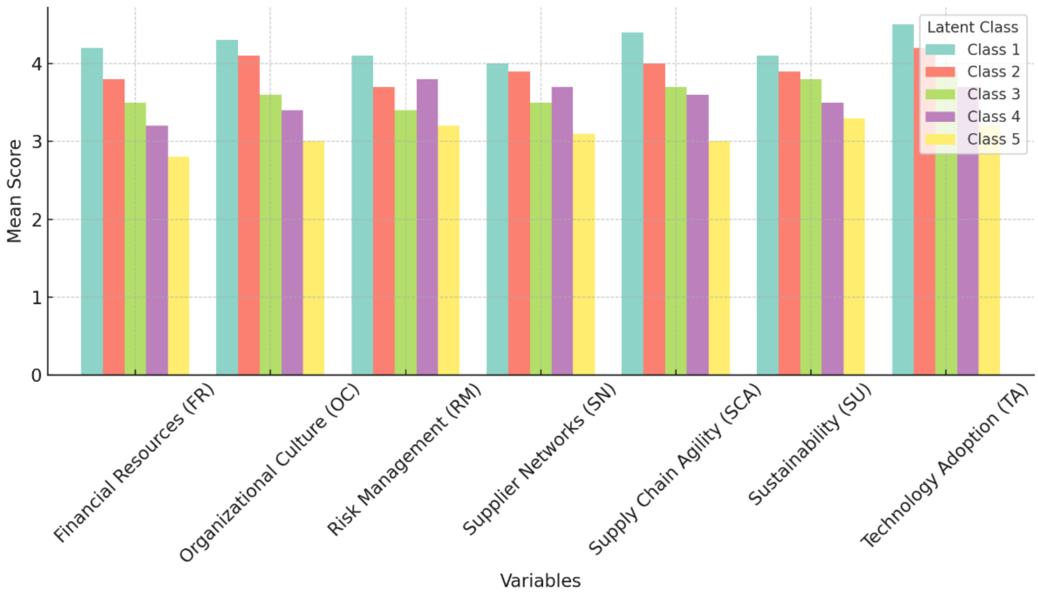


**Figure 7. Comparison of Latent Classes across Variables**

### 4.8. Latent Semantic Analysis (LSA)

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

Data from the survey about supply chain agility was analysed using Latent Semantic Analysis (LSA) to explore the undisclosed relationship among variables. The two essential semantic dimensions that explained together almost all the variance in perception of respondents were discovered by LSA. In fact, Component 1: General Agility Perception had high loadings from Financial Resources (FR), Organizational Culture (OC), Supply Chain Agility (SCA), and Technology Adoption (TA) showing that respondents viewing themselves to be rich in terms of finance and well adaptable in culture would tend to see their supply chains as agile. Component 2 distinguished operationality from strategic orientation by indicating the operational practice Supplier Networks (SN) and Risk Management (RM) and strategic initiatives such as Technology Adoption (TA) and Sustainability (SU). Organizations scoring high in this dimension either manage operational risk or strategic technological advancement. For this reason, it could be envisioned as Component 2 being reflective of a trade-off between operational stability and strategic innovation, indicating the subtle ways in which respondents interpret supply chain agility within small-scale industries.

**Table 7. Top Contributors in LSA**

| Component | Top 1 | Top 2 | Top 3 |
|---|---|---|---|
| PC1 | Financial Resources (FR) | Organizational Culture (OC) | Supply Chain Agility (SCA) |
| PC2 | Supplier Networks (SN) | Risk Management (RM) | Technology Adoption (TA) |

The two high loadings of Financial Resources (FR) and Organizational Culture (OC) on Principal Component 1 (PC1) signal the fact that these two are some of the possibilities that should shape an overall perception of supply chain agility. In contrast, the effects of Principal Component 2 (PC2) are along the separation of the operational focus (Supplier Networks (SN) and Risk Management (RM)) from the strategic focus (Technology Adoption (TA)) as shown in table 7. These variables differ in impact among higher-level classes, with one relying on financial stability and culture adaptability (Class 1) while another is more inclined to operate practice versus strategic innovation differences that reflect varying routes to agility within small-scale industries.

**Table 8. Comparison of Top Contributors in different Classes**

| Latent Class | PC1 Mean Score | PC2 Mean Score |
|---|---|---|
| Class 1 | 4.3 | 4.1 |
| Class 2 | 4 | 3.8 |
| Class 3 | 3.7 | 3.6 |
| Class 4 | 3.4 | 3.9 |
| Class 5 | 3 | 3.2 |

Class 1, High Agility and Resourcefulness, had the highest scores on both dimensions, leading to a balanced perception of general agility and strategic-operational alignment. High on PC1, emphasizing cultural and financial factors, but low on PC2, indicating a lesser focus on strategic elements, is Class 2, Culturally Driven Agility. Risk-Managed Agility ranks high on PC2 than PC1, thus indoor activities are focused on managing operational risks rather than on general agility. Class 5 scores the lowest on both components, showing little or no integration of both strategic and operational agility practices.

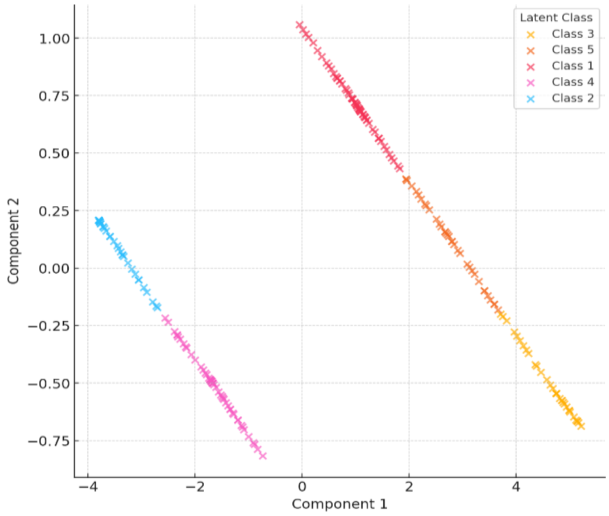


**Figure 8. LSA Component Plot**

The latent semantic pattern analysis reveals distinct clusters that match with latent classes such that Classes 1 and 2 form closer clusters indicating a similarity in semantic patterns while Class 5 is distanced comparatively from the remaining classes. Component 1 is, thus, likely a measure of general positivity or agreement, while Component 2 provides variability in expression.

## 5. DISCUSSION

### 5.1. Synthesis of Findings

The research has brought to light determinant factors that affected supply chain agility in the small-scale sector with Technology Adoption (TA) and Organizational Culture (OC) being the most important. On the Random Forest analysis, it was shown that TA was 15.23% in feature importance of SCA followed by OC 14.73%, thus indicating that digital integration and adaptive cultural practices determine agility. On analyzing one-way ANOVA, the differences among the variables were confirmed to be statistically significant with Supply Chain Agility (SCA) showing the highest F-statistic denoting maximum variation of opinions regarding agility. Latent Class Analysis (LCA) identified five profiles: Class 1 (High Agility and Resourcefulness) emerged as the highly agile class with high scores on financial resources, culture, and technology, whereas Class 5 (Low agility and Limited Resource Integration) presents major financial and technological challenges. The PCA and LSA confirmed the classification that operational practices and strategic innovation are the principal dimensions. Spearman's correlation analysis revealed a strong positive relationship between TA and OC with SCA, suggesting that the enhancement of cultural adaptability and digital competency is paramount for agile supply chain management.

### 5.2. Comparing Results with Existing Literature

The findings of the research also support prior research concluding that technology adoption is crucial for supply chain agility. In line with [9] organizations that integrated technology better reported significantly greater agility scores, thus indicating the ability of digital technologies in easing the disruptions. Besides, the study also validates [14] viewpoint that organizational culture is an essential agent of resilience and agility. This study further argues against the prior works which stressed financial stability purely as one factor; rather, it demonstrates that financial resources in support of agile practices must complement culture and technology. A major divergence from existing literature has been with regard to risk management. Though traditionally considered a core component in agility, this

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

study ascertains that risk in and of itself is not a strong differentiation factor for agile classes. It tends to exert its influence only when in conjunction with robust supplier networks and adaptive cultural practices, thus contesting the thought that risk management by itself is the sole driver of responsiveness in a supply chain and moreover advocates for an integrated strategic view toward agility for the focus on Commissioning and Research.

5.3. Implications for Supply Chain Management in SSIs

Cross-sector management will benefit from the findings of the study along with policymakers trying to improve supply chain agility for the small-and-medium enterprises (SMEs). The adoption of technology will stay at the top of the priority list because it emerged as the single most important factor in effecting digitalization. The investment will cater for smart technologies integration into digital platforms to trigger responsiveness and flexibility. Above all, building an adaptive organizational culture should be considered as a condition because it has an important effect on how agility is perceived. This can be achieved through inclusive decision-making and cross-training, as well as leadership practices that are open to innovation. Balanced resource management is also a factor though financial stability alone is not effective; it needs a cultural proactive approach in addition to technological integration to amplify its effectiveness. Context-specific interventions designed according to latent class profiles are recommended. For example, Class 5 (Low Agility) organizations should pay toward financial empowerment and digital literacy, whereas Class 4 (Risk-Managed Agility) requires the convergence of practices on risk management with cultural adaptability. These strategies can facilitate improvements in agility in SSIs through better responses to changes affecting them.

5.4. Alignment with Sustainable Development Goals (SDGs)

The results of this study coincide with many Sustainable Development Goals (SDGs) in that they address the problems beyond enhancing the supply chain agility of small-scale industries (SSIs). This is in reference to SDG 8 (Decent Work and Economic Growth). When inclusion is made regarding technology adoption as well as an adaptive culture, the businesses would be resilient enough to survive disruptions. Again with SDG 9 (Industry, Innovation, and Infrastructure), it is stressed that digital integration and innovative practices must build sustainable and resilient industrial practices. The study also aligns itself with SDG 12 by promoting sustainability in supply chains, advocating for adaptation strategies that would reduce the environmental impacts of operations. It ties into SDG 17 (Partnerships for the Goals) in terms of how supplier networks are organized, emphasizing joint efforts to strengthen resilience in the supply chain through partnerships. Given that, with technology, cultural adaptability, and sustainability in place, SSIs could achieve agile supply chains which not only make operations more efficient but also better positioned in socio-economic resilience to meet international targets concerning sustainability.

## 6. CONCLUSION

A survey into the analysis of supply chain agility in small-scale industries (SSIs) pointed to five latent classes: Class 1, High Agility and Resourcefulness, which was represented by 68 (26.4%) of respondents; Class 2, Culturally Driven Agility, represented by 52 respondents (20.2%); Class 3, Moderate Agility and Sustainability Focus, with 48 respondents (18.6%) along with Class 5, Low Agility and Limited Resource Integration, in contrast to Class 4, Risk-Managed Agility, with 42 respondents (16.3%). The Random Forest analysis provided a validated view, proposing Technology Adoption (15.23%) and Organizational Culture (14.73%). Significant differences inclusive of an F-statistic value of 7.21 were recorded in ANOVA, with Supply Chain Agility having the highest followed by Organizational Culture with 6.58 and Technology Adoption with 5.89-an indication of the differential perception of agility manifested by digital integration and cultural fit. Spearman's rank correlation coefficient analysis confirmed the extremely high positive correlation coefficient of Technology Adoption and Organizational Culture (0.998)-implying that when technology is integrated, cultural adaptation is also pursued. Principal

Component Analysis (PCA) results gave two components with General Perception of Agility (62% variance) opposing the Differentiation between Operational and Strategic factors (18% variance)-thus confirming the intertwining relationship between financial resources, cultural adaptability, and technology adoption. Such findings were corroborated by Latent Semantic Analysis (LSA) that also underlined the two-pronged nature of strategic innovation and practice into operations. Together, these underscore how technology and culture are key enablers of agility whereas Class 5-Low Agility-disagreed that it could further its cause through enhancing finances and technology. Limitations of this study revolve around the likely response bias because of self-reporting and the cross-sectional design applied in the study. Recommendations for future studies will be to utilize longitudinal frameworks whilst also embracing a more diverse spectrum of industrial sectors to enhance the generalisability of the findings.

## REFERENCES

[1] A. Raffington and A. Joseph, "A Qualitative Investigation into Agricultural Industry Supply Chain Efficiency During the COVID-19 Pandemic," *Researchgate. Net,* vol. 10.

[2] Z. Zhang and H. Sharifi, "A methodology for achieving agility in manufacturing organisations," *International journal of operations & production management,* vol. 20, no. 4, pp. 496-513, 2000.

[3] A. Gunasekaran and Y. Y. Yusuf, "Agile manufacturing: a taxonomy of strategic and technological imperatives," *International Journal of Production Research,* vol. 40, no. 6, pp. 1357-1385, 2002.

[4] V. Kumar, K. A. Fantazy, U. Kumar, and T. A. Boyle, "Implementation and management framework for supply chain flexibility," *Journal of Enterprise Information Management,* vol. 19, no. 3, pp. 303-319, 2006.

[5] D. J. Ketchen Jr and G. T. M. Hult, "Bridging organization theory and supply chain management: The case of best value supply chains," *Journal of operations management,* vol. 25, no. 2, pp. 573-580, 2007.

[6] S. Seuring and M. Müller, "From a literature review to a conceptual framework for sustainable supply chain management," *Journal of cleaner production,* vol. 16, no. 15, pp. 1699-1710, 2008.

[7] W. Klibi and A. Martel, "Modeling approaches for the design of resilient supply networks under disruptions," *International Journal of Production Economics,* vol. 135, no. 2, pp. 882-898, 2012.

[8] M. Nakano and A. K. Lau, "A systematic review on supply chain risk management: using the strategy-structure-process-performance framework," *International Journal of Logistics Research and Applications,* vol. 23, no. 5, pp. 443-473, 2020.

[9] D. Ivanov and A. Dolgui, "A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0," *Production Planning & Control,* vol. 32, no. 9, pp. 775-788, 2021.

[10] I. Lee and G. Mangalaraj, "Big data analytics in supply chain management: A systematic literature review and research directions," *Big data and cognitive computing,* vol. 6, no. 1, p. 17, 2022.

[11] N. Ngoc-Vinh, P. Tien-Dung, and S. Das, "Digitization of business; need for recombination during COVID-19," in *Sustainable development and innovation of digital enterprises for living with COVID-19*: Springer, 2022, pp. 1-17.

[12] R. Panwar, J. Pinkse, and V. De Marchi, "The future of global supply chains in a post-COVID-19 world," *California Management Review,* vol. 64, no. 2, pp. 5-23, 2022.

[13] W. Phillips, J. K. Roehrich, D. Kapletia, and E. Alexander, "Global value chain reconfiguration and COVID-19: Investigating the case for more resilient redistributed models of production," *California Management Review,* vol. 64, no. 2, pp. 71-96, 2022.

[14] M. Christopher and D. Towill, "An integrated model for the design of agile supply chains," *International Journal of Physical Distribution & Logistics Management,* vol. 31, no. 4, pp. 235-246, 2001.

[15] P. Sarkar, M. W. Mohamed Ismail, and T. Tkachev, "Bridging the supply chain resilience research and practice gaps: pre and post COVID-19 perspectives," *Journal of Global Operations and Strategic Sourcing,* vol. 15, no. 4, pp. 599-627, 2022.

[16] T. T. Le and A. Behl, "Linking artificial intelligence and supply chain resilience: roles of dynamic capabilities mediator and open innovation moderator," *IEEE Transactions on Engineering Management,* vol. 71, pp. 8577-8590, 2023.

[17] V. Pathma Devi, "Exploring the organizational resilience and sustainability of the service related industries during and after covid-19 pandemic," UTAR, 2023.

[18] V. Santhosh Kumar *et al.*, "The Impact and Restoration of Supply Chain Sustainability Across Diverse Industrial Sectors Post-pandemics," in *International Conference on Recent Advances in Industrial and Systems Engineering*, 2023: Springer, pp. 531-538.

[19] M. Shetty, F. Habib, S. Imran Ali, A. Haq, and M. Khan, "Impact of Digitalisation in Developing Procurement and Supply Chain Resilience in the Post Pandemic Era—A Study of the Global Manufacturing Sector," in *Advanced Technologies and the Management of Disruptive Supply Chains: The Post-COVID Era*: Springer, 2023, pp. 109-151.

[20] S. Maheshwari and C. K. Jaggi, "Enhancing supply chain resilience through industry-specific approaches to mitigating disruptions," *OPSEARCH,* pp. 1-34, 2024.

[21] N. McDougall and A. Davis, "The local supply chain during disruption: Establishing resilient networks for the future," *Journal of Cleaner Production,* vol. 462, p. 142743, 2024.

[22] M. Shamsuddoha, E. A. Khan, M. M. H. Chowdhury, and T. Nasir, "Revolutionizing Supply Chains: Unleashing the Power of AI-Driven Intelligent Automation and Real-Time Information Flow," *Information,* vol. 16, no. 1, p. 26, 2025.