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Supply Chain Disruption Factors and Influences in Industrial Manufacturing and Technology Industries

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ABSTRACT

Objective: This paper investigates the main supply chain disruption factors and influences in a set of industrial manufacturing and technology industries as well as the relationships that exist between them. Background: Disruption factors are obstacles that impede a manufacturing company filling customer orders and are treated as the main causal factors in this study. The number of unfilled orders of an industry is any obligation to provide a good or service that has not been met and is used as the main response variable in this research. Methods: Principal component analysis and exploratory factor analysis are both variable reduction techniques that were utilized together in order to isolate latent constructs behind disruption factors and identify significant disruption factors contributing to the unfilled orders for each industry. Results: Across a majority of manufacturing industries, insufficient supply of materials, equipment limitations, logistics/transportation constraints, and storage limitations were observed to be amplified significantly as disruption factors by the pandemic. Conclusions: This research reveals the disruption factors that were exacerbated by the pandemic in a set of certain industrial manufacturing and technology industries that were not extensively examined by previous research and strongly corroborate existing literature on the general challenges imposed by the pandemic on supply chain networks. This work also provides a future research objective of improving supply chain resilience.

Introduction

The COVID-19 pandemic has had a significantly detrimental impact on the performance and efficiency of companies in a variety of industries. Manufacturing companies within the nation have perhaps been one of the most negatively affected groups of companies by the ongoing crisis. The successful operation of the manufacturing sector is essential to the daily functioning of society, with certain industries seeing a fluctuation in demand, and thus, production, during the pandemic. For instance, the global personal computer sales were up by 11% in the second quarter of 2020 compared to the previous quarter, with the magnitude of growth being even higher in the third quarter, up 15% (Okubo & Stewart, 2020). Such developments in turn caused the demand for production by computer and electronic products manufacturers to increase sharply during the crisis. Some manufacturing industries, such as the electrical appliances and components manufacturing industries have seen their relative demand levels remain consistently high amidst the pandemic, while other manufacturers, such as the primary metals manufacturing industry, experienced a sudden initial plummet in demand during the crisis ("Analysis," 2021; Pinto & Dutta, 2020). However, with the variation in demand across industries and other challenges imposed by the crisis, a multitude of vulnerabilities in the production strategies and supply chain networks of manufacturers have been exposed (Shih, 2022). Consequently, in order to accordingly improve the resiliency of the supply chains of manufacturing companies while maintaining a high level of competitiveness and efficiency, it is necessary to identify the nature of the production challenges encountered by the manufacturers in the ongoing crisis. The purpose of this study is to identify the specific disruption factors amplified by the pandemic within a set of certain industrial manufacturing and technology industries that have not been extensively examined by existing literature, as well as the general disruption factors observed across a majority of these industries.

Background

There are a wide range of events that can impact the efficiency and performance of companies under the manufacturing industry sector. These events can generally be classified as low probability-low impact, low probability-high impact, high probability-low impact, and high probability-high impact events.

The pandemic has been evidenced to be a low probability-high impact event by the existing corpus of research on the topic in question. Unlike other previous outbreaks, the COVID-19 pandemic has impacted all the nodes (supply chain members) and edges (ties) in supply chains simultaneously (Chowdhury et al., 2021). In particular, the challenges that have been noted to reduce the capacities of manufacturing companies include lockdown in the supply market, interruption in vehicle movements and transportation, labor shortage, and border closures (Chowdhury et al., 2021).

This paper aims to pinpoint the nature of the disruption factors exacerbated by the pandemic within five main manufacturing industries which include the primary metals, machinery, computer and electronic products, electrical appliance and components, and transportation equipment manufacturing industries in addition to general disruption factors amplified across manufacturing industries and addresses the following research questions:

1. What are the main disruption factors amplified by pandemic on manufacturing industries?
2. What are potential latent factors that are contributing to the amplification of the disruption factors and what links exist between them?
3. What is the recommended course of action or amends to be made by each manufacturing sector with respect to their production strategies and supply chain networks?

In order to comprehend the analysis that this study reveals, it is necessary to explain and clarify the concepts and terminology utilized in the aforementioned questions.

In the context of this paper, a disruption factor is defined to be an obstacle in any given level of a company's supply chain network that is hindering the production of the respective organization's goods or products. In more concrete terms, this study limited its focus to the set of potential disruption factors outlined in the Checkbox Data of the US Census Bureau's Quarterly Surveys of Plant Capacity Utilization ("Quarterly Survey," 2021). The factors were divided into two main categories: reasons for a change in full production capacity from the previous quarter and reasons for the difference in actual operations vs. full production capability. Due to their relevance to the study, the group of disruption factors from the latter set of factors that were thought to be explicitly associated with the pandemic were considered as the main exogenous and causal variables in this research. The complete set of disruption factors are: Insufficient supply of materials, Insufficient orders, Not profitable to operate at full capacity, Insufficient supply of labor, Equipment limitations, Storage limitations, and Logistics/transportation constraints ("Quarterly Survey," 2021).

One of the standard metrics of the production capacity of an industry is the capacity utilization rate. The capacity utilization rate for a company or industry is defined to be the percentage of the respective organization's potential production output that is being met (Kenton, 2022a). More precisely, the basic formula for this quantity is:

$$(\text{Actual Production Output} / \text{Full Production Output}) * 100\% = \text{Capacity Utilization Rate} \quad (1)$$

While the capacity utilization rate does capture the extent to which the organizations in question are achieving their full production potential, it was not used as the major endogenous variable in this study due to the other potential causal factors that affect it, such as a company's funding in increasing in capacity, that would not be captured by the main proposed latent variable models. Instead, a quantity known as the number of unfilled orders was used as the primary dependent variable.

The unfilled orders of an industry are defined to be any obligation to provide a good or service that has not been met ("Unfilled Orders," n.d.). This quantity can be an indicator of a backlog in production and the number and amount of time that orders go unfilled is a good measure of the efficiency of a company's supply chain (Kenton, 2022b; "Unfilled Orders," n.d.). As such, the number of unfilled orders per industry was used as the main response variable in the study. This variable was determined to be the best indicator of manufacturers' supply chain efficiency and performance due to the low number of external causal factors. For instance, if quarterly revenue or value of shipments was utilized as the main endogenous variable in the study, factors such as inflation would not be accurately accounted for in the latent variable models. The full capacity utilization rate was not included as a variable in the models due to aforementioned reasons.

Data

The primary sources of data used in this study were the Quarterly Survey of Plant Utilization (QPC) Tables and M3 Press Release data provided by the US Census Bureau.

Each of the QPC Tables contains the full capacity utilization rates of each surveyed industry (denoted by the appropriate NAICS code) in the respective quarter along with checkbox data detailed in the previous section. Each cell in the checkbox data table denotes what percent of the companies surveyed under the corresponding NAICS industry (row title) indicated that the associated disruption factor (column title) contributed to either a change in the full capacity utilization rate with respect to the previous quarter or a difference between actual operations vs. full production capability (depending on the categorization of the factor itself).

The monthly Unfilled Orders (UOs) table from the M3 Press Release data was also used in this study. As of now, this table contains all of the monthly numbers of unfilled orders for each M3 industry from the year 1992 to the second quarter of 2022. From this table the quarterly number of unfilled orders were calculated for each industry by simply summing and subsequently combining every three-monthly entries.

For the purposes of this study, only table data from 2015 Q1 to 2022 Q1 was used to accurately identify the major disruption factors exacerbated by the pandemic within each of the five industries considered. For each industry, the quarterly values for the checkbox data and unfilled orders for 2015 Q1 to 2019 Q4 were grouped into a single table as entries for Pre-Pandemic data. The values for 2020 Q1 to 2022 Q1 were also accordingly grouped into a single table as entries for During/Post-Pandemic data.

A separate grouping was used to determine the disruption factors most amplified by the pandemic across a majority of manufacturing industries. In this grouping, the entries of the Pre-Pandemic table were the 2019 Q4 checkbox data and the unfilled orders z-scores for each of the NAICS industries (NAICS 331 - NAICS 337 and the remaining manufacturing industries included in the MTU aggregate series). Similarly, the entries of the During/Post-Pandemic table were the checkbox data entries and unfilled orders z-scores for each of the aforementioned NAICS industries from 2020 Q4. The z-scores for the quarterly UOs for each of the industries were calculated in order to account for the fact that different industries had a different average value of the number of quarterly UOs and accurately standardize the performance of industries prior to carrying out the methods specified in the next section. Prior to calculating the z-scores, Q-Q plots of the quarterly UOs for each of the NAICS industries from 2015 Q1 to 2022 Q1 were generated in order to verify that the values fit in the error thresholds of the plot and followed a normal distribution. Figure 1 shows a sample Q-Q plot of the quarterly UOs of the NAICS 331 industry:

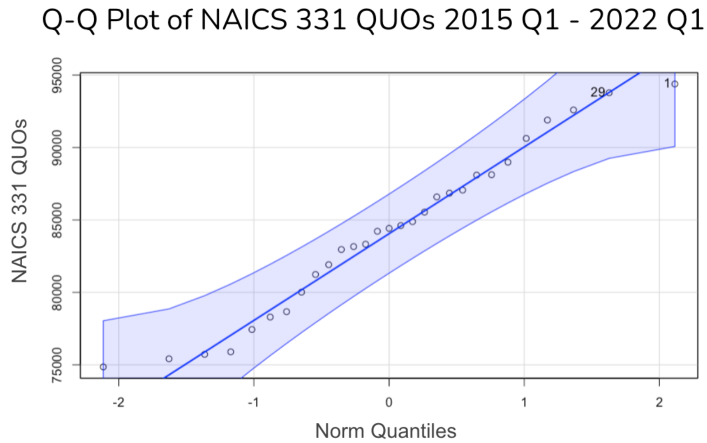

Figure 1. Q-Q Plot of NAICS 331 QUOs 2015 Q1 - 2022 Q1.

Prior to conducting any of the methods outlined below, all data was cleaned and normalized accordingly using RStudio (Version 4.2.1 (2022-06-23) -- "Funny-Looking Kid").

Methods

Principal component analysis (PCA) and exploratory factor analysis (EFA) were the two primary statistical analysis techniques that were utilized in this study. For each data table, PCA was performed first in order to generate a scree plot and determine the number of appropriate components/dimensions of the data to use when performing the EFA and capture an ample amount of variation in the data. Subsequently, EFA was performed on the table to generate a table of the correlations of the disruption factors with each of the isolated components. Also, a chi-squared test is done to test the hypothesis that an adequate number of components are used and consider additional components if necessary. In order to perform the methods outlined above, the relevant functions in the existing R packages were used.

Principal component analysis is a multivariate dimensionality reduction technique that is used to extract important information from tables and represent it as a set of new orthogonal variables called principal components (Abdi and Williams). In R, the execution of PCA follows from the standard mathematical derivation of the technique ("Princomp," n.d.). Accordingly, this involves first computing the covariance matrix of the variables being considered (in this case, the disruption factors and the UOs) and finding the eigenvalues and corresponding eigenvectors by solving for the characteristic polynomial of the matrix (rotations can be performed to better interpret the data). Then, the results of the PCA that are reported are the eigenvectors/components isolated by the analysis along with the associated amount of variance that they explain; these results can also be represented visually in a scree plot. The number of components to consider can then be determined by selecting the components that have relatively larger explained variances than the others. The number of components considered in the analysis is then passed as a parameter and used in the EFA. Figure 2 shows a sample scree plot that is the result of conducting a PCA on the Pre-Pandemic NAICS 331 data. Here, factors and components are interchangeable terms.

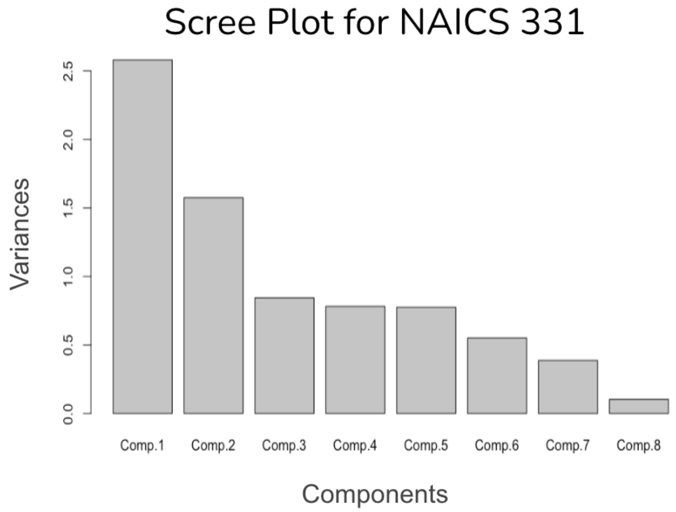

Figure 2. Scree Plot of PCA on Pre-Pandemic Data for NAICS 331.

Exploratory factor analysis is a variable reduction technique which identifies the number of latent constructs and the underlying factor structure of a set of variables (Cudeck, 2000; Suhr, 2007). Though they are similar techniques, the mathematics of factor analysis and principal component analysis have some distinct differences (Bock, 2022). The results of performing EFA in R include the uniqueness of each of the measured variables, the correlations of the variables with the factors/latent constructs that were evidenced to exist, and the p-value of a chi-squared test that is conducted to determine the goodness of fit of the model. EFA was utilized in this study in order to determine which groups of disruption factors contributed most to the variation observed in the UOs and also identify consistent associations and shared latent factors behind the disruption factors in question. There are two primary proposed latent variable models in this study:

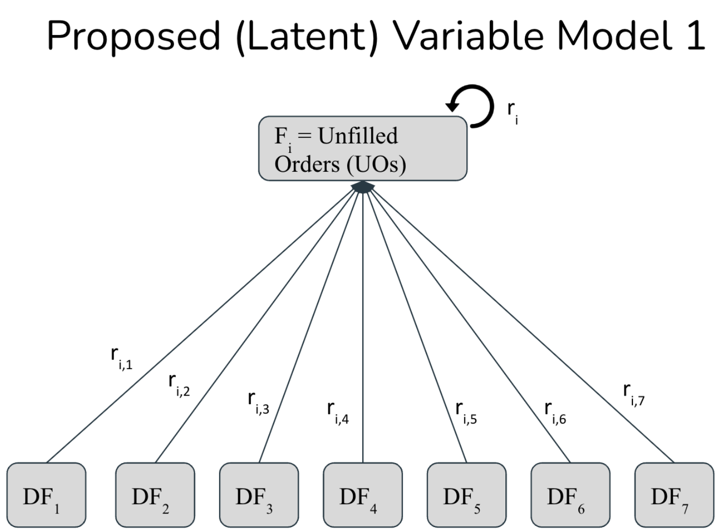

Figure 3. Proposed (Latent) Variable Model 1.

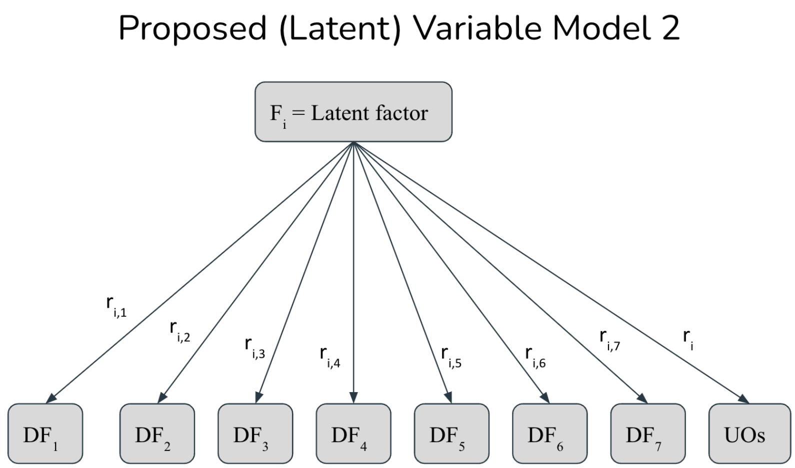

Figure 4. Proposed (Latent) Variable Model 2.

Disruption Factor Mappings

DF_1: Not profitable to operate at full capacity

DF_2: Insufficient supply of materials

DF_3: Insufficient orders

DF_4: Insufficient supply of labor

DF_5: Equipment limitations

DF_6: Storage limitations

DF_7: Logistics/Transportation Constraints

Figure 5. Disruption Factor Mappings.

The correlation of the UOs with a given component isolated by the EFA is treated as a measure of how significantly the disruption factors in the component contributed to the observed variation in the UOs. If the magnitude of this correlation is relatively high, the model shown in Figure 3 represents the factor structure for the given component. Potentially high correlation values of the disruption factors with the component are noted to be significant and grouped together on the basis of similar properties. It can be noted that the correlations between the isolated factors and variables are bidirectional by convention. If the correlation value is very weak, the model shown in Figure 4 represents the factor structure for the component and a separate latent factor that affects the disruption factors is explored.

Results

Below are the summarized results of the factor analysis per industry. The tables include both the pre-pandemic and during/post-pandemic factor loadings/correlations for each industry. Certain entries have markings, which are detailed under each table. In a given factor, both weak and strong UO correlation values are considered to be significant and indicate that the factor structure is represented by model 1 (disruption factors are causal). For these factors with significant UO correlations, only disruption factors that were either strong or weak in magnitude and had the same sign as the UO correlation value were marked. In factors where the UO correlation values were not significant, the factor structure is represented by model 2 and only disruption factor correlations that were high in magnitude were noted. Additionally, all final p-values were recorded to be greater than the 0.05 statistical significance level, indicating that an appropriate number of factors were considered for each factor analysis.

Table 1
NAICS 331 (Primary Metals Manufacturing) Factor Loadings.

	Pre-Pandemic Factor Loadings		During/Post-Pandemic Factor Loadings
Disruption Factors	Factor1	Factor2	Factor1
Not profitable to operate at full capacity		0.474	-0.32
Insufficient supply of materials	0.51	-0.142	0.728**
Insufficient orders	-0.997***		-0.969
Insufficient supply of labor	0.725***	0.458*	0.929**
Equipment limitations	0.408	0.59**	0.715**
Storage limitations	0.134	0.541**	-0.185
Logistics/Transportation Constraints		0.541**	0.459*
Unfilled Orders		0.638**	0.949**
SS Loadings	1.978	1.557	4.094
Proportion Var	0.247	0.195	0.512
Cumulative Var	0.247	0.442	0.512
p-value	0.909		0.238

*Weak correlation with a factor with a significant UO correlation. **Strong correlation with a factor with a significant UO correlation. ***Strong correlation with a factor with very weak or no UO correlation.

For the primary metals manufacturing industry, insufficient supply of labor, equipment limitations, storage limitations, and logistics/transportation constraints were the most significant disruption factors contributing to unfilled orders prior to the pandemic. Prior to the pandemic, insufficient orders and insufficient supply of labor appear to be strongly correlated to a certain latent factor. Hypothetically, this factor could be a shift in the demand curve of this industry as this would indicate that the supply of labor did not compensate for the increase in demand for the products of this industry.

During and after the pandemic, insufficient supply of materials, insufficient supply of labor, equipment limitations, and logistics/transportation constraints became the most significant disruption factors.

Based on the correlation strengths, insufficient supply of materials and insufficient supply of labor were observed to be amplified significantly by the pandemic and equipment limitations and logistics constraints remained equally significant disruptors for this industry. It can also be noted that insufficient orders had a strong negative correlation with the number of unfilled orders in the post-pandemic data, which is logically consistent.

Table 2
NAICS 333 (Machinery Manufacturing) Factor Loadings.

	Pre-Pandemic Factor Loadings			During/Post-Pandemic Factor Loadings		
Disruption Factors	Factor1	Factor2	Factor3	Factor1	Factor2	Factor3
Not profitable to operate at full capacity	0.183	0.144	0.242			-0.905***
Insufficient supply of materials	0.726***	0.159	0.546*	0.778**	0.492	0.385
Insufficient orders	-0.744***	-0.337	-0.239	-0.63	-0.536	-0.397
Insufficient supply of labor	0.964***	0.174	0.187	0.671*	0.531	0.48
Equipment limitations	0.497		0.555*	0.969**	0.236	
Storage limitations	0.174	0.546*	0.19	0.366	0.921**	-0.114
Logistics/Transportation Constraints	0.114	0.971**	-0.196	0.694**	0.389	0.596***
Unfilled Orders	0.154	0.746**	0.511*	0.797**	0.52*	0.251
SS Loadings	2.357	2.022	1.091	3.652	2.14	1.787
Proportion Var	0.295	0.253	0.136	0.456	0.268	0.223
Cumulative Var	0.295	0.547	0.684	0.456	0.724	0.947
p-value	0.27			0.0599		

*Weak correlation with a factor with a significant UO correlation. **Strong correlation with a factor with a significant UO correlation. ***Strong correlation with a factor with very weak or no UO correlation.

For the machinery manufacturing industry, logistics constraints and storage limitations were the most significant disruption factors contributing to unfilled orders prior to the pandemic. Other potentially significant pre-pandemic disruption factors are insufficient supply of materials and equipment limitations. Prior to the pandemic, insufficient supply of materials, insufficient orders, and insufficient supply of labor appear to be strongly correlated to a certain latent factor, which might be either demand or a fundamental design flaw with the supply chain structure.

During and after the pandemic, logistics constraints, equipment limitations, insufficient supply of labor, and insufficient supply of materials became the most significant disruption factors. Storage limitations are another potentially significant post-pandemic disruption factor. Not profitable to operate at full capacity and logistics constraints appear to be strongly correlated to another separate latent factor, which might be an expansion of the industry due to the pandemic (which, in turn, would challenge an inefficient supply chain network). Based on the correlation strengths, insufficient supply of materials, insufficient supply of labor, and equipment limitations were observed to be amplified significantly by the pandemic for this industry.

Table 3

NAICS 334 (Computer and Electronics Manufacturing) Factor Loadings.

	Pre-Pandemic Factor Loadings			During/Post-Pandemic Factor Loadings	
Disruption Factors	Factor1	Factor2	Factor3	Factor1	Factor2
Not profitable to operate at full capacity		-0.154	0.77	0.181	-0.178
Insufficient supply of materials	0.672*	0.302		0.977**	0.12
Insufficient orders	-0.695	-0.492	0.52*	-0.957	-0.112
Insufficient supply of labor	0.708**	0.56	-0.221	0.973**	-0.22
Equipment limitations	0.397*	0.561	-0.191		0.502*
Storage limitations	-0.103	-0.168	0.262	0.352	0.581*
Logistics/Transportation Constraints	-0.105	-0.479	0.16	0.914**	0.289
Unfilled Orders	0.971**		0.215*	0.901**	0.288*
SS Loadings	2.557	1.25	1.097	4.621	0.864
Proportion Var	0.32	0.156	0.137	0.578	0.108
Cumulative Var	0.32	0.476	0.613	0.578	0.686
p-value	0.668			0.117	

*Weak correlation with a factor with a significant UO correlation. **Strong correlation with a factor with a significant UO correlation. ***Strong correlation with a factor with very weak or no UO correlation.

For the computer and electronics manufacturing industry, insufficient supply of labor was the most significant disruption factor contributing to unfilled orders prior to the pandemic. Other potentially significant pre-pandemic disruption factors are insufficient supply of materials and equipment limitations.

During and after the pandemic, insufficient supply of labor, insufficient supply of materials, and logistics constraints were the most significant disruption factors. Storage limitations and equipment limitations are other potentially significant post-pandemic disruption factors.

Based on the correlation strengths, insufficient supply of materials and logistics/transportation constraints were observed to be amplified significantly by the pandemic for this industry.

Table 4
NAICS 335 (Electrical Equipment, Appliances, and Components Manufacturing) Factor Loadings.

	Pre-Pandemic Factor Loadings				During/Post-Pandemic Factor Loadings	
Disruption Factors	Factor1	Factor2	Factor3	Factor4	Factor1	Factor2
Not profitable to operate at full capacity	-0.206	-0.118	-0.357		-0.576	
Insufficient supply of materials	0.153	0.207	-0.491		0.834**	0.529
Insufficient orders		-0.201	0.918	0.335	-0.926	-0.174
Insufficient supply of labor		0.585**			0.515*	0.734**
Equipment limitations	0.618*	0.222*	0.12		0.91**	-0.408
Storage limitations			0.151	0.98	0.203	-0.453
Logistics/Transportation Constraints	0.982**		-0.133		0.195	0.704**
Unfilled Orders	0.213*	0.968**	-0.11		0.864**	0.44*
SS Loadings	1.463	1.438	1.284	1.088	3.804	1.911
Proportion Var	0.183	0.18	0.161	0.136	0.475	0.239
Cumulative Var	0.183	0.363	0.523	0.659	0.475	0.714
p-value	0.675				0.452	

*Weak correlation with a factor with a significant UO correlation. **Strong correlation with a factor with a significant UO correlation. ***Strong correlation with a factor with very weak or no UO correlation.

For the electrical equipment, appliances, and components manufacturing industry, insufficient supply of labor was the most significant disruption factor contributing to unfilled orders prior to the pandemic. Another potentially significant pre-pandemic disruption factor is logistics constraints. Insufficient orders can also be mapped to a latent construct for the state of this industry before the pandemic. During and after the pandemic, insufficient supply of materials and equipment limitations were the most significant disruption factors. Logistics constraints and insufficient supply of labor were other potentially significant post-pandemic disruption factors. Storage limitations can also possibly be mapped to another latent construct. Based on the correlation strengths, insufficient supply of materials and equipment limitations were observed to be amplified significantly by the pandemic for this industry.

Table 5
NAICS 336 (Transportation Equipment Manufacturing) Factor Loadings.

Pre-Pandemic Factor Loadings					During/Post-Pandemic Factor Loadings	
Disruption Factors	Factor1	Factor2	Factor3	Factor4	Factor1	Factor2
Not profitable to operate at full capacity		-0.148		0.98	-0.509*	0.465
Insufficient supply of materials	0.321	-0.458	0.194*	0.102	0.972	
Insufficient orders	-0.278*	0.818		-0.133	-0.704*	
Insufficient supply of labor	0.858	-0.367	-0.351		0.93	
Equipment limitations	0.573	-0.101			-0.164	0.984***
Storage limitations		0.242	0.116	0.272	0.208	0.843***
Logistics/Transportation Constraints		0.42	0.124		0.716	
Unfilled Orders	-0.2*		0.973**		-0.325*	
SS Loadings	1.295	1.29	1.149	1.071	3.253	1.912
Proportion Var	0.162	0.161	0.144	0.134	0.407	0.239
Cumulative Var	0.162	0.323	0.467	0.601	0.407	0.646
p-value	0.573				0.701	

*Weak correlation with a factor with a significant UO correlation. **Strong correlation with a factor with a significant UO correlation. ***Strong correlation with a factor with very weak or no UO correlation.

There appears to be no particularly strong correlation entry for this industry with respect to the UOs, which might indicate that the transportation equipment manufacturing industry was not heavily impacted by the pandemic in production. However, it can be noted that equipment limitations and storage limitations both have strong correlations to an isolated latent factor, which might be the extent of the physical constraints imposed by the pandemic and possibly the continual expansion of the industry amidst the pandemic.

Table 6

All Manufacturing Industries with UOs (MTU Aggregate) Factor Loadings.

	Pre-Pandemic Factor Loadings		During/Post-Pandemic Factor Loadings	
Disruption Factors	Factor1	Factor2	Factor1	Factor2
Insufficient supply of materials	0.468*	0.534***	0.81**	
Insufficient orders	-0.239	-0.262	-0.384	
Insufficient supply of labor	0.963**	0.625***	-0.133	-0.676
Equipment limitations	0.343*	0.937***	0.778**	0.106
Storage limitations	-0.924	-0.214	-0.666	0.743**
Logistics/Transportation Constraints	-0.335	-0.11		0.683**
Unfilled Orders	0.662**		0.793**	0.242*
SS Loadings	2.726	1.682	3.026	1.522
Proportion Var	0.389	0.24	0.432	0.222
Cumulative Var	0.389	0.63	0.432	0.654
p-value	0.575		0.977	

*Weak correlation with a factor with a significant UO correlation. **Strong correlation with a factor with a significant UO correlation. ***Strong correlation with a factor with very weak or no UO correlation.

For all of the manufacturing industries in the MTU aggregate, insufficient supply of labor was the most significant disruption factor contributing to unfilled orders prior to the pandemic. There is a strong correlation between a latent factor (which might be any of the aforementioned latent constructs) and three disruption factors which include insufficient supply of materials, insufficient supply of labor, and equipment limitations. During and after the pandemic, insufficient supply of materials and equipment limitations (which can be thought of as the group of tools and inventory-related disruption factors identified by the EFA) were the most significant disruption factors. Logistics constraints and storage limitations (which can be thought of as the group of physical constraint disruption factors isolated by the EFA) were other potentially significant post-pandemic disruption factors.

Based on the correlation strengths, insufficient supply of materials, equipment limitations, logistics/transportation constraints, and storage limitations were observed to be amplified significantly by the pandemic for all of these industries. Figure 6 comprehensively summarizes the main findings of this study across all industrial manufacturing and technology industries.

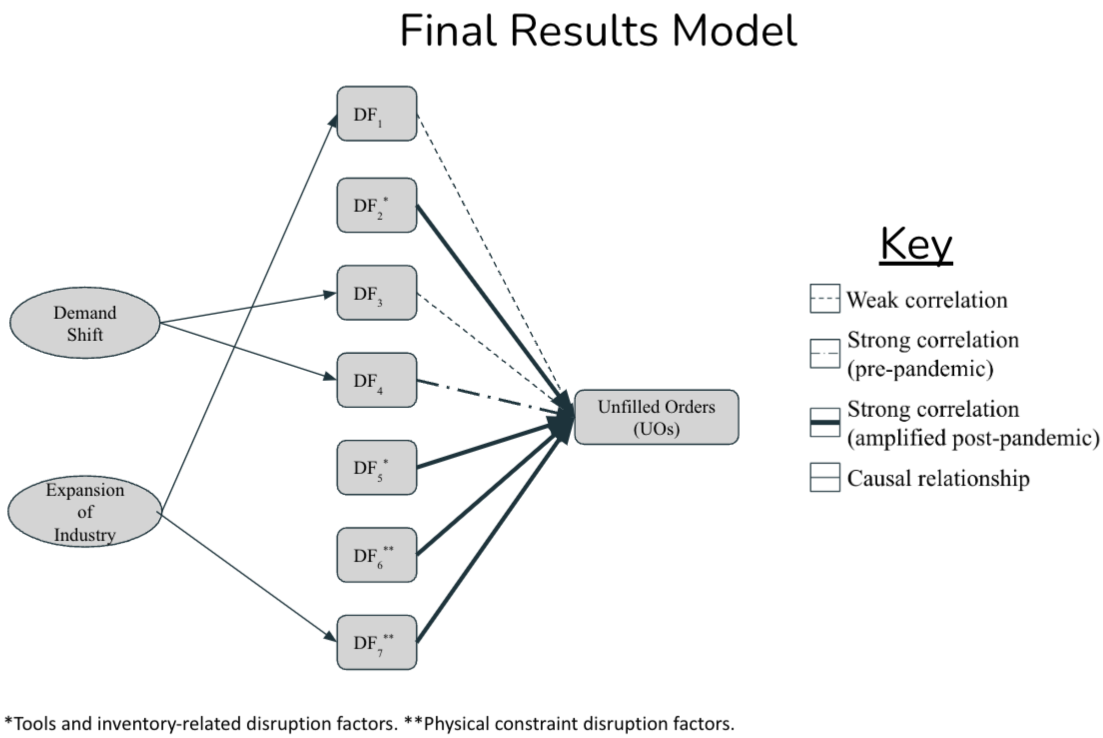

Figure 6. Final Results Model.

Conclusions and Discussion

The results of this study reveal the key supply chain disruption factors that were exacerbated by the pandemic in a set of certain industrial manufacturing and technology industries that were not extensively examined by previous research and strongly corroborate existing literature on the general challenges imposed by the pandemic on supply chain networks. Firstly, as a reiteration, insufficient supply of materials, equipment limitations, logistics/transportation constraints, and storage limitations were observed to be amplified significantly by the pandemic for a majority of manufacturing industries. For certain industries, insufficient supply of labor also continued to be a significant disruptor. As stated in existing literature, the production capacity of companies has been reduced due to several policy decisions, such as reduced office hours and alternate workdays, which have in turn led to workforce shortages and machinery impairments (Chowdhury et al., 2021). In terms of inventory and logistics management, the shift online and the loss or limited operations of physical channels has adversely impacted the flow of supply chains despite the efforts of companies to increase their capacity (Chowdhury et al., 2021). Certain industries such as computer and electronics manufacturing that are dependent on the foreign import of materials industries might have also been affected by global disruptions (Esper, 2020). In addition, such industries with complex supply chain networks are more vulnerable to having an insufficient supply of materials and logistics constraints as major disruption factors (Helper & Soltas, 2021).

Additionally, the latent constructs, with which disruption factors such as insufficient orders, insufficient supply of materials, insufficient supply of labor, and equipment limitations had a strong correlation within certain industries, could be attributed to both elemental supply chain design flaws and demand fluctuations caused by the pandemic. Demand uncertainty was one of the most fundamental challenges encountered during the pandemic as many companies were forced to match demand-supply equations on a daily basis (Chowdhury et al., 2021; Sharma et al., 2020).

The widespread adoption of lean production practices such as Just in Time (JIT) manufacturing by a variety of industries in the nation has allowed for the optimization of the production to waste ratio but has also made companies more susceptible to the disruptors outlined in this study and overall supply chain collapse. Thus, future research should be aimed towards determining ways to make the supply chain networks of manufacturing industries more resilient so that they are able to dynamically adapt to sudden alterations in external circumstances and industry-specific conditions. As the manufacturing industry forms the backbone of the national economy, its daily operation and production efficiency must be sustained and continually improved.

Limitations

Of course, this research does not capture the performance of individual companies and only provides a macroscopic insight into the disruption factors being studied. Additionally, the data used in this study is subject to both sampling and nonsampling errors. Potential nonsampling errors include various response and operational errors, such as errors during data collection, reporting errors, transcription errors, and bias due to nonresponse ("Quarterly Survey," 2021).

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