Original Research Article

Determinants of Industrial Automation Adoption in Bangladesh's Manufacturing Sector

Abstract:
This study analyzes the potential factors that determine the adoption of industrial automation in the manufacturing industry in Bangladesh using modern time series econometric methodologies from 1991 to 2022. The empirical results indicate that the production volume is a potential determinant of automation adoption in the manufacturing sector. However, increasing per capita income levels may limit the adoption of automation. On the other hand, rapid industrial automation is expected to increase import volume while necessitating significant investment.This study suggests that although automation will improve export performance, further improving manufacturing export performance through product diversity is a prerequisite for an import-dependent economy, as frequent adoption of automation will result in increased import volume, and higher exports will help to stabilize the country's trade imbalance.
Keywords: Industrial Automation Adoption, Manufacturing Industries, Income, and Productivity.

1. Introduction

The world is increasingly leveraging the benefits of the fourth industrial revolution, Industry 4.0, through automation technology in industrial production (Rüßmann et al., 2015). The use of industrial robots, artificial intelligence, and machine learning is surprisingly contributing to the replacement of human workers (Wisskirchen et al., 2017). The cheap labor force in developing nations gives them a comparative advantage in manufacturing.Using industrial automation allows for competitive and cost-effective production, but it may disrupt the labor market, particularly for unskilled labor in developing countries (Acemoglu& Restrepo, 2018; Kazmi & Abbas, 2020). It is globally recognized that automation can significantly increase industrial production while reducing production costs by up to 40% (Manyika et al., 2017).The developed and industrialized nations have started to use automation in production due to their technological advancement and capital adequacy(Kurt, 2019). They can maintain competitive production at an optimum level by increasing the use of technology despite the shortage of human labor.Developing countries face capital shortages and technological constraints that limit their ability to adopt automation technology in manufacturing despite having a vast labor supply (Rodrik, 2018). However, in order to maintain a competitive production base, automation adoption in industrial production is necessary.To fully benefit from Industry 4.0, Bangladesh requires significant investment and a skilled workforce to transition to technology-based manufacturing (Bhuiyan et al., 2020).Bangladesh's economy heavily relies on the ready-made garments (RMG) sector, with the country being the second-largest RMG exporter worldwide (Swazan& Das, 2022).Failure to automate the manufacturing process could lead to a decline in the economy's ability to compete in global exports, ultimately resulting in increased unemployment due to the decline in industrial production, especially in the RMG industries.Adopting automation in manufacturing will reduce production costs and energy consumption, aiding sustainability in the face of energy scarcity (Javaid et al., 2022).Industrial automation can increase productivity, foster exports, and create jobs.Moreover, automation in industrial production increases the demand for skilled labor, while cost-efficient production processes increase the demand for unskilled labor (Bührer& Hagist, 2017). This has the potential to reduce unemployment rates.In order to implement automation at an industrial level it requires a significant amount of investment and skilled workforce. Proper strategies for managing investment and developing a skilled workforce are required prerequisites for adopting automation as a response to Industry 4.0 (Yang & Gu, 2021). Otherwise, it can take much time to catch up, which can result in a decrease in production and export competitiveness and may lead to unemployment problems as well.Bangladesh has been benefitting from a population dividend, and its manufacturing sector is predominantly reliant on labor, hiring both skilled and unskilled workers, with a notable number of women employees (Falore& Cho, 2017).Production in the economy is determined by high labor share when cheap labor is abundant rather than capital share.In the era of Industry 4.0, it is essential to transform the economy by automating manufacturing processes to optimize production and maintain global export competitiveness. However, it is equally important to have a proper strategy to manage the large labor force while taking advantage of Industry 4.0 through the adoption of automation in manufacturing industries.

As a labor-intensive country, Bangladesh faces a critical concern in the wake of rapid industrialization. Being a resource-poor developing economy with inadequate technological advancement and limited investment opportunities, what are the key factors that need to be considered when deploying industrial automation in the manufacturing sector?Moreover, determining the automation utilization in manufacturing is essential to benefit from the fourth industrial revolution.With the fundamental research hypothesis in mind, this empirical study aims to comprehensively identify the determinants behind the utilization of industrial automation in the manufacturing industries of Bangladesh.The study is organized into different sections. Section 2 contains the literature review, Section 3 presents the theoretical framework, Section 4 focuses on the empirical framework, Section 5 discusses the results of the analyses, and Section 6 concludes with policy implications.

2. Literature Review

In order to comprehend the factors that influence the adoption of automation in manufacturing, it is crucial to understand the effects of automation utilization in this sector. By comprehending the mechanism of how automation affects manufacturing, we can explain the determinants of industrial automation in manufacturing. Due to the automation of manufacturing industries, concerns about its impact on the labor market, productivity, and wages of industrial workers are rising across the world (Kergroach, 2017;Acemoglu & Restrepo, 2020). There is a lively debate in research communities regarding the relationship between automation and labor markets in developing and developed countries (Mondolo, 2021). The inconclusive findings of researchers have created uncertainty surrounding the impact of automation on employment (Hahn &Narjoko, 2013; Falck, 2022). Many experts argue that automation will not lead to significant job displacement in manufacturing sectors. While some low-end workers may temporarily lose their jobs, overall productivity is likely to increase, leading to more employment opportunities in the long run. However, other researchers predict that automation may impact labor-intensive countries by reducing the wages of workers in manufacturing industries (Autor, 2015; Bessen et al., 2019; Bordot, 2022).

In light of the adoption of automation and technological advancements in manufacturing industries, researchers are increasingly curious about the ultimate impact of automation on manufacturing jobs and productivity.Several studies attempted to assess the impact of automation on employment in the manufacturing sector across different countries, including Kromann et al. (2011), Acemoglu & Restrepo (2018), Barcia de Mattos (2020), Anzolin (2021), and Parschau& Hauge (2022).These studies aim to identify the factors that contribute

to the impact of automation on employment and the challenges that hinder the adoption of automation technology in developing economies.Research has shown that the introduction of automation and new technology may initially have a negative impact on employment. However, in the long term, as productivity increases, it creates new job opportunities and boosts employment. Dai et al. (2022) studied how China's labor-intensive manufacturing industries are affected by upgrading and transforming automation. This study discovered that automation in manufacturing industries increases labor wages through the improvement of human capital. However, it decreases employment levels through labor productivity, which varies across different industry segments.
Aghion et al. (2020) have estimated the effects of automation on the labor and product markets in France. The study found that automation could lead to increased productivity and that the benefits could be shared among workers, consumers, and firm owners.At the firm level, automation can have a positive impact on employment. However, its effects on employment in emerging market countries are primarily adverse. On the other hand, advanced countries can make the most of their labor-saving strategies by adopting automation (Barbieri et al., 2019; Aghion et al., 2022). There are two main effects of industrial automation on manufacturing industries: the displacement effect and the productivity effect. In practice, the use of robots in production can lead to a reduction in the labor force, but it can also increase productivity (Chiacchio et al., 2018). After reviewing various studies, it becomes clear that adopting industrial automation leads to increased productivity and cost savings, as well as significant employment generation. In essence, industrial automation is primarily aimed at ensuring optimal and competitive production worldwide. For this instance, this study aims to examine the factors that influence the use of industrial automation in labor-intensive manufacturing economies such as Bangladesh.

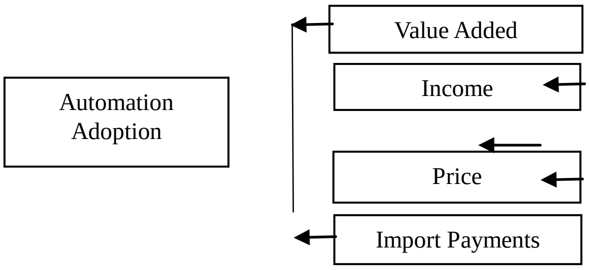
3.Theoretical Framework

The macroeconomic relationship among the production factors where production is managed through labor, capital, and technology can be used to explain the analytical relationship in determining the factors that influence automation adoption in manufacturing industries.Kromann et al. (2020) demonstrated how the Cobb-Douglas production function can be used to determine total factor productivity based on labor and capital inputs. They also distinguished between two types of capital, namely non-technological capital and automation or technological capital.This framework can be generalized such that industrial value added is determined by a variety of factors, with automation adoption and other control factors being key indicators.If we rearrange the factors, the expression could show industrial automation utilization determined by total value added, where labor input negatively impacts.Other factors, such as price, have a negative impact. The remaining indicators have mixed effects depending on the economic phenomenon. The expression can be written as follows.

$$Industrial\ Automation\ Adoption = f(Value\ Added, Labor, Inflation, Import \ldots) \quad (1)$$

The framework presented above allows for an explanation of the adoption of automation in manufacturing based on its impact on productivity. The potential for increased productivity and optimal production can influence the utilization of industrial automation in manufacturing industries.The following diagrammatic representation can be used to define the macroeconomic framework for describing the factors that influence the uptake of industrial robots in manufacturing.

Figure 1 Determinants of Automation Adoption in Manufacturing



Source: Author's compilation

However, while the inflation movement may have negative consequences, industrial value addition, overall income level, and import situation may have favorable effects in determining the adoption of industrial automation.

4. Empirical Framework

The Johansen cointegration approach will investigate the primary factors of automation utilization in the manufacturing sector. Non-stationary time series variables may be stationary at their difference. When the variables are I(1) means stationary at the first difference, the Johansen technique identifies a long-run cointegration at level variables.The vector error correction mechanism (VECM), which reflects the short-run relationship of the difference variables, could be used to identify the short-run dynamic adjustments. The following empirical model can be used to express the statistical relationship while taking into account the specification from Jung and Lim (2020):

$lnIIR_t = \beta_0 + \beta_1 lnMP_t + \beta_2 lnPCI_t + \beta_3 lnCPI_t + \beta_4 lnIMP_t + \varepsilon_t (2)$

The above model includes several indicators, including IIR, which defines industrial robot import payments as an endogenous factor, and, as predictors, MP for manufacturing output as a measure of industrial value addition, PCI for per capita GDP as the measure of overall income level, CPI (consumer price index) for inflation, FDI (foreign direct investment) for foreign investment, and IMP for import payments, which measure the country's importsituation.β's and ε represent the regression intercept, including coefficients and the error term, respectively, whereas t indicates the different periods.

When the time series variables are not stationary, I(0), and their first difference becomes stationary, I(1), indicating first-order integration, they are mutually cointegrated. Following the stationarity tests, the Johansen cointegration technique (Johansen, 1991) will be used to determine the cointegration.The vector error correction mechanism (VECM) (Engert & Hendry, 1998), which primarily focuses on how short-run disequilibrium will be adjusted to the long-run equilibrium point, will be used to identify the short-run dynamics in the cointegrating relationship. The Wald or VEC Granger causality test will examine the short-run causal relationship (Engle & Granger, 1987). In terms of error correction, the equation (4) can be written as follows:

$\Delta lnIIR_t = \beta_0 + \sum \beta_{1i} \Delta lnMP_{t-i} + \sum \beta_{2i} \Delta lnPCI_{t-i} + \sum \beta_{3i} \Delta lnCPI_{t-i} + \sum \beta_{4i} \Delta lnIMP_{t-i} + \delta ECM_{t-1} + \varepsilon_t (3)$

Because all of the variables are stationary at their first difference, i.e., I(1), the VEC Granger causality test, or the Wald (Chi-square) test, an extended version of the Granger causality test will be performed at each variable's first difference to reveal the short-term causation between variables.

4.1Variable Definition and Data Source

For the empirical analysis, annual time series data from 1991 to 2022 have been employed. The current US$ per capita GDP is per capita income (PCI). ThePCI data were obtained from World Bank data (WDI). The volume of industrial robot import payments has been used to focus on industrial automation utilization (IIR). Import payments (IMP) denote the entire amount of import expenses. We obtained IIR and IMP information from Bangladesh Bank (BB). Manufacturing output (MP) is the value that manufacturing adds to the GDP. Using the consumer price index (CPI), the price of the commodities basket in 2005–2006 = 100 is used to calculate the inflation movement. The data for the MP and CPI were provided by the Bangladesh Bureau of Statistics (BBS).

Table 1 Data and Variables

Indicators	Notations	Description	Source
Per capita income	PCI	Per capita GDP (in current US$)	WDI
Industrial automationadoption	IIR	Import payments for Industrial Robots (in million US$)	BB
Importpayments	IMP	Total importvolume (in million US$)	BB
Manufacturing output	MP	The volume of manufacturing output (in million US$)	BBS
Inflation	CPI	Consumer price index (Base: 2005-2006=100)	BBS

Note: WDI = World Bank data, BB = Bangladesh Bank, and BBS = Bangladesh Bureau of Statistics.

5. Result and Discussion

Table 2's summary statistics for the research variables reveal thatall studied indicators follow the normality assumption because the Jarque-Bera test's probability assumes that the observations come from a normal distribution.Because the variables under research meet the statistical criteria for normal distribution, statistical tools may be used to examine the empirical relationship between the variables under consideration.For econometric analysis employing time series data, the variable's data series may suffer from non-stationarity issues. At the same time, the statistical model may be applied depending on the order of integration presented in the data series.

Table 2 Descriptive Statistical Feature

	lnIIR	lnPCI	lnCPI	lnMP	lnIMP
Mean	-1.34	6.53	4.73	9.60	9.68
Median	-1.13	6.26	4.63	9.37	9.67
Maximum	0.69	7.89	5.72	11.15	11.28
Minimum	-3.61	5.64	3.85	8.37	8.04
Std. Dev.	1.21	0.71	0.59	0.88	0.96
Skewness	-0.13	0.55	0.15	0.39	-0.13
Kurtosis	1.90	1.96	1.66	1.86	1.79
Jarque-Bera	1.69	3.06	2.50	2.54	2.04
Probability	0.428	0.215	0.285	0.280	0.359
Observations	32	32	32	32	32

Source: Author's calculation.

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were used to determine whether the time series variables included for determining the relationship above are stationary.Table 3 summarizes the unit root test results, revealing that all variables exhibit first-order integration and are not stationary. The variables in a time series econometric phenomena are I(1) rather than I(0); thus, they may have a cointegrating relationship. A cointegration test should be done to determine whether or not cointegration exists among variables.

Table 3 Results of Stationarity Tests

Augmented Dickey-Fuller (ADF) Test (Panel 1)		
Variables	Level	1st Difference
lnIIR	Non-stationary	Stationary***
lnMP	Non-stationary	Stationary***
lnPCI	Non-stationary	Stationary***
lnCPI	Non-stationary	Stationary*
lnIMP	Non-stationary	Stationary***
Phillips-Perron (PP) Test (Panel 2)		
Variables	Level	1st Difference
lnIIR	Non-stationary	Stationary***
lnMP	Non-stationary	Stationary***
lnPCI	Non-stationary	Stationary***
lnCPI	Non-stationary	Stationary*
lnIMP	Non-stationary	Stationary***

Source: Author's calculation. Note: *** and *are significant at 1% and 10%, respectively.

The cointegration relationship is investigated using the Johansen cointegration technique. The trace statistic test and the maximum eigenvalue test are typically used to determine how many cointegrating equations are present in the long-run relationship.Table 4 presents the results of the tests mentioned above for inspecting the number of cointegrating equations. This indicates that both test techniques emphasize that one cointegrating equation exists in the long-run relationship.This confirmation of one cointegrating equation can also be translated as the Johansen approach establishing one cointegrating vector in the long run, which is also evidence of a cointegration connection.

Table 4 Results of Cointegration Rank Tests

Panel 1: Unrestricted Cointegration Rank Test (Trace)				
No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value	P-value**
None *	0.698	81.508	69.818	0.004
At most 1	0.564	45.582	47.856	0.080
At most 2	0.350	20.676	29.797	0.378
At most 3	0.218	7.716	15.494	0.496
At most 4	0.010	0.302	3.8414	0.582
Panel 2: Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
No. of CE(s)	Eigenvalue	Max-Eig Statistic	Critical Value	P-value**
None*	0.698	35.925	33.876	0.028
At most 1	0.564	24.906	27.584	0.106
At most 2	0.350	12.959	21.131	0.456
At most 3	0.218	7.414	14.264	0.441
At most 4	0.010	0.302	3.841	0.582

Source: Author's calculation.
Notes:* denotes hypothesis rejection at the 0.05 level and**MacKinnon-Haug-Michelis (1999) p-values.

Once one cointegration equation has been established, the coefficients of the long-run relationship can be computed using the Johansen technique, which suggests standardizing the relationship into a single equation.Table 5 incorporates the calculated coefficients in the long-run relationship, revealing that changes in manufacturing output and per capita income level have a considerable association in determining industrial automation utilization in

Bangladesh.Rising manufacturing output has had a significant impact and a higher influence on automation adoption, implying that rising industrial output is a cause of the recent increase in the usage of industrial robots in manufacturing. Although industrial robots are not widely used in the economy, the country has steadily begun to increase their usage in industrial production.Furthermore, rising income levels have a greater and significant negative impact on industrial automation adoption, indicating that in a labor-intensive economy, rising per capita income means a more significant contribution of labor to production, limiting the growing use of industrial automation in manufacturing.

Table 5 Results of Long-Run Coefficients

lnIIR	lnMP	lnPCI	lnCPI	lnIMP	C
1.000	-15.506***	13.678***	3.985	0.414	37.953
	(1.931)	(1.856)	(2.657)	(1.049)	
	[-8.028]	[7.368]	[1.499]	[0.395]	

Source: Author's calculation.
Note: *** indicates the 1% significance level; Standard errors in ( ) and t-statistics in [ ].

The calculated short-run dynamics of the vector error correction model (VECM) in the long-run connection show that the pace of adjustment in per capita income level is statistically significant (Table 6).Regarding per capita income, the convergence to equilibrium via short-run disequilibrium is roughly 4%. This suggests that a 4% inaccuracy in the long-run link of automation adoption through per capita income level has been corrected by a year. In a consistent statistical manner, industrial automation's stability hasonly been adjusted in the short run through the per capita income level.

Table 6 Results of Vector Error Correction Estimates

Vector Error Correction Estimates					
Error Correction:	D(lnIIR)	D(lnMP)	D(lnPCI)	D(lnCPI)	D(lnIMP)
CointEq1	-0.068	0.049	-0.043***	-0.001	0.029
	(0.126)	(0.022)	(0.015)	(0.005)	(0.035)
	[-0.538]	[2.250]	[-2.782]	[-0.116]	[0.826]

Source: Author's calculation. Note: *** indicates the 1% level of significance.

The vector error correction (VEC) Granger causality test or block exogeneity Wald (Chi-Square) test is performed to investigate the short-run causal link between the research variables. Whether or not the lagged variables affect each other using the"differences" form of variables since they are non-stationary at their level and demonstrated the first order of integration.Table 7 shows the estimated causality; it only represents a unidirectional causality that runs from the deployment of industrial automation to changes in the volume of import payments. The adoption of industrial automation in Bangladesh heavily depends on imported capital machinery because the country's technological advancements are insufficient, so it must import industrial robots for manufacturing. This shows the evidence of a short-run causal link between import and industrial automation.

Table 7 Results of the Causality Test

Dependent variable: D(lnIIR)		
Causal/Excluded Variable	Chi-square	Prob>Chi-square
D(lnMP)	0.0003	0.984
D(lnPCI)	0.316	0.573
D(lnCPI)	0.158	0.690
D(lnIMP)	0.066	0.797

Dependent variable: D(lnMP)		
Causal/Excluded Variable	Chi-square	Prob>Chi-square
D(lnIIR)	1.039	0.308
D(lnPCI)	0.310	0.577
D(lnCPI)	0.043	0.833
D(lnIMP)	0.225	0.635
Dependent variable: D(lnPCI)		
Causal/Excluded Variable	Chi-square	Prob>Chi-square
D(lnIIR)	0.076	0.782
D(lnMP)	1.963	0.161
D(lnCPI)	1.021	0.312
D(lnIMP)	0.352	0.552
Dependent variable: D(lnCPI)		
Causal/Excluded Variable	Chi-square	Prob>Chi-square
D(lnIIR)	0.962	0.326
D(lnMP)	0.808	0.368
D(lnPCI)	0.074	0.784
D(lnIMP)	0.304	0.581
Dependent variable: D(lnIMP)		
Causal/Excluded Variable	Chi-square	Prob>Chi-square
D(lnIIR)	5.320**	0.021
D(lnMP)	0.239	0.624
D(lnPCI)	0.006	0.936
D(lnCPI)	0.003	0.950

Source: Author’s calculation. Note: ** indicate the 5% level of significance.

The empirical association results in determining industrial automation adoption at the industrial level support the theory that increasing manufacturing volume leads to increased automation adoption. On the other hand, labor-intensive production leads to a decline in industrial automation, as seen by rising income levels and decreased utilization of industrial robots.Automation is used in competitive production with a cost-effective nature while employing more capital through automation adoption can boost production to an optimal level. The analysis’s conclusions are consistent with this theoretical notion: to maintain competitiveness in the global market, the benefit of deploying automation is essential for practical industrialization usage.This study also found evidence that using cheap labor in manufacturing with growing income levels promotes a decrease in automation utilization to some extent. In defining industrial automation in manufacturing, increasing output levels would significantly influence. In the short term, increasing industrial robot import payments may impact the country’s overall import volume because the economy must rely on industrial robot imports to implement industrial automation due to technological constraints; hence, imports must rise.

6. Conclusion

This study aims to assess the determinants of industrial automation adoption in Bangladesh manufacturing.The empirical model developed with econometric tools reveals thatincreasing manufacturing output has a more significant impact on industrial automation use. However, using more of a nation’s cheap labor that definitely raises per capita income results in a fall in the use of industrial robots in manufacturing. The outcome also demonstrates that deploying the industrial robot results in more outstanding import payments because of the nation’s insufficient technological advancement.

The economy must adopt rapid industrial automation to benefit from Industry 4.0 and achieve competitive production with maximum volume since the study found that growing manufacturing volume leads to increased automation use. As a result of resource limits and inadequate technology, the economy will require massive investment, either domestically or overseas, as it is forced to rely on imported automation technology or industrial robots.The adoption of industrial automation will require an increase in import payments for the economy of Bangladesh that relies on imports, whether in the exporting or consumer goods sectors. To avoid a massive trade deficit and maintain a balanced trade, it is necessary for the economy to gradually improve its export performance by diversifying its export products.
Instead of relying on macro-level data and time series econometrics, it would be more beneficial to use micro-data with more relevant indicators and different regression techniques to study the determinants of industrial automation utilization in the manufacturing industries of Bangladesh. This approach can help fill the research gap and achieve better outcomes in this context.

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