

Impact of Digitalization on the Employment in the Manufacturing Industries of Bangladesh

Submitted by
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Abstract

The rapid and continuous development of digital technologies is transforming the global manufacturing landscape, restructuring employment patterns, organizational structures, and strategic decision-making process by implementing and adopting Artificial Intelligence, Internet of Things (IoT), and Data-Driven technologies. While digitalization enhances operational efficiency, productivity, and competitiveness, its effect on employment remains widely debated, insufficiently examined, inadequately addressed and empirically underexplored in the existing literature, particularly in developing countries. The main aim of this research is to examine the impact of digitalization on employment dynamics in the manufacturing industry in Bangladesh. The study investigates and analyzes workforce transformation, changing skill requirements, organizational strategies, Research and Development (R&D) investment, and policy implications associated with digitalization. This study carries out a bibliometric analysis, which comprehends the global research trends over the past three decades, with a systematic literature review, which summarizes the major theories, facts and contextual background. The conceptual model was constructed through integrating existing theoretical models, such as Creative Destruction, Labor Market Segmentation, Human Capital Theory, Diffusion of Innovation, Skill-Biased Technological Change Model and Technology Acceptance Model, the study develops a theoretically grounded “Moderated plus Direct Effect Model Framework” integrating multiple perspectives on technological change and Labour Market Dynamics. In this study, a mixed-methods research approach is used. In the qualitative analysis, the purposive non-probability sampling method is employed, generating data from 53 semi-structured interviews and four focus groups across diverse sub-sectors of the manufacturing industries. In the quantitative phase, data were collected from 213 respondents representing different manufacturing industries, providing a broad and representative foundation for statistical analysis. Across both phases, participants included employees, industry leaders, policymakers, technical and operational professionals, and academic experts. Responses were examined and analyzed through SPSS Statistics 26.0, and SmartPLS v.4. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used

to test Measurement Reliability, Construct validation, and Structural Relationships among digitalization, employment outcomes, organizational strategies, R&D, and firm level moderating characteristics. A pilot study is done before the full-scale study to optimize the research design and evaluate the measurement model.

Qualitative analysis shows that workplace structures are rapidly transforming due to automation and AI. There are concerns about job displacement and growing demand for digital skills, and the need for investment, collaboration, and structured upskilling for sustainable employment transitions. In Quantitative analysis, measurement model validates a high level of internal consistency, with Cronbach Alpha and Composite Reliability rating higher than the usual level of 0.70 and AVE higher than 0.50, and this establishes Convergent and Discriminant Validity. The results of Structural Equation Modeling (SEM) were found to support path coefficients (β), t-statistics, and p-values, stating that digitalization has heterogeneous effects on employment in the manufacturing industry with significant explanatory power ($R^2 = 0.812$; Adjusted $R^2 = 0.796$), significant predictive relevance ($Q^2 > 0.35$), and acceptable model fit. The effect sizes estimates ($f^2 = 0.05-0.23$) show moderate to strong effects of IT investment, R&D, Strategy and Policy and Digital Skills that are emerging as the key determinants on Labour Market Dynamics. The moderation analysis also indicates that Industry Size and Type have a significant impact on the association between digitalization and employment adaptation. The multicollinearity test ($VIF < 3.3$) and Bootstrapping procedures prove the stability and strength of the model.

This research contributes to the digitalization and employment of literature by integrating multiple theoretical perspectives into a unified empirical framework applicable to developing industrial contexts as well as offering practical recommendations to the policymakers, industrial players, and institutions. The research also offers a replicable analytical model for examining technology-driven labor transformation in emerging industrial economies.

Keywords: *Digitalization, AI, Employment, Manufacturing Industry, Firm Strategy, Average Variance Extracted, PLS-SEM, VIF, Labor Market Dynamics.*

Approval Page

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A thesis submitted to the Department of Management Information Systems,
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Declaration

I hereby declare that this thesis, titled *“Impact of Digitalization on the Employment in the Manufacturing Industries of Bangladesh,”* is my original work and has not been submitted previously for any degree or academic qualification at any other institution.

This research is conducted in accordance with ethical guidelines, and all sources of information, references, and contributions from other researchers have been duly acknowledged. Any data, analysis, or findings presented in this thesis are based on my independent research, and any assistance received has been appropriately credited.

Abu Sadat Muhammad Ashif

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Signature

Dedication

This thesis is dedicated to my parents, siblings and relatives, whose unwavering support, sacrifices, praise and encouragement have been my foundation throughout this academic journey.

To my little daughter and caring spouse, I am deeply grateful for your patience, love, and understanding, which have carried me through the challenges of this demanding yet rewarding endeavor.

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Finally, I remain grateful to all individuals who directly or indirectly contributed to the successful completion of this thesis. Any remaining errors or omissions are solely my own.

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Chapter 1: Introduction

The rapid rise of digital technologies is reshaping the manufacturing world, changing how industries operate, how jobs are structured, and how strategies are defined. Tools such as artificial intelligence (AI), the Internet of Things (IoT), and advanced robotics are not only improving efficiency but also transforming employment and labor markets. Studies show that AI and robotics are increasingly integrated into production processes, enabling smarter work practices, adaptive automation, and novel task allocations, which alter job content, create new high-skill roles, and displace routine tasks (Intahchomphoo *et al.*, 2024; Marguerit, 2025). Moreover, digital transformation in manufacturing is changing work organization and skill requirements, prompting firms to redefine strategies and workforce development to remain competitive in a highly digitalized global economy (Babashahi *et al.*, 2024).

In Bangladesh, where manufacturing is one of the central to economic growth, digitalization presents both opportunities and challenges. Automation and advanced technologies can boost productivity and global competitiveness, but they also risk displacing low-skilled workers, widening skill gaps, and increasing socio-economic inequalities (Rahman *et al.*, 2024; Islam *et al.*, 2024). Addressing these challenges requires targeted upskilling, workforce development, and digital infrastructure improvements to ensure inclusive and sustainable industrial growth.

According to national economic data (BBS, 2024), Bangladesh's manufacturing sector contributed about 23.19 % of GDP in FY 2024–25, highlighting its role as a key driver of economic growth and structural transformation. Concurrently, the sector provides employment to an estimated 14 % of the total workforce, underscoring its importance as a source of formal jobs and labor absorption in an increasingly urbanized economy. These figures are consistent with broader international labor assessments indicating that manufacturing remains central to sustainable development despite ongoing global technological changes (United Nations Industrial Development Organization, 2024; Sanem, 2025).

Digitalization is emerging as a transformative force in the manufacturing sector of Bangladesh, fundamentally reshaping employment structures, skill composition, and workplace organization. The manufacturing industry—particularly readymade garments, textiles, leather, pharmaceuticals, cements, food processing & beverages, ceramics, and light engineering—has traditionally been the backbone of Bangladesh's economic growth, contributing significantly to GDP and providing large-scale employment. However, the gradual diffusion of Industry 4.0 technologies such as artificial intelligence (AI), robotics, Internet of Things (IoT), cloud computing, and advanced data analytics is changing the nature of industrial production from labor-intensive systems to technology-driven and automated environments (OECD, 2019; World Bank, 2019).

From an employment perspective, digitalization is generating a structural transformation in the labor market. Routine and repetitive manual tasks are increasingly being automated, reducing the demand for low-skilled labor in specific production segments. At the same time, new employment opportunities are emerging in areas such as machine operation, digital production management, predictive maintenance, industrial data analysis, and quality control systems. This shift reflects a broader global trend where digital technologies are not only displacing certain jobs but also creating new categories of skill-intensive employment (Frey & Osborne, 2017; Acemoglu & Restrepo, 2020). In the context of Bangladesh, this transformation is particularly significant because the manufacturing sector remains highly labor dependent. The introduction of automation and smart manufacturing systems is gradually changing the employment composition of firms, especially in export-oriented industries such as garments and textiles. While digital technologies enhance productivity, efficiency, and global competitiveness, they simultaneously create pressure on low-skilled workers who often lack the required digital competencies to transition into new job roles (ILO, 2021; UNCTAD, 2021).

A critical challenge in Bangladesh is the widening skills gap created by digital transformation. Many manufacturing workers have limited access to technical education, vocational training, and reskilling opportunities. As a result, firms adopting advanced technologies face difficulties in sourcing adequately skilled labor, leading to a mismatch between labor supply and demand. These skills mismatch not only affect employment

security but also limits the full productivity benefits of digitalization (World Bank, 2019). Another important dimension is the uneven adoption of digital technologies across manufacturing firms. Large enterprises are increasingly investing in automation, enterprise resource planning systems, and AI-enabled production technologies, which leads to higher productivity but also greater labor restructuring. In contrast, small and medium-sized enterprises (SMEs) face financial, technological, and institutional barriers that slow down their digital transformation process. This creates heterogeneous employment impacts across firms, sub-sectors, and regions within the manufacturing industry of Bangladesh (UNCTAD, 2021). Despite concerns regarding job displacement, the employment effects of digitalization are not purely negative. Instead, digital transformation is leading to job reconfiguration rather than simple job loss. While some low-skilled roles are declining, new opportunities are emerging in technical, supervisory, and digitally enabled positions. The net employment outcome therefore depends on the balance between job displacement, job creation, and the ability of firms and workers to adapt through reskilling and organizational adjustment strategies (Brynjolfsson & McAfee, 2014; Verhoef et al., 2021).

Digitalization in Bangladesh's manufacturing sector represents a dual-edged transformation: it enhances productivity and global competitiveness while simultaneously restructuring employment patterns and skill requirements. Understanding this dual impact is essential for designing effective industrial policies, workforce development strategies, and firm-level adaptation mechanisms that ensure inclusive and sustainable industrial growth. Empirical evidence also suggests that the impact of digitalization on employment is context specific. In developing economies like Bangladesh, institutional constraints such as limited infrastructure, weak training systems, and informal labor market structures intensify the adjustment costs of technological change. Therefore, the employment effects of digitalization cannot be generalized and must be analyzed within the specific industrial and socio-economic context of Bangladesh's manufacturing sector (Raihan, 2018; ILO, 2021).

Introduction chapter highlights and shows the basis for researching the complicated relationship between digitalization and the employment in Bangladesh's manufacturing sector. Subsequently, it reaches into the problem statement, underscoring the labor market

disruptions caused by digitalization and identified the gaps in the current traditional knowledge base.

This chapter further articulates the research objectives and research questions, emphasizing their association with pressing Industrial, Governmental and stakeholders' policies, and presenting societal challenges and opportunities.

This chapter also defines the scope and limitations of the research, providing a clear framework for the study while ensuring its relevance to academics, policymakers, industry stakeholders, and firms through a comprehensive and inclusive approach. By addressing these viewpoints, the chapter not only sets the podium for the study but also focuses its significance on the wider context of digital revolution, economic and social development, and workforce sustainability.

The insights from this research are deliberate to contribute to both academic discussions and industry practices, while also supporting evidence-based policymaking. Main aim to provide practical guidance for industrial stakeholders as they navigate the opportunities and challenges of digitalization in a developing economy like Bangladesh. By addressing these critical issues, the study offers recommendations that can help firms not only harness the benefits of digital transformation but also manage its potential risks. Ultimately, the findings and recommendations of this study will help industry leaders and organizations adapt to the changing technological landscape and strengthen their ability and skills to remain competitive in the global marketplace.

1.1 Overview of the Chapter

The introductory chapter sets outline for understanding the deep implications of digitalization on employment within Bangladesh's manufacturing industries. This chapter begins with a background of the study that highlights the manufacturing sector's critical role in the country's economy, its contribution to GDP and its critical role as a source of employment for thousands and millions. The background part also underscores the driving potential of digital technologies, including Business Intelligences, advanced technology, AI, and IoT etc. Background part also recognizes the multifaceted challenge of employment like job displacement and skill realignment due to advanced technologies and digitalization.

After Background, the problem statement begins by addressing the pressing need to understand Labor Market Dynamics caused by digitalization and automation. It examines gaps in knowledge regarding the extent of job displacement, the emergence of new opportunities and threats, and the evolving skill requirements within the sector. The discussion highlights the importance of introducing effective policies and strategies that balance technological advancement with workforce sustainability.

Following this, research questions are organized to examine the relationships among technological advancements, organizational strategies, R&D, and Labor Market Dynamics. They focus on critical areas such as job creation, skill development, IT infrastructure, and the socioeconomic implications of digitalization, thereby providing a clear roadmap for the study's investigation.

Then the objectives of the study are highlighted, focusing on exploring the impacts of digitalization, analyzing workforce transformations, and providing practical recommendations to support sustainable employment dynamics in the manufacturing sector (Verhoef et al., 2021; World Bank, 2019; UNCTAD, 2021). These objectives are clearly defined, offering a comprehensive framework for guiding the research.

Next part, significance of the study which is emphasized and highlighted its contributions to academic knowledge, policy development, and industry strategies. The chapter underscores the need for insights that can help the policymakers, industry leaders and its stakeholders to leverage digital transformation for fostering inclusive economic sustainability and growth, also addressed challenges such as skill gaps, knowledge deficiencies, and inequality.

The scope and limitations describe the outline of the research, acknowledging its focus on Bangladesh's manufacturing sector, the limitations of data availability, the changing and adopting nature of digital technologies. This confirms a transparent insight into the study's context and its contribution within the domain.

Finally, this chapter lays an organized foundation and background, clearly articulates the problem statement, sets the research objectives, identifies the research questions, highlights the significance of the study, and outlines its scope and limitation, thereby guiding subsequent chapters to build upon themes and undertake in-depth analyses.

1.2 Background of the Study

The manufacturing sector has historically been a cornerstone of Bangladesh's economy, contributing approximately 22–23 % of the country's GDP and providing direct employment to around 14 % of the total workforce. Key industries—including pharmaceuticals, textiles, garments, food processing, beverages, cement, ceramics, leather and footwear, and consumer goods manufacturing—play a vital role in driving economic growth, generating export revenue, and supporting industrial development. The sector not only underpins the nation's industrialization but also serves as a significant source of formal employment, particularly in urban and semi-urban areas, thereby shaping Labor Market Dynamics and supporting inclusive economic progress.

In recent years, advanced technologies like Robotics, Artificial Intelligence (AI), Cloud Computing, and the Internet of Things (IoT) are no longer just tools of efficiency; they are reshaping how products are made and processed, how work is organized, and how industries compete. In Bangladesh, this wave of digitalization brings both opportunities and poses significant challenges. There is a dual effect of digitalization, on the one hand it helps higher productivity with better resource utilization, it also raises real concerns for traditional employment, particularly among low-skilled workers who face the risk of being replaced by automated systems.

In Bangladesh adoption and integration of technology is uneven between large firms and SME. Large, resource-rich companies are quickly adopting advanced technologies, integrating them into their operations at a faster pace. In contrast, small and medium-sized enterprises (SMEs) face significant financial and technical constraints that slow their progress toward digital transformation. This trajectory reflects the multifaceted challenges of digitalization in Bangladesh's manufacturing sector and underscores the importance of examining its broader implications for employment, skills, and industrial development across all segments of the industry.

The beginning of Industry 4.0 (IR4.0), and the emerging discourse around Industry 5.0 (IR5.0), is gripping manufacturing firms to embrace the extensive use of digital technologies. Existing research on digitalization and its effect on employment has predominantly focused on broad, macro-level outcomes—such as national employment

trends, automation's impact on overall job markets, or cross-industry comparisons (Autor, 2015; Brynjolfsson & McAfee, 2014). These studies typically emphasize technological displacement, job polarization, and shifts in skill requirements. However, comparatively less attention has been paid to sector-specific implications, particularly in the context of developing economies like Bangladesh.

The primary weakness in the existing literature lies in its generalized approach, which overlooks:

- The heterogeneous impact of digitalization across different manufacturing sub-sectors (e.g., garments, textiles, pharmaceuticals, leather, electronics & Engineering, Constructions, food processing,).
- The unique structural and institutional challenges of Bangladesh, such as informal labor markets, limited digital infrastructure, and policy gaps.
- The absence of empirical evidence focusing on firm-level strategies and employment outcomes specific to the Bangladeshi manufacturing context.

This study addresses these gaps by providing a focused, empirical investigation into how digitalization affects employment dynamics in Bangladesh's manufacturing industries. It aims to explore not only the macroeconomic implications but also the micro-level realities experienced by firms and workers alike.

1.3 Statement of the Problem

In recent years, the rapid advancement and diffusion of digital technologies—such as Robotics, Artificial Intelligence (AI), Generative AI (GenAI), and the Internet of Things (IoT)—have initiated a profound transformation in the global manufacturing landscape. These technologies are core components of the Fourth Industrial Revolution (Industry 4.0) and are fundamentally reshaping production systems by enabling greater connectivity, data-driven decision-making, automation, and real-time monitoring across manufacturing processes (Edverton, 2024). Digital technologies not only enhance resource efficiency and operational excellence, but they also improve productivity, product quality, and competitive advantage by facilitating smart and interconnected production environments known as “smart factories” (OECD, 2020; Lee et al., 2018).

Manufacturing industries increasingly adopt advanced technologies, that leads to transformation of traditional labor. This transformation is expected to lead to job displacement or reduction, change the nature of skill requirements, and exacerbate existing socio-economic disparities (Frey & Osborne, 2017; Ahmed *et al.*, 2014). The effect and consequences of these transformations remain negligibly understood and studied in Bangladesh, especially considering its unique economic structure, informal labor markets, limited digital infrastructure, and education-skills mismatch (Raihan, 2018; ILO, 2021). Despite the critical importance of the issue, there remains a significant lack of comprehensive, context-specific research that investigates how digitalization is affecting employment within Bangladesh's manufacturing industries.

Addressing this knowledge gap is vital. It requires understanding:

- The nature, extent and degree of job displacement driven by automation and digital technologies.
- The emergence of new employment opportunities that require advanced digital and technical skills.
- The evolving skill demands across sub-sectors within the manufacturing industry; and
- The socioeconomic implications of these technological transformations.

This study seeks to bridge these critical gaps by systematically examining the impact of digitalization on employment in Bangladesh's manufacturing industries. By combining empirical analysis with contextual insights and understanding, it aims to identify both the challenges and opportunities presented by technological transformation. The findings will provide evidence-based recommendations to help policymakers, employers, employees, job seekers, academia, industry stakeholders, and workforce development agencies connect digitalization in ways that maximize economic benefits while safeguarding employment and promoting long-term, inclusive industrial development.

1.4 Research Questions

The research addresses both the direct and indirect effects of digitalization on employment, skill requirements, and workforce adaptation, as considering the role of organizational

strategies, policies, and IT investments. The following research questions are framed to guide the in-depth research and investigation and offer insights into these key areas:

1.4.1 Primary Research Questions

- i. How do digital transformation drivers — Technological Advancements, Digital Skills, IT Investment, Strategy and Policy, and Research & Development — influence Labor Market Dynamics in Bangladesh’s manufacturing sector?
- ii. What is the role of firm-level characteristics, specifically company Type and firm Size, in shaping Labor Market Dynamics within the manufacturing industry?
- iii. How do firm-level factors (company Type and Size) moderate the relationships between digital transformation drivers and Labor Market Dynamics?
- iv. What strategic and policy interventions can firm, and policymakers adopt to ensure digital transformation contributes to employment sustainability in Bangladesh’s manufacturing sector?

1.4.2 Secondary Research Questions

- i. To what extent do Technological Advancements, Digital Skills, IT Investment, Strategy and Policy, and Research & Development affect Labor Market Dynamics in Bangladesh’s manufacturing sector?
- ii. How do firm-level characteristics, particularly company Type and company Size, independently influence Labor Market Dynamics in the manufacturing industry?
- iii. In what ways does company type moderate the relationship between digital transformation drivers (Technological Advancements, Digital Skills, IT Investment, Strategy and Policy, R&D) and Labor Market Dynamics?
- iv. In what ways does firm Size moderate the relationship between digital transformation drivers and Labor Market Dynamics?
- v. What Strategic and Policy measures can firm, and policymakers adopt to ensure digital transformation contributes positively to employment sustainability in Bangladesh’s manufacturing sector?

1.5 Objectives of the Study

The rapid integration of advanced technologies is reshaping the industries globally Bangladesh is also at its forefront to these changes. While advanced technology offers

significant opportunities for the manufacturing sector, it also presents substantial challenges. To deal with dual effect of Digitalization requires training and build a workforce equipped with diverse technical and professional competencies, particularly in emerging digital technologies.

From last few decades, Bangladesh's manufacturing sector has largely depended on price-led competitiveness, low wages, and the availability of a large labor force for labor-intensive production. However, the global manufacturing landscape is shifting. Even labor-intensive markets are now moving toward technology-driven productivity and innovation, highlighting the urgent need for Bangladesh to transition toward advanced manufacturing methods. Advanced and innovative digital technologies have immense potential to increase productivity, improve efficiency, and secure long-term competitiveness. As Bangladesh's continued dependence on labor-intensive models, coupled with its limited digital infrastructure, poses significant challenges to cope with the global market.

The Fourth Industrial Revolution (IR4.0) has already redefined international trade and manufacturing practices by integrating advanced digital technologies—such as Automation, Artificial Intelligence (AI), the Internet of Things (IoT), and Data Analytics—into global value chains, enabling smarter production, enhanced supply chain performance, and more agile responses to market dynamics (Jain et al., 2024; Smith & Chen, 2023). In this evolving context, Bangladesh can no longer rely indefinitely on low-cost labor as its primary competitive advantage; rising wages, automation pressures, and shifting global buyer expectations increasingly favor productivity, technology adoption, and innovation over purely labor-intensive models (UNDP, 2023). To sustain growth and industrial progress, Bangladeshi manufacturers must therefore pursue continuous innovation, digital adoption, and technological upgrading—not only to remain competitive in international trade, but also to enhance supply chain visibility, efficiency, and product quality in an era where smart manufacturing is becoming the global standard (Gomes et al., 2024).

Considering all these this study set the objectives to explore how these technological advancements affect and impact the employment dynamics within Bangladesh's manufacturing sector and to identify strategies for routing these transitions successfully.

1.5.1 Broad Objective

- i. To critically examine the impact of digital and contextual transformation drivers (Technological Advancements, Digital Skills, IT Investment, Strategy and Policy, and R&D) on Labor Market Dynamics within Bangladesh's manufacturing sector.
- ii. To evaluate the role of organizational characteristics, particularly firm Type and firm Size, in shaping Labor Market Dynamics.
- iii. To provide policy and strategic recommendations for firms and policymakers to manage the employment implications of digitalization in the manufacturing industry.

1.5.2 Specific Objectives

- i. To analyze the direct influence of Technological Advancements, Digital Skills, IT Investment, Strategy and Policy, and Research & Development on Labor Market Dynamics in Bangladesh's manufacturing sector.
- ii. To evaluate the independent effects of firm-level characteristics, specifically company Type and firm Size on Labor Market Dynamics.
- iii. To investigate the moderating role of company Type in the relationship between digital transformation drivers and Labor Market Dynamics.
- iv. To assess the moderating role of firm Size in the relationship between digital transformation drivers and Labor Market Dynamics.
- v. To synthesize empirical evidence into Strategic and Policy recommendations that enable firms and policymakers to balance technological progress with employment sustainability.

1.6 Significance of the Study

The manufacturing sector plays a pivotal role in Bangladesh's economy, contributing approximately 22–23 % of GDP (FY-2023-24) and providing employment to around 14 % of the total workforce—which equates to roughly 9.9 to 10.8 million workers, given the country's total labor force of about 73.7 million people (BBS, 2024-25). The sector not only strengthens economic output but also shapes Labor Market Dynamics, offering both formal employment opportunities and pathways for skill development across urban and

semi-urban areas. This study is significant in multiple dimensions as it seeks to explore how digitalization impacts employment in Bangladesh's manufacturing industries.

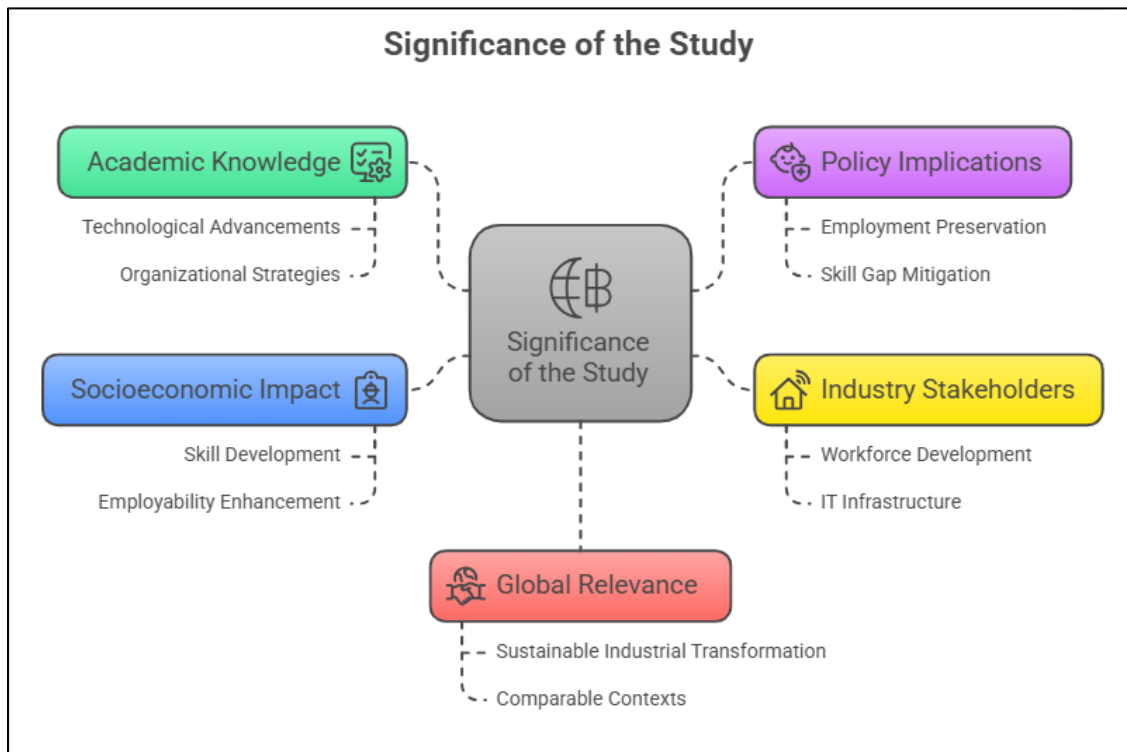


Figure 1.1: Significance of Study

As illustrated in Figure 1.1, the significance of this study extends to academic knowledge, industry practices, socioeconomic development, policy implications, and global relevance in the context of digitalization and employment (Brynjolfsson & McAfee, 2014; Autor, 2015; World Bank, 2019).

1.6.1 Contribution to Academic Knowledge

This research contributes to the growing body of literature on digitalization and Labor Market Dynamics, particularly in the context of developing economies. Existing studies often focus on macroeconomic effects or the technological aspects of digitalization, with limited attention to sector-specific employment impacts in countries like Bangladesh. By addressing this gap, the study provides a nuanced understanding of how technological advancements, organizational strategies, and workforce transformation are shaping employment trends within the manufacturing sector that will be a vast area of study for the academia.

1.6.2 Policy and Decision-Making Implications

Digital advanced technologies bring new opportunities; it also poses risks of job losses and widening skill gaps. The findings of this research highlight that thoughtful effective policies will help to create new pathways for employment in a digital economy. Recommendations and suggestions derived from this study can help policymakers craft strategies to reduce job displacement, bridge skill divides, and support a more adaptable workforce. Ultimately, effective policy action will ensure that digital transformation drives inclusive and sustainable growth, leaving no group of workers behind.

1.6.3 Application to Industry Stakeholders

For industry stakeholders, particularly within Bangladesh's manufacturing sector such as pharmaceuticals, engineering, cements, textiles, electronics, leather & Footwear, and beverages and food processing etc., this study provides actionable insights on how digital technologies can be strategically adopted and integrated to drive both workforce development and industrial growth. The findings underscore that digital transformation is not solely about introducing advanced technologies—it also requires coherent organizational policies, forward-looking strategies, sustained investments in research and development (R&D), and strong IT infrastructure.

1.6.4 Socioeconomic Impact

For labor force and society at large, this study underscores the need for capacity building, IT skills, and knowledge development to adapt to the shifting nature of work environment. By recognizing the skill and knowledge gaps and emerging requirements in a digitalized economy, the research offers actionable insights to different concerned authorities, educational institutions, training organizations, and workforce development agencies to design programs that enhance employability and resilience among workers.

1.6.5 Global Relevance

Although the study focused on Bangladesh, the findings of this study also have broader implications for other developing countries undergoing similar transitions. The lessons learned from the challenges and opportunities of digitalization in Bangladesh's manufacturing sector can serve as a valuable, insightful reference for stakeholders in

comparable contexts, enhancing the global address on sustainable industrial transformation.

By referring these critical important factors, this study not only spreads theoretical knowledge but also provides actionable application solutions to ensure that digitalization serves as a catalyst for inclusive and sustainable economic growth in Bangladesh.

1.7 Scope and Limitations

This section outlines the scope and limitations of the study, detailing the areas covered and the boundaries within which the research has been conducted. The scope of this study is centered on exploring the impact of digitalization on employment within Bangladesh's manufacturing sector. At the same time, the study operates within certain limitations like geographical, data availability, time etc.



Figure 1.2: Scope and Limitation of the study

As illustrated in Figure 1.2, the study focuses on the impact of digitalization on employment in Bangladesh's manufacturing industries while considering organizational strategy and policy dimensions (Autor, 2015; Brynjolfsson & McAfee, 2014; OECD, 2019).

1.7.1 Scope

The study explores the impact of digitalization on employment in the manufacturing industries in Bangladesh, with a focus and highlights on both the opportunities and challenges it presents for the workforce. The research examines various forms of digital technologies, including Automation, AI, GenAI, IoT, Robotics, and Digital platforms, and their role in transforming employment structures within the sector. The scope of the study encompasses:

- i. **Digitalization Trends in Manufacturing:** Analyze the current state and trajectory of digital transformation in the manufacturing sector of Bangladesh.
- ii. **Impact on Employment Types:** Investigate how digitalization affects and influences job creation, displacement, skill requirements, and employment types (full-time, part-time, gig, etc.).
- iii. **Sector-Specific Case Studies:** This study mainly focuses on specific sub-sectors within manufacturing, such as pharmaceuticals, cement, ceramics, leather & leather goods, food & beverage, electronics and appliances, and consumer goods, to understand sectoral dynamics and nature.
- iv. **Social and Economic Implications:** Both Social and economic consequences of digitalization are studied.
- v. **Policy Recommendations:** One of the major goals to recommend and introduce timely relevant insights to the policymakers, industry leaders and the stakeholders.

1.7.2 Limitations

Along with the scopes there are some limitations described as follows

- i. **Geographical Limitation:** The study concentrations solely on the sub sector of the manufacturing industries such as Pharmaceuticals, Textile, Cements, Constructions and Engineering, Food and beverage etc. in Bangladesh, which may not fully capture the total picture of digitalization impact on employment in other sectors.
- ii. **Data Availability:** Lack of data on digitalization and their direct impact on employment in the manufacturing sector is another limitation of this study.
- iii. **Scope of Technological Innovations:** The study's main attentions on digital drivers - IT investment, Advance Technology like AI, IoT, and Robotics. Non

consideration of other emerging technologies like Cloud and Blockchain are not included in the analysis due to the changing nature of digital innovations.

- iv. **Time Constraints:** There is a time constraint because huge amounts of critical qualitative and quantitative data required that needed years but given the rapidly evolving landscape of digitalization, the study captures a snapshot of the current trends and impacts at the time of research, which may change as technological advancements continue.
- v. **Sectoral Focus:** The research emphasizes certain key manufacturing sectors but may not fully address the impact of digitalization on smaller, informal manufacturing enterprises that also play a significant role in Bangladesh's economy.

These limitations are acknowledged and considered in the interpretation of the findings, which provide valuable insights into the complex relationship between digitalization and employment in Bangladesh's manufacturing industries.

1.8 Structure of the Thesis

Chapter 1: Introduction

This chapter introduces the study, highlighting the background, research problems, research questions and objectives. It emphasizes the significance of the study and its relevance to Bangladesh's manufacturing sector. The chapter also defines the scope and limitations of the research and provides a roadmap for the structure of the thesis.

Chapter 2: Literature Review

This chapter provides a comprehensive review of existing literature on digitalization in manufacturing industries, with a special focus on Bangladesh. It explores global trends, theoretical frameworks like technological change and employment dynamics, and concepts like automation, skill transformation, and economic impacts. The literature part finds and highlights research gaps and reviews the challenges and opportunities of digitalization's impact on the employment of Bangladesh's and other countries manufacturing sector.

Chapter 3: Model Development

This chapter presents the Model development process. Proposed Model integrate key components and constructs such as technological advancements, digital skills, IT investment, research & development, organizational strategy & policy, company size, and company type to analyze their direct and interaction effects on labor market changes also relevant theories like Creative Destruction Theory, Diffusion of Innovation, Labor Market Segmentation, Human capital Theory, Skill-Biased Technological Change (SBTC), and Technology Acceptance Model that provided strong foundation for the framework and hypothesis development.

Chapter 4: Research Methodology

This part explained the full process and detailed Research methodology. A mixed-methods approach, combining both Qualitative and Quantitative methods applied for comprehensive in-depth analysis of digitalization's impact on Labor Market Dynamics (LMD) in Bangladesh's manufacturing sector.

The qualitative methods include interviews, focus group discussion and opinions of industry stakeholders who shared contextual insights in the context of digitalization-driven employment shifts, challenges, and strategic responses.

The quantitative methods involve survey of structured questionnaires and then analyzed the data using Structural Equation Modeling (SEM) to test the reliability, validity of the construct also examine relationships and impacts between digitalization and employment dynamics.

Chapter 5: Qualitative Analysis

This chapter thoroughly explained the Qualitative analysis process also interpreted the results derived from qualitative analysis. Theme, perceptions and opinion collected from industry professionals, policymakers, academia and business leaders to understand the impact of digitalization on Labor Market Dynamics (LMD). In qualitative analysis, using thematic analysis, key trends, challenges. Insights from interviews and discussion that complement the qualitative findings, ensuring a deeper contextual understanding through triangulation.

Chapter 6: Quantitative Analysis

In this chapter, details of a quantitative approach explained where structured questionnaires were used to collect relevant data from various manufacturing organizations. The data were then analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the effects of digitalization, its impact on employment, and the role of firm strategies within the manufacturing sector. Statistical techniques like correlation and path-coefficient analysis are applied to test hypotheses and assess relationships between variables. The analysis draws on theoretical frameworks like creative destruction and Technology Acceptance Model to explore how digitalization influences employment and business strategies. The data analysis is conducted using software such as SPSS Statistics 26.0, and SmartPLS v.4.1.0.0 to ensure the reliability and validity of the results. The findings will provide insights into policy recommendations in the sector.

Chapter 7: Discussion and Conclusion

This chapter interprets both the quantitative and qualitative results and their findings, connecting them to the study's hypotheses, theoretical and conceptual frameworks. Quantitative analysis to reveals significant relationships between digitalization and employment outcomes in Bangladesh's manufacturing sector, with changes in firm strategies and labor market segmentation. Qualitative interviews provide deeper insights into how digital technology is perceived and implemented by industry leaders, revealing challenges such as resistance to change and skill gaps. Qualitative data also highlights the role of policy in shaping digitalization strategies. Together, these findings will give suggestions on how digitalization offers growth opportunities, there are substantial barriers to overcome, including the need for workforce training and policy support to ensure equitable outcomes.

The conclusion part synthesizes the key quantitative and qualitative findings, emphasizing the dual role of digitalization in transforming both employment patterns and firm strategies in Bangladesh's manufacturing sector. The study calls for targeted policies to support digital adoption, skill development, and inclusive growth. Future research should focus on longitudinal studies to track digitalization's evolving impact on the workforce and business

strategies. The study contributes valuable insights for both academia and policymakers aiming to leverage digitalization for sustainable development in the sector.

Chapter 8: List of Abbreviations

This chapter presents a list of key abbreviations used throughout the thesis to help readers understand the terms and concepts more easily and without confusion.

Chapter 9: References

This chapter presents a comprehensive compilation of all sources cited in the thesis, including scholarly articles, books, journals, and industry reports. It provides proper acknowledgment of the academic and professional contributions that informed and supported the research.

Chapter 10: Appendices

This chapter includes supplementary materials relevant to the study, such as research questionnaires, data collection protocols, and raw datasets. These materials provide additional context and transparency, facilitating a deeper understanding of the research methodology and supporting the validity and reproducibility of the findings.

Chapter 2: Literature Review

2.1 Introduction

This chapter presents a comprehensive in-depth review of the theoretical and empirical literature related to the digital transformation of the manufacturing sector and its effects on the employment, with a specific attention on the Bangladeshi context. The main objective of this chapter is to establish a conceptual foundation for examining how digitalization impacts on Labor Market Dynamics. Literature integrates insight from global trends with local realities, key theories and prior studies to provide a holistic perspective on the study.

In Bangladesh, the manufacturing sector—comprising key industries such as pharmaceuticals, textiles, garments, food processing, beverages, cement, ceramics, leather & footwear, consumer goods, and electronics—has historically been labor-intensive, offering vast employment opportunities for the country's growing workforce (ADB, 2021). The textile and garment industries alone are major contributors to employment and export revenues, employing millions of workers, mostly women (Rahman & Bhattacharya, 2022). However, as Bangladesh integrates more deeply into the global economy and faces increasing competition from technologically advanced nations, the pressures of global competitiveness, resource limitations, and the need for innovation are becoming critical factors for survival in the sector.

The adoption of digital technologies in manufacturing industries in Bangladesh is varied, with some firms lagging in adopting new technologies due to limitations in financial resources, managerial capabilities, and infrastructure (Rahman & Bhattacharya, 2022). This digital divide means that larger firms or those with better access to global markets are more likely to invest in and benefit from advanced technologies, while smaller firms may struggle to stay competitive. Digital transformation in manufacturing and service systems has increasingly been linked with operational excellence and workforce restructuring (Antony et al., 2025). In this context, the digital transformation of the manufacturing sector is not a uniform process, and its outcomes are likely to differ depending on firm size, industry, and access to technology.

From an employment perspective, digitalization presents a complex, dual-faceted narrative. From one dimension, it offers significant opportunities for job creation in

emerging fields such as artificial intelligence (AI), data analytics, cybersecurity, and machine learning (Autor, 2025; Bessen, 2021). Brynjolfsson and McAfee (2014) argue that digital technologies are fostering the emergence of "new kinds of work" that demand advanced cognitive and technical skills, thus expanding employment possibilities in specialized, high-tech domains. In the context of advanced manufacturing, the integration of robotics, the Internet of Things (IoT), and cyber-physical systems has led to increased demand for technicians and engineers capable of programming, operating, and maintaining such technologies (Chui et al., 2017; ILO, 2021). These evolving occupational categories, however, typically require a workforce equipped with substantial technical education and digital literacy, which remains a key challenge in developing countries like Bangladesh. Many workers in the Bangladeshi manufacturing sector—particularly in garments and textiles—possess limited formal education and have minimal access to technical or vocational training (Uddin & Islam, 2024; World Bank, 2023).

Recent ADB reports on 2022, highlighted that the risk of automation-induced unemployment is particularly acute in labor-abundant economies like Bangladesh, where a significant share of the workforce is engaged in repetitive, low-value-added tasks within the manufacturing sector (ADB, 2022). This scenario raises pressing concerns about the long-term sustainability of employment and the socioeconomic consequences of digital transitions, especially for marginalized and unskilled labor groups (ILO, 2021; Uddin & Islam, 2024).

A recent round table discussion (Daily Star, 2025) with policy makers, industry leaders with Bangladesh government, recognizing these challenges, has taken steps to address the potential negative impact of digitalization on employment. This includes promoting digital literacy and training programs aimed at reskilling the workforce for higher-skill jobs in technology and digital industries (Daily Star, 2025). These policy efforts align with institutional theories of Technology Acceptance Model and the Diffusion of Innovation Theory (Rogers, 2003). In the case of Bangladesh, these factors are influenced by institutional contexts, including government policies, organizational capacities, and the readiness of the workforce to adopt new technologies. By leveraging institutional theories of Technology Acceptance Model, labor market theories, and empirical evidence from other developing economies, this chapter lays the foundation for understanding how

digitalization will impact employment outcomes in Bangladesh’s manufacturing sector. This framework will guide the development of a conceptual model to explore the relationship between digitalization, employment, and firm strategies in the sector, providing insights into the broader implications of digital transformation for Bangladesh’s labor market

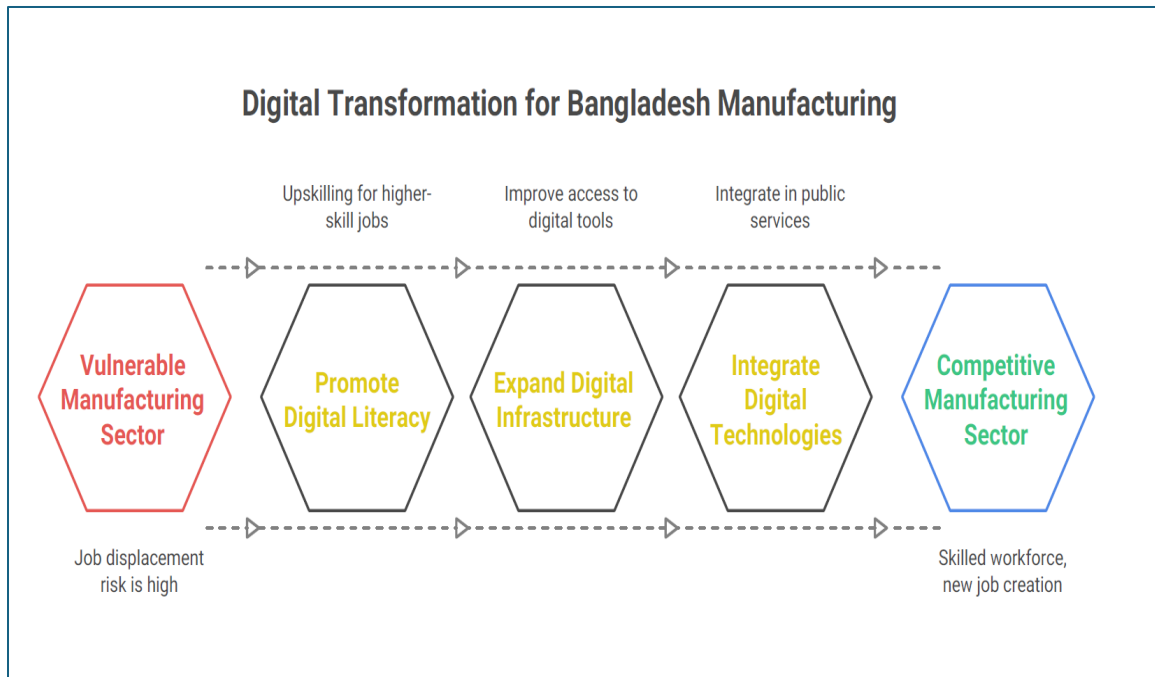


Figure 2.1: Digital transformation of the Manufacturing Industry

As presented in Figure 2.1, the digital transformation of the manufacturing industry encompasses technological integration, automation, data-driven decision-making, and process optimization within manufacturing operations. The figure provides a conceptual overview of how digital transformation influences organizational processes and employment dynamics in the manufacturing sector (Frank et al., 2019; Schwab, 2016; Brynjolfsson & McAfee, 2014). Digital transformation is widely recognized as a key driver of organizational change, affecting productivity, innovation, and employment structures (Shaji & George, 2024).

2.2 Rationale and Scope of the Literature Review

The main purpose of the literature review in this research is to critically examine existing established theories, prior studies, empirical findings, research gap, and methodological approaches related to the impact of digitalization on Labor Market Dynamics also develop

the actionable concept relevant for Bangladesh Labor Market Dynamics especially in the manufacturing industries. As Bangladesh's manufacturing sector continues to expand and grow, it becomes essential to understand how global technological transformations impact employment patterns, skill requirements, job creation, and displacement. The literature review serves to:

2.2.1 Contextualize the Research Problem

By reviewing the relevant contemporary literature on digitalization, it aims to establish a foundation for understanding how technological advancements and transformation affect employment in the manufacturing sector. Global trends such as job displacement, job alternation due to automation and AI (Brynjolfsson & McAfee, 2014, Mollah et al., 2020) identified that little research conducted in developing countries that's why there is a necessity for more research focusing specifically on the unique context of Bangladesh (Mollah et al., 2020). This part will investigate, review and discover both global and Bangladesh trends and contextualize them within Bangladesh's industrial landscape.

2.2.2 Research Gaps and Future Directions

While studies have examined digitalization and manufacturing employment, few focus on developing countries like Bangladesh. Recent evidence shows that automation and technological progress could displace hundreds of thousands of workers in textiles and apparel, particularly without skills upgrading (Uddin & Islam, 2024). At the same time, cross-country evidence shows that developing economies tend to experience stronger job-substitution effects from digital transformation compared with developed countries, highlighting the vulnerability of labor markets with high shares of routine and low-skill jobs (Zhang *et al.*, 2024). These findings suggest a persistent research gap in understanding how digital technologies affect labor markets in emerging and developing economies like Bangladesh, where challenges such as low-skilled labor and limited digital infrastructure shape unique outcomes

Despite extensive literature on the macroeconomic impacts of digitalization, sector-specific studies on how digital technologies affect employment in manufacturing remain underdeveloped in the context of developing economies like

Bangladesh. Recent empirical research finds that digital transformation tends to produce employment substitution effects across industries globally, with digital adoption associated with reduced labor demand due to productivity-driven substitution, yet detailed sectoral analyses in developing country contexts are still scarce (Uddin & Islam, 2024).

In Bangladesh, studies on the impact of Industry 4.0 and digital adoption have highlighted early challenges in SMEs and the broader labor market—including skill gaps and limited digital infrastructure—but have not fully examined how organizational attributes like firm size and type moderate employment outcomes (Ahammed, Asad, & Sakib, 2024). This gap underscores the need for focused research to understand labor market transitions and the role of firm characteristics in shaping employment dynamics amid digitalization in emerging economies.

All these analyses consolidate recent foundational research, offering a strong foundation for examining and analyzing the relationship between digitalization and employment dynamics in Bangladesh’s manufacturing sector. It establishes the strong ground for meaningful contributions to academic research, policymakers, and industry practices, with a focus on developing strategies that support a successful digital transition in developing economies like Bangladesh.

2.3 The Bibliometric Review

A preliminary bibliometric mapping using Scopus and Web of Science databases—covering approximately 70,372 journal articles and papers published between 1992 and 2024—reveals a growing body of research on digital transformation and its impact on employment, particularly within developed economies. The frequency of keywords such as “*Industry 4.0*,” “*Automation*,” “*Manufacturing*,” and “*Employment*” has increased significantly since 2018, indicating heightened scholarly interest in the subject. Much of this literature focuses on the implications of automation and digitalization for labor markets in advanced industrialized nations, emphasizing how emerging technologies are reshaping patterns of job creation, job displacement, and the demand for new workforce skills (Ashif, 2024).

General Trends of Publications:

Figure 2.2 shows the growth the trend in the publication of the articles in the fields of Digitalization and Employment, it is evident from the figure that this field has drawn a significant surge in research interest is expanding and there exists an exponential growth after 2010, in 2011 the number of publications were 192 and in 10 years it reached in top 1468, but in between 1992-2005 the publications were almost static and numbers were between 65 to 100 in every year.

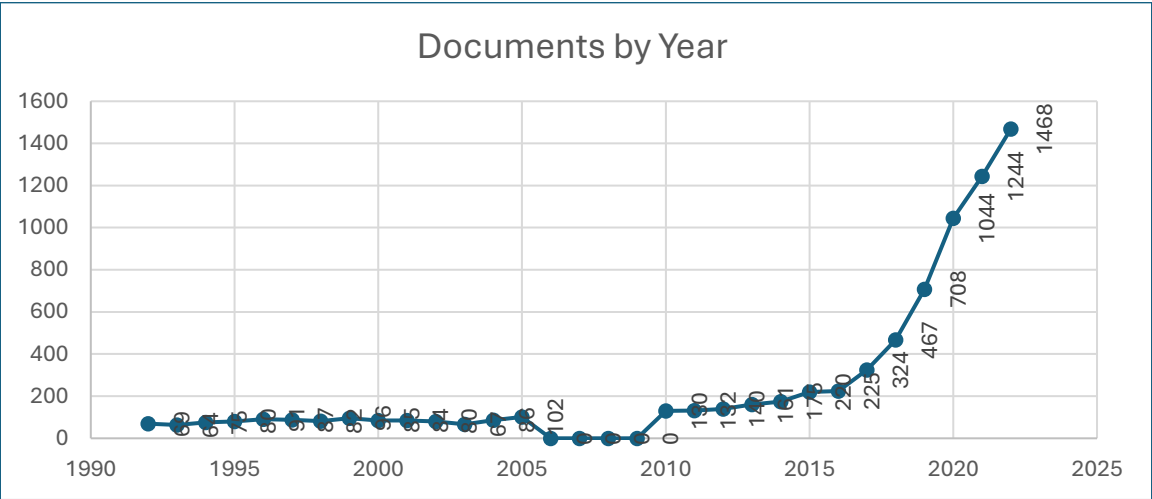


Figure 2.2: Publications by Year (1993-2024)

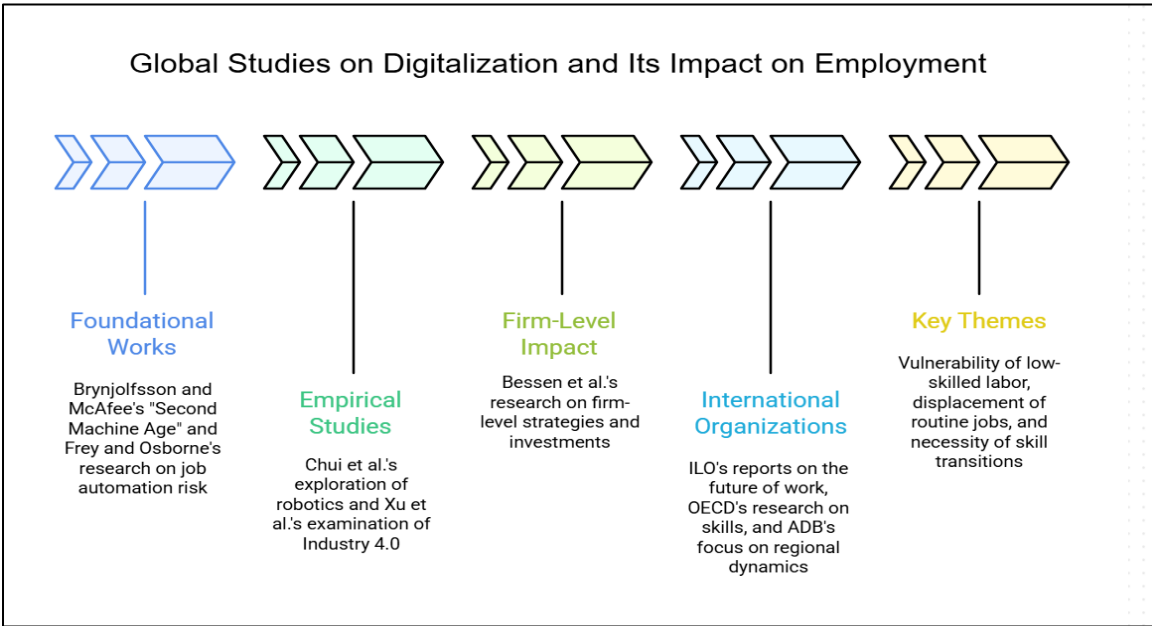


Figure 2.3: A Decade of Global Studies on Digitalization and Employment – Key Insights

Figure 2.3 A bibliometric analysis of key global studies reveals a multidimensional understanding of digitalization’s impact on employment. Foundational works such as

Brynjolfsson and McAfee's Second Machine Age and Frey & Osborne's (2017) job automation risk estimates have significantly shaped the discourse on automation and labor markets. Empirical studies by Chui et al. (2016), and Bessen et al. (2017) explore robotics, Industry Revolution 4IR, and firm-level impacts, while reports by the ILO, OECD, and ADB address regional dynamics, inequality, and policy resilience. Collectively, these studies highlight how automation affects low-skilled labor, displaces routine jobs, and necessitates skill transitions, forming the global scholarly context for investigating Bangladesh's manufacturing sector.

Top published countries:

Notably, existing research on the relationship between digitalization and employment in manufacturing has largely originated from advanced industrialized countries such as the United States, Germany, and China. This body of literature emphasizes increased automation, job displacement, and a growing demand for higher-skilled labor within manufacturing sectors, particularly in the European Union. Consequently, studies on Industry 4.0 and smart manufacturing remain concentrated in contexts characterized by high levels of digital technology adoption and well-developed infrastructure (Khouja et al., 2020).

From figure 2.4 and Figure 2.5 we can find that the literature mainly comes from developed countries such as USA, China and Europe. The data show that USA, UK, China, India has a significant influence in this area of research, followed by the Germany, Australia and Italy.

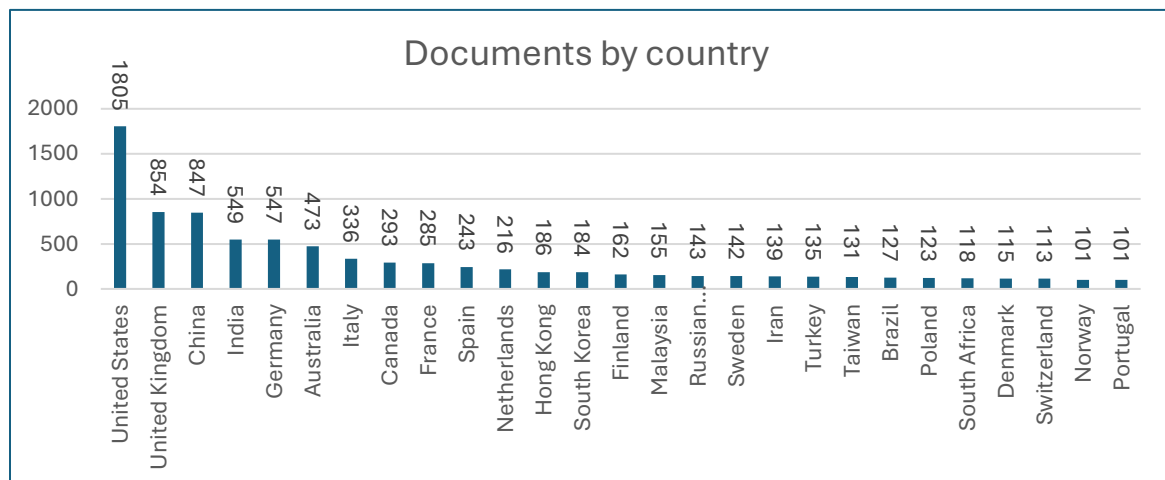


Figure 2.4: Documents by Country (1993 - 2024)

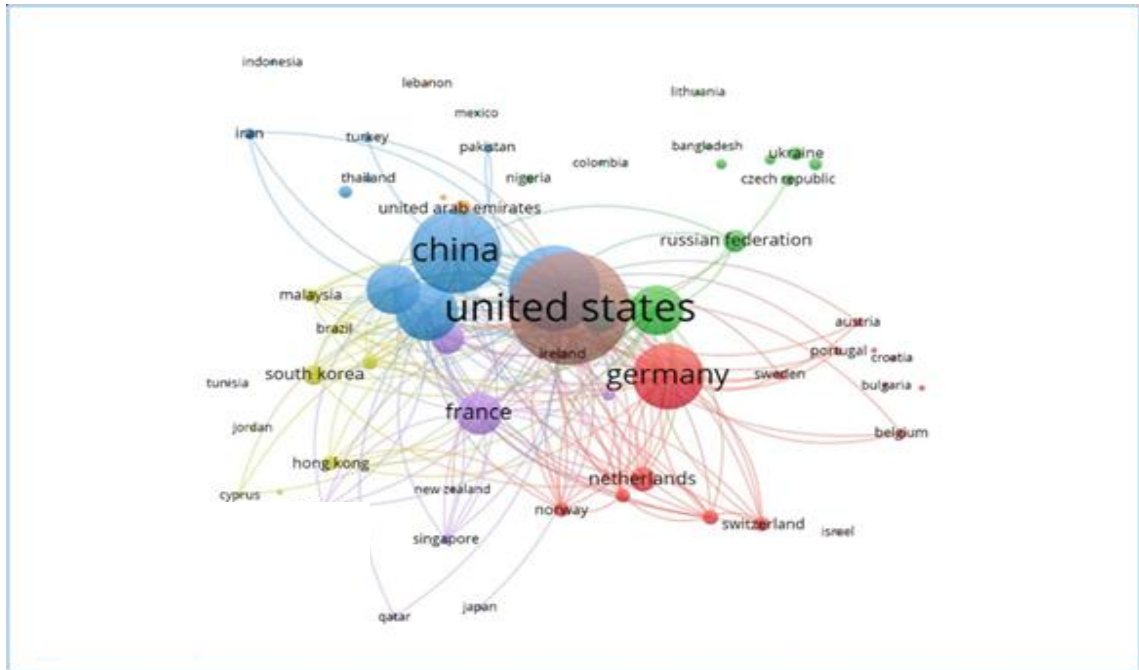


Figure 2.5: Biographic Coupling relationship – country

Figure 2.5 shows, most of the literature on the digitalization-employment connection in the manufacturing sector has been concentrated in highly industrialized countries, such as the United States, Germany, France and China highlights how the adoption of Industry 4.0 technologies in the European Union has led to higher automation, a reduction in low-skilled manufacturing jobs, and a transition toward more specialized, higher-skill employment (Khouja et al., 2020). Similarly, studies on smart manufacturing and Industry 4.0 (Xu et al., 2018; Li et al., 2020) focus on the implications of these technologies in more developed economies, where robust digital infrastructure and a highly skilled workforce are present.

The literature on the impact of Digitalization on employment in Bangladesh's manufacturing sector remains very limited. There is a huge gap in research related to South Asia, and Bangladesh in particular, that highlights the need for more context and evidence-based studies. The technological and industrial contexts of South Asian economies are distinct from those of developed nations, and digitalization's impact on employment may not align with the trends observed in high-income economies. Sarkar & Kundu (2019).

Research suggests that although Bangladesh's manufacturing sector is increasingly integrating digital technologies, there remains a significant lack of context-specific

empirical research. The existing literature highlights important gaps, emphasizing the need for more studies on the impact of digitalization on employment in developing economies such as Bangladesh. While global studies provide valuable insights, they often fail to capture the unique industrial structures and labor market dynamics of developing countries (World Bank, 2019; ILO, 2023; OECD, 2023; Autor, 2015).

This study aims to address these gaps by exploring the impact of digitalization on employment in Bangladesh’s manufacturing sector. By aligning global digital transformation trends with local industrial dynamics, this research seeks to provide a inclusive understanding of how digital technologies is reshaping the labor market in Bangladesh’s manufacturing industries. The findings of this study will provide practical guidance for policymakers, industry leaders, academia, and workers in other developing economies facing similar challenges.

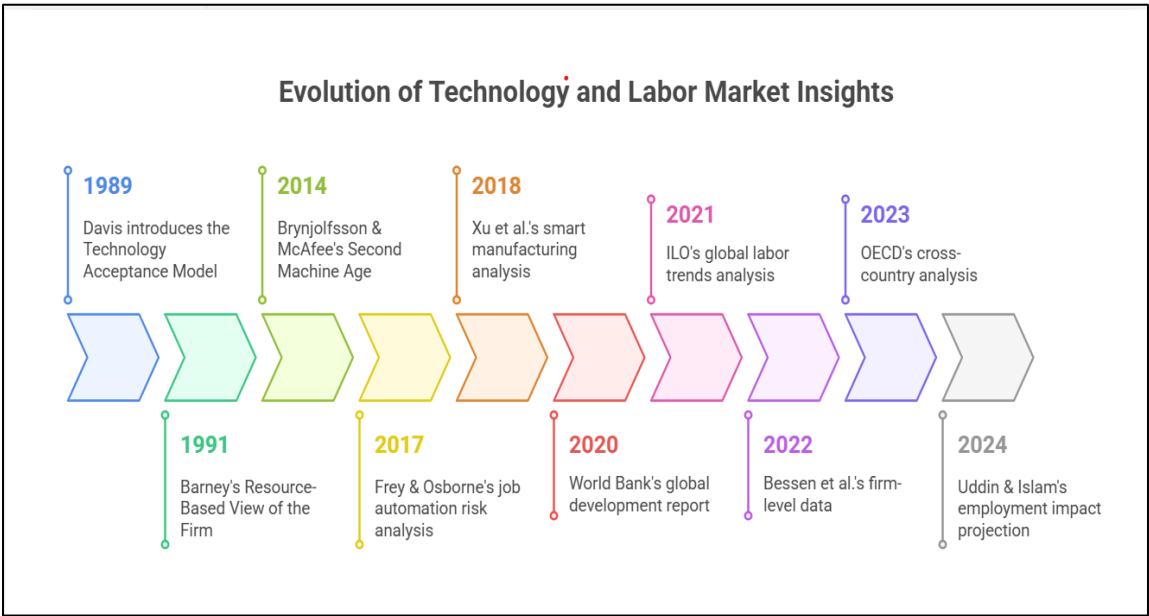


Figure 2.6: The Evolution of Digitalization and Employment: A Decade of Insight

Figure 2.6 illustrates the evolution of digitalization and employment over the past decade, highlighting the changing relationship between technological advancement, automation, workforce adaptation, and employment patterns within the manufacturing industry. The figure demonstrates how digital transformation has progressively influenced organizational operations and labor market dynamics over time (International Labour Organization, 2023; OECD, 2023; World Economic Forum, 2025).

Past and Current Studies - Evidence from Global and Bangladesh Contexts:

The literature on digitalization in manufacturing has evolved from early discussions on automation and ICT adoption to the contemporary discourse on Industry 4.0, smart manufacturing, and data-driven production systems. Earlier studies emphasized the role of information and communication technologies in improving productivity, operational efficiency, and cost reduction in manufacturing firms, laying the foundation for understanding technology-driven industrial transformation (Autor, 2015; Bessen, 2019). These studies established that technological change is strongly associated with shifts in labor demand, particularly the displacement of routine-based tasks and increased demand for higher-skilled labor (Acemoglu & Autor, 2011). More recent research extends this framework by incorporating advanced digital technologies such as artificial intelligence, Internet of Things (IoT), big data analytics, cyber-physical systems, and robotics under the industry 4.0 paradigm, highlighting their transformative impact on production systems, supply chain integration, and organizational competitiveness (Lasi et al., 2014; Kagermann et al., 2013).

In the international manufacturing context, empirical evidence suggests that digitalization significantly enhances productivity and supply chain performance while simultaneously reshaping employment structures. Studies from developed economies such as Germany, the United States, and China show that Industry 4.0 adoption improves efficiency and innovation capacity but leads to labor market polarization, where medium-skilled routine jobs decline while high-skilled technical roles expand (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018). Recent studies further emphasize that the impact of digitalization is heterogeneous across firms, depending on organizational capabilities, digital readiness, and investment capacity (Khan et al., 2024).

In developing countries, the adoption of digital manufacturing technologies remains uneven due to infrastructural constraints, limited financial resources, and skill shortages. Nevertheless, emerging evidence indicates that firms adopting digital technologies experience improvements in productivity and supply chain responsiveness, although employment effects remain mixed and context-dependent (World Bank, 2022). Studies highlight that developing economies face a dual challenge of technological upgrading and

workforce reskilling, which influences the net employment effects of digital transformation.

In the context of Bangladesh, Studies indicate that Bangladeshi manufacturing firms are gradually adopting Enterprise Resource Planning (ERP) systems, automation technologies, and digital supply chain tools to enhance operational efficiency and global competitiveness (Hossain et al., 2025; Das et al., 2025). Industry 4.0 readiness studies in the RMG sector suggest that while firms recognize the importance of digital transformation, significant barriers exist, including high implementation costs, limited technical expertise, and inadequate infrastructure (Rahman et al., 2023; Mondal et al., 2023). Furthermore, HRM digitalization studies in Bangladesh's RMG sector indicate positive effects on employee performance but also highlight concerns regarding skill mismatches and workforce adaptation challenges (Haque & Nishat, 2022). In addition, empirical projections suggest that automation may reshape employment in the manufacturing sector by reducing routine labor demand while creating new opportunities in technical and digital roles (Uddin & Islam, 2024).

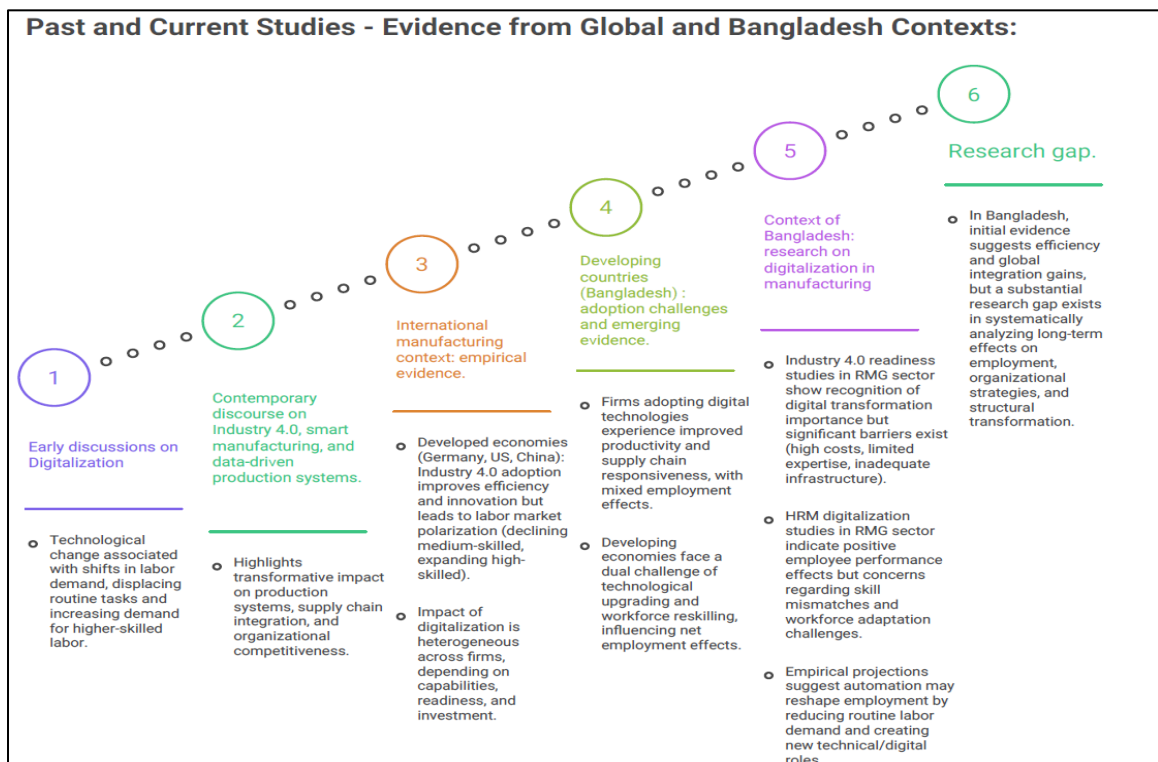


Figure 2.7: Past and Current Studies - Global and Bangladesh Contexts

Figure 2.7 shows that the literature demonstrates both global and Bangladesh-specific evidence to provide a more comprehensive understanding of digitalization's impact on manufacturing employment dynamics. Figure 2.7 also demonstrates that while global evidence highlights productivity gains alongside employment restructuring—particularly job polarization—emerging studies from Bangladesh indicate initial improvements in efficiency and global integration (*Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018; World Bank, 2022*). Nevertheless, there remains a significant research gap in systematically examining the long-term implications of digitalization on employment patterns, organizational strategies, and structural transformation in the manufacturing sector (*Bessen, 2019; Lasi et al., 2014*). This study addresses this gap by integrating global and Bangladesh-specific evidence to develop a more comprehensive understanding of digitalization's impact on manufacturing employment dynamics (*Hossain et al., 2025; Rahman et al., 2023; Das et al., 2025*).

2.4 The Systematic Literature Review

The systematic review of the literature underlines that digitalization in the manufacturing sector has weighty implications on the employment dynamics, particularly in developing economies like Bangladesh. While digital technologies bring about job displacement in low-skilled roles, they also create new opportunities in high-skilled sectors. The theory of creative destruction helps in explaining the dynamic relationship between job loss and creation, while labor market segmentation reveals the uneven distribution of digitalization's benefits. The diffusion of innovation and Technology Acceptance Model highlight the challenges and barriers that influence the rate of technology uptake, particularly in the context of Bangladesh's unique economic and infrastructural conditions. The dual fold scope of the literature presented in the study, first the study address both global and local perspectives, drawing insights from a different sectors and industries, and then focus on the implications and impact of digitalization on the employment in the manufacturing industry specially focused in developing countries like Bangladesh.

2.4.1 The Global Manufacturing Landscape

The global manufacturing sector has experienced a paradigm shift in recent decades, primarily driven by digital technologies under the umbrella of the Fourth Industrial

Revolution (4IR). Unlike earlier industrial revolutions focused on mechanization or basic automation, 4IR emphasizes the deep integration of digital and physical systems through cyber-physical systems, the Industrial Internet of Things (IoT), advanced data analytics, cloud computing, and artificial intelligence (AI)—enabling real-time data exchange, decentralized decision-making, and hyper-connectivity across value chains (Tsolakis *et al.*, 2023). These advancements have given rise to smart factories, where machinery, products, and processes communicate and adapt autonomously, greatly enhancing operational flexibility, efficiency, and responsiveness to market changes (George, A. S. 2024; Birkel & Müller, 2021). Collectively, 4IR technologies are transforming traditional manufacturing into digitally aware, interconnected ecosystems that blur the boundaries between digital and physical realms, driving productivity and innovation in ways previously unseen

Smart manufacturing, facilitated by these technologies, has redefined production processes. Recent research highlights that smart manufacturing leverages advanced digital technologies such as IoT, AI, cloud computing, and data analytics to enable predictive maintenance, mass customization, improved efficiency, reduced operational costs, and minimized human error in complex production environments (Frank et al., 2019; Lu, 2017; Xu et al., 2018; OECD, 2023).

The rise of digital platforms and interconnected systems is accelerating global production networks by streamlining cross-border logistics, enhancing supply-chain visibility, and enabling cloud-based, service-oriented manufacturing models that support distributed production and agile resource allocation (OECD, 2025). Additionally, the modern global manufacturing ecosystem is increasingly characterized by interconnectedness, digital interdependence, and innovation-driven competitiveness, as data-driven processes and cyber-physical systems create highly adaptable and networked production and supply chains worldwide (OECD, 2025).

2.4.2 Global Trends in Digitalization and Employment

This part assesses literature on global digital trends and their effects on labor markets. Recent research shows that digital technologies such as artificial intelligence (AI), automation, and robotics are profoundly reshaping employment patterns across economies. For example, Acemoglu and Restrepo (2020) demonstrate that automation can displace

workers in routine jobs while increasing demand for high-skill roles, and Autor, Mindell, and Reynolds (2020) highlight how AI and intelligent machines are transforming job structures by augmenting certain tasks and replacing others. Moreover, OECD (2023) finds that advanced digital technologies contribute to skill-biased labor market shifts and wage inequality across both developed and developing countries. These global insights provide a benchmark for comparing the potential impact of digitalization on employment in Bangladesh's manufacturing sector, particularly regarding job loss, job transformation, and new opportunities for skilled labor.

Several case studies from around the world highlight the opportunities and challenges presented by digitalization in manufacturing.

- **Germany's Industry 4.0:**

Germany's Industry 4.0 integrates cyber-physical systems, IoT, and digital technologies into manufacturing, boosting efficiency and product quality. While it creates opportunities for high-skilled workers, it also raises concerns about displacement of routine, low-skill jobs. Germany's experience demonstrates that digitalization, employee mobility, and continuous training are key drivers of labor productivity growth (Fitzenberger & Kagerl, 2025).

- **Made in China 2025 and their Relevance to Bangladesh's Manufacturing Sector**

The slogan "Made in China 2025" initiative to upgrade its manufacturing sector by promoting innovation and digital transformation. In China, the rise of dark factories has been driven by industrial policies like "Made in China 2025",

Dark factories, also known as light-out manufacturing, are fully automated production facilities that operate with minimal to no human intervention, prioritizing Digitalization, Robotics, and Artificial Intelligence. These facilities use AI-driven robots and interconnected systems to run continuously, reducing labour dependency while enhancing productivity, precision, and efficiency (Industry Analytics Inc., 2025). Companies such as Foxconn are advancing automation strategies, including talks about deploying humanoid robots in production to further reduce manual labour and boost competitive capacity, reflecting broader industrial moves toward highly automated manufacturing (Reuters; 2025). Additionally, large manufacturers like Xiaomi have implemented "dark factory" models that operate 24/7 without human

workers, showcasing how AI and robotics can transform traditional manufacturing processes (VnExpress International, 2025).

For Bangladesh's manufacturing sector, the shift toward automation presents significant employment challenges. While highly automated “smart” or dark factories enhance efficiency and reduce operational costs, they also increase the risk of job displacement, particularly for low-skilled workers, through labor-substituting technological change (Acemoglu & Restrepo, 2020; OECD, 2023; ILO, 2023). However, unlike China, Bangladesh's labor market remains heavily reliant on human-intensive production. A full-scale transition to dark factories is constrained by infrastructural limitations and the country's economic dependence on labor-driven exports (Rahman & Hossain, 2023). A hybrid automation approach—where selective digitalization enhances productivity without replacing large-scale employment—could be a more viable strategy for Bangladesh. Policymakers must focus on workforce upskilling, technology adaptation, and employment protection measures to ensure that digital transformation aligns with economic and social sustainability.

2.4.3 Global and Local Employment Trends in Manufacturing

Since last decade, almost all types of manufacturing Industries are experiencing major shifts in employment trends, influenced by technological advancements, innovation, demographic diversity, and evolving economic conditions. However, the sector faces several challenges in maintaining employment growth within rapid digitalization and evolving global demands. On one side Adoption of automation and advanced manufacturing technologies improving productivity, on other side also threatens to displace low-skilled workers. The workforce in Bangladesh's manufacturing sector remains mostly unprepared for the demands of Industry 4.0 due to limited access to training, knowledge and education on advanced technological skills. The sector also struggles with an aging workforce, poor labor conditions, and limited support policies. Economic uncertainties, such as political situation, global inflationary pressures and supply chain disruptions affect job security and employment levels. Some major challenges are highlighted below

- **Shifts in Employment Structure**

Industry 4.0, AI, IoT, Automation, Smart Technologies, and Digitalization are driving fundamental changes in employment structures within the manufacturing sector. These technologies are shifting labour demand away from routine manual tasks toward roles requiring higher technical and digital skills, reshaping job content and skill profiles (Charles & Coutts, 2021). At the same time, automation and digital transformation contribute to job displacement risks for low-skilled workers, while increasing demand for advanced technical roles, data-oriented occupations, and adaptive workforce competencies—posing significant challenges for large segments of the workforce.

- **Decline in Low-Skill Jobs**

Historically, traditional manufacturing relied heavily on low-skilled, manual labor. However, with advances in Automation, AI, Robotics, and Smart Technologies, many repetitive and routine tasks—such as assembly, packaging, and material handling—are increasingly being performed by machines, reducing the need for low-skill workers (OECD, 2023; World Bank, 2025). For example, analysis shows that industrial robots and digital technologies are displacing workers in routine production roles, even as new high-skill roles emerge, and many manufacturing jobs involving repetitive physical tasks are at particularly high risk of automation (OECD, 2023; World Bank, 2025). These shifts have led to significant job displacement among manual workers, underscoring the changing skill demands in modern manufacturing.

- **Increase in High-Skill Jobs**

While there is a decline in demand for low skill jobs on the other hand, the adoption of advanced technologies has led to a rising demand for skilled workers. As manufacturing companies transition toward Industry 4.0, the need for workers proficient in robotics programming, data analytics, and AI have soared (Frey & Osborne, 2017). These jobs are typically high-wage positions and require specialized knowledge in areas such as digital design, cybersecurity, and systems engineering (Chui et al., 2017). As a result, employment in these high-skill areas is increasing,

contributing to higher wages and more job security for workers with the required digital skills.

- **Job Polarization**

Job polarization meant a growing split in the labor market, where employment opportunities increase in high-skill, high-wage occupations and low-skill, low-wage jobs, while middle-skill positions decrease. Technological advancements and automation are key drivers of job polarization in the employment dynamics. This polarization trend has been observed in both developed and developing countries as automations replaced the routine manual and cognitive tasks that leave workers with few prospects for middle-skill employment (Autor, 2015; Arntz et al., 2016). In Bangladesh, this phenomenon is becoming evident, particularly within the manufacturing sector. A study by Uddin & Islam (2024) analyzing the impact of automation on the manufacturing sector revealed that a 15% increase in productivity due to technological advancements could lead to the elimination of approximately 688,000 jobs. If productivity were to increase by 30%, the job losses could rise to 1.22 million, and a 50% increase might result in 1.8 million job losses. The textiles and apparel sectors are expected to be the most affected, with regions like Dhaka, Chittagong, Rajshahi, and Khulna facing significant employment challenges (Uddin & Islam. 2024)

To deal with these challenges, there is a growing need for government and private sector collaboration to invest in skill development programs, enhance workplace conditions, and implement strategies for Technology Acceptance Model that prioritize inclusive employment. These measures will be crucial in ensuring sustainable employment growth in Bangladesh's manufacturing sector amidst ongoing transformations.

2.4.4 The Manufacturing Landscape in Bangladesh

Bangladesh's manufacturing sector plays a pivotal role in its economic development, contributing approximately 22% to GDP and employing over 8 million workers (BBS, 2022). The sector is predominantly labor-intensive, with the ready-made garment industry accounting for nearly 84% of the country's export earnings and providing direct employment to around 4 million individuals, predominantly women (BGMEA, 2023).

However, the sector faces several structural challenges that undermine its long-term competitiveness. These include limited technological upgrading, low productivity, skill mismatches, fragmented supply chains, and inadequate investment in research and innovation (ADB, 2024; World Bank, 2025). Most manufacturing firms, especially small and medium enterprises (SMEs), operate using traditional methods, relying heavily on low-cost labor and manual processes (Islam & Siddiqui, 2020). Furthermore, the lack of industrial diversification and value addition remains a persistent issue, making the sector vulnerable to global market shocks and shifts in buyer preferences (Jerin, Jantan, & Hamid, 2024)

2.4.5 Digitalization in Bangladesh's Manufacturing Sector: Trends and Gaps

Despite the global push toward digital transformation, the adoption of digital technologies in Bangladesh's manufacturing sector remains limited and uneven. While larger, export-oriented firms—particularly in the RMG and pharmaceutical sectors—have begun integrating technologies such as Enterprise Resource Planning (ERP), automated cutting machines, and supply chain management systems, many SMEs lack both the financial capacity and technical know-how for digital adoption (Rahman & Bhattacharya, 2022; Mollah et al., 2020).

Government initiatives such as Digital Bangladesh Vision 2021 and Perspective Plan 2041 emphasize the importance of industrial automation, skill development, and the establishment of digital infrastructure (Planning Commission, 2021). However, there remains a significant policy gap in ensuring inclusive digital transformation, particularly for marginalized firms and low-skilled workers (Daily Star, 2025; CPD, 2023). Studies have noted considerable disparities in digital readiness among firms based on size, ownership structure, export orientation, and managerial perception of technology (Hossain & Rahman, 2023; Uddin & Islam, 2024).

2.4.6 Digitalization and Employment: A Dual-Edged Dynamic

The employment implications of digitalization in Bangladesh's manufacturing sector are context-dependent and shaped by structural, institutional, and technological variables. While automation has yet to lead to widespread job displacement, early signs of skill-biased technological change are emerging, especially in larger firms that are gradually

shifting towards high-skill, IT-intensive roles in quality control, inventory management, and design (ILO, 2021).

Research indicates that there is a growing mismatch between existing labor force capabilities and the skill requirements of digitalized production systems (Klein & Qureshi, 2021; BIDA, 2023). Without strategic investment in upskilling and reskilling programs, digitalization may exacerbate social inequalities, particularly affecting women and low-educated workers who dominate labor-intensive manufacturing (Sarkar & Kundu, 2019).

2.4.7 Digitalization and Employment: Emerging Patterns and Policy Implications

While the benefits of digitalization in enhancing productivity and economic output are well-established, its implications for employment remain complex and often contradictory. On the positive side, digital transformation drives innovation and the creation of new roles in areas such as digital design, data analytics, AI integration, and systems maintenance—roles that demand higher cognitive and non-routine skills and often offer higher wages (OECD, 2023; World Bank, 2025). These advancements restructure traditional job functions and contribute to entirely new occupations within a knowledge-based economy. Conversely, automation and artificial intelligence pose risks to routine, low- and middle-skill jobs—particularly in sectors like manufacturing, logistics, and administrative services—by substituting tasks previously performed by human workers (OECD, 2023; World Bank, 2025). The evidence also points to patterns of labour market polarization, where middle-skill jobs decline while high- and certain low-skill jobs persist or grow, reshaping employment landscapes in both developed and emerging economies.

Moreover, the impact of digitalization on employment is mediated by several contextual variables, including institutional capacity, labor market regulation, education systems, and organizational strategies (ILO, 2019; Bessen, 2020). This duality highlights the need for a nuanced understanding of how Technology Acceptance Model affects different labor segments across countries and industries.

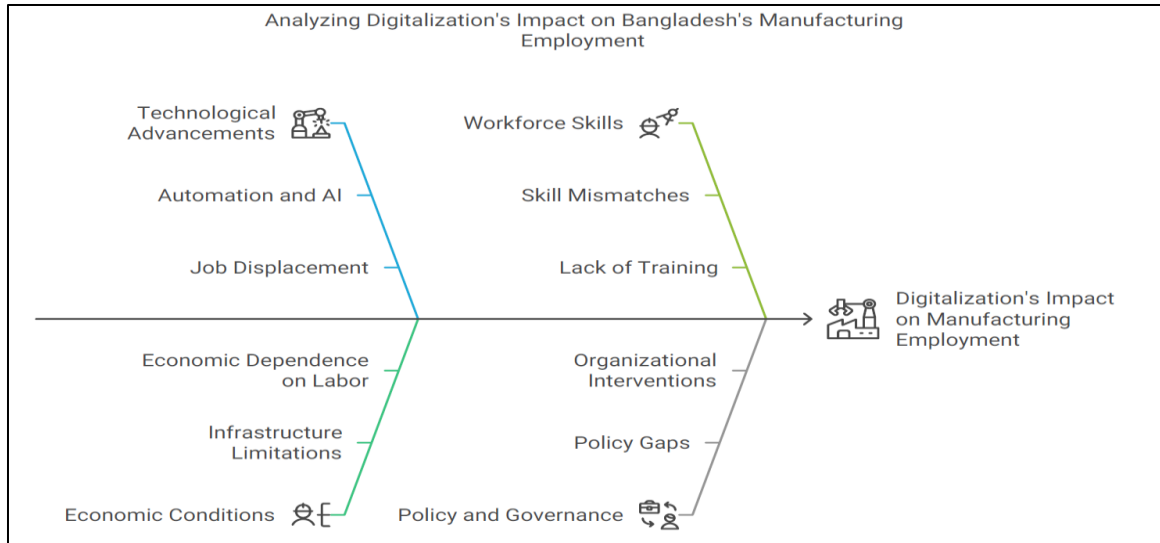


Figure 2.8: Digitalization's Impact on Bangladesh Manufacturing Employment

Figure 2.8 illustrates the impact of digitalization on employment in Bangladesh's manufacturing sector, highlighting the effects of automation, technological adoption, changing skill requirements, and workforce transformation. The figure demonstrates how digitalization influences employment patterns through both job displacement and job creation mechanisms, thereby reshaping labor demand and organizational practices within the manufacturing industry (Uddin & Islam, 2024; OECD, 2023; World Economic Forum, 2025).

2.5 Challenges

The quick and rapid adoption of digital technologies in manufacturing industries intensely reshaping the dynamics of workforce all over the world and Bangladesh is not exception of this trend. Advance technology offers greater productivity, efficient process, and global competitiveness, they also present complex challenges in managing the transition of the existing workforce. This section highlights the structural challenges and policy-related barriers that constrain the labor force's ability to adapt to digital transformation in Bangladesh's manufacturing sector.

2.5.1 *Structural Challenges: Skills, Inequality, and Policy Gaps*

Bangladesh currently faces a significant challenge arising from digitalization: the widening mismatch between the skills available in the labor market and those demanded by modern industries. As technologies such as Artificial Intelligence (AI),

Robotics, and the Internet of Things (IoT) become embedded in production processes, the demand for digitally competent workers has risen sharply. Yet a large share of the workforce lacks both foundational and technical skills required to operate and sustain these systems, placing young and moderately educated workers at risk of displacement (World Bank, 2025; The Daily Star, 2025).

Bangladesh's education and vocational training systems remain largely traditional, focusing on basic computer literacy and rote learning rather than industry-relevant, hands-on training. Recent assessments show that vocational programmers still emphasize basic MS Office skills, leaving many graduates poorly prepared for digital and technology-intensive roles (The Daily Star, 2025; The Business Standard, 2025). Strengthening partnerships among educational institutions, industry stakeholders, and government agencies is critical to ensure that training programmers are responsive to evolving labor market needs and that curricula align with current and future industrial requirements. The Business Standard (2025)

2.5.2 Labor Market Polarization and Economic Inequality

Recent evidence shows that high-skill workers with advanced technical expertise, problem-solving abilities, and adaptability to digital systems generally benefit more from digital transformation, gaining better employment prospects and wage premiums. In contrast, workers without these qualifications face greater risks of displacement, stagnant wages, or exclusion from formal labour markets, contributing to widening inequality (Marguerit, 2025; World Bank, 2025). Studies on job polarization find that increased automation and AI adoption tend to substitute routine and middle-skill tasks while expanding demand for high-skill roles, leading to asymmetric labour market outcomes and reinforcing wage disparities across skill levels. In developing economies, the uneven distribution of digital skills and access also amplifies these polarization effects, making inequality and labor market segmentation more pronounced (World Bank, 2025).

In Bangladesh, Manufacturing has traditionally relied on low-skilled labor that also poses the risks of labor market polarization. As demand grows for digitally skilled professionals, low-skilled workers may become increasingly narrowed to hazardous,

low-wage, or informal employment, with limited opportunities for upward mobility. This trajectory risks deepening income inequality and exacerbating socio-economic divides. To mitigate these risks, proactive policies are essential. Targeted upskilling and reskilling initiatives, combined with accessible lifelong learning opportunities, can help workers adapt to new realities. At the same time, stronger social protection mechanisms are needed to safeguard vulnerable groups and facilitate their integration into the digital economy. Without such interventions, digitalization could reinforce structural inequalities instead of driving inclusive growth.

2.5.3 Inadequate Policy Frameworks and Institutional Readiness

Bangladesh faces limited policy and institutional readiness to manage the impacts of AI, robotics, and Industry 4.0 on employment. Regulatory frameworks, labor laws, and digital strategies are often outdated, while digital skills and infrastructure gaps constrain workforce adaptation. Strengthening reskilling programs, lifelong learning, fiscal incentives for digital investment, and social safety nets, alongside robust labor market intelligence systems, is critical to align education and training with evolving industrial needs (World Bank, 2025; The Daily Star, 2025).

Emerging technologies such as AI, Robotics, and Industry 4.0 tools demand a policy environment that is both agile and anticipatory. This includes promoting reskilling and lifelong learning initiatives, providing fiscal incentives for digital infrastructure investment, and strengthening social safety nets for workers displaced by automation—approaches highlighted as essential in global digital policy discussions (World Bank, 2025). In Bangladesh, development of labour market intelligence systems and data-driven skills forecasting platforms (e.g., UNESCO AI Readiness frameworks and national workforce analytics) is also crucial to align education, training, and industry needs for future employment trends (Bangladesh digital transformation roadmap, 2025)

2.6 Synthesizing the Literature: Bangladesh Context

Bangladesh's manufacturing sector has recently been characterized by a growing need for digitalization, automation, and innovation to enhance productivity and competitiveness. However, the sector faces significant challenges, including limited access to advanced technologies, inadequate infrastructure, and a workforce that is predominantly low-skilled

and non-technical. This study critically reviews existing literature to identify the key challenges and opportunities associated with digital transformation in Bangladesh's manufacturing industries (Hossain & Karim, 2023). Drawing on these insights, the study provides evidence-based recommendations for developing effective industrial policies and strategic guidelines for industry leaders, policymakers, and academic institutions. These recommendations emphasize the design and implementation of comprehensive workforce training programs and clarify the roles of government, industry stakeholders, and educational institutions in facilitating and supporting the adoption of digital technologies. By integrating these perspectives, the study aims to inform strategies that promote sustainable, inclusive, and efficient digital transformation, addressing both skill development and organizational readiness within the sector.

- **Labor-Intensive Manufacturing**

While Bangladesh has capitalized on its low-wage workforce, particularly in the garment industry, the digital transformation of manufacturing presents a paradox. As automation technologies such as Robotics and AI become more prevalent, the labor-intensive nature of Bangladesh's manufacturing sector may face disruption. The workforce, predominantly low-skilled, may struggle to adapt to the technological demands of a digitalized manufacturing environment (Bari et al., 2021). The gap in digital skills could exacerbate unemployment, especially for those workers engaged in routine, manual tasks that are prone to automation (Rahman & Islam, 2021).

- **Challenges in Automation**

Despite its lots of potentiality, Bangladesh's manufacturing sector lags in adopting automation technologies. In Bangladesh, high initial costs, limited technological know-how, and a shortage of skilled workers are the main obstacle to impede widespread automation adoption (Amin et al., 2020). Moreover, the country's infrastructure and socioeconomic factors especially in rural areas—remains underdeveloped, limiting the access of advanced digital technologies (Rahman & Islam, 2020). These factors exhibit challenges for Bangladesh's ability to adopt technology to compete in an increasingly digital global market.

- **Demographics and Employment**

Diversified multicultural population, with over 160 million people. The country's workforce is historically and traditionally employed in the agriculture and SEM sector, (BBS, 2020). However, most workers in the manufacturing sector are low-skilled and work in informal settings. Digitalization poses a threat to these workers as automation technologies may replace them, especially in the more labor-intensive industries such as textiles and garments (Hasan, 2021).

- **Skills Gap and Education**

For long time Bangladesh's educational system has been complained about not aligning with contemporary needs, specifically in terms of digital and technical skills. Primary, secondary and tertiary educations have been slow to integrate digital literacy into their curricula, leaving the workforce unprepared for the digital transformation of industries (Rahman & Islam, 2020). The government and private sector must rethink and upgrade the educational systems to ensure that the workforce is trained to handle the demands of a digitalized manufacturing sector (Khan et al., 2021).

- **Gender Disparities**

The gender dynamics in Bangladesh's manufacturing sector further complicate the digitalization process. The garment industry, which employs a large proportion of women, is heavily dependent on manual labor on the other manufacturing industry the female presences are negligible. As digitalization progresses, the risk of job displacement may disproportionately affect female workers, exacerbating gender inequalities in employment (Bari et al., 2021). Digital training and opportunities will be essential for a more inclusive digital transformation.

- **Digital Infrastructure**

Digital infrastructure like mobile phone penetration, access to high-speed internet and modern technology are critical for the adoption of advanced manufacturing technologies. Modern technological solutions remain limited, particularly in rural areas (Rahman & Islam, 2020). For the manufacturing sector to benefit from digitalization, there must be substantial investments in digital infrastructure, including internet connectivity, cloud computing, and IoT (Rahman & Islam,

2020). Without such development the full potential of digitalization cannot be realized.

- **Investment in Research and Development (R&D)**

Bangladesh's manufacturing sector has traditionally short of investing in R&D framework, relying more on low-cost labor than on technological innovation (Bari et al., 2021). To remain competitive in the global market, Bangladesh must invest R&D, particularly in emerging areas like AI, robotics, and smart manufacturing, will be crucial to drive the digitalization process (Rahman et al., 2021).

- **Public-Private Partnerships (PPP)**

Collaboration among the government, private enterprises, and academia are crucial to dealing with the challenges posed by digitalization. Public policies need to be aligned with industry requirements for successful progression towards digitalization (Amin et al., 2020). All sectors should play a proactive role in adopting new technologies and creating innovative solutions. Strong collaboration between these sectors can create a conducive ecosystem for the growth of digital technologies and innovation in manufacturing (Hasan, 2021).

- **Impact on Low-Skilled Workers**

Digitalization poses the Job vulnerability for low-skilled workers in Bangladesh's manufacturing sector, mainly in roles that involve repetitive manual tasks (Bari et al., 2021). To mitigate this, vocational training and reskilling programs are essential. The government, industry leaders, all concerned stakeholders must take proper initiative to help workers to get technical knowledge and digital skill so that they can adopt, adjust and explores with this transformation (Rahman & Islam, 2020).

- **Government Policies**

Policies that focus on digital literacy, support technology adoption, and incentives for automation can help the sector modernize while minimizing adverse employment outcomes. Proper policy and government initiatives may ensure the safeguard of displaced workers by automation with safety nets and access to reskilling programs (Khan et al., 2021).

- **Inclusive Digitalization**

Skill gaps, polarization, and wide discrimination happen because most of the policies, actions and initiatives focused towards to urban centers, big businesses and the rich communities. The benefits of digitalization should not be concentrated and focus only on urban centers or among high-skilled workers, there must be revised inclusive efforts must be made to ensure that rural populations and low-skilled workers are also included in the digitalization process. (Amin et al., 2020).

Contextualizing and empirical study on Bangladesh helped to understand how different factors and elements interact that are crucial for identifying effective strategies that can maximize the benefits of digitalization and mitigate its potential negative impacts on employment in Bangladesh's manufacturing sector.

2.7 Theoretical and Policy Synthesis

To structure the review systematically, the existing literature is organized into four major thematic areas: global studies on digitalization and employment, Bangladesh-focused studies, key theoretical frameworks guiding technology adoption and labor market changes, and emerging policy implications. This thematic review and analysis enable a comprehensive synthesis of insights from advanced and developing economies, highlights critical research gaps, and establishes a robust foundation for the conceptual model and hypothesis development presented in subsequent chapters.

2.7.1 Global Studies on Digitalization and Employment

To contextualize the global transformation in the manufacturing sector, a review of prominent studies on digitalization and its impact on labor markets is presented. These studies, primarily conducted in advanced economies, highlight the dynamics of automation, skill-biased technological change, and employment restructuring. Table 2.1 summarizes the major global research contributions that form the backdrop for understanding how similar forces may affect developing economies like Bangladesh.

Author(s)/ References	Methodology	Main Findings	Important Components
Brynjolfsson & McAfee (2014)	Conceptual/ Review	Automation displaces routine jobs; creates demand for high-skill tech jobs.	Second Machine Age, Digitalization Effects
Chui et al. (2017)	Conceptual/ Empirical (Case Studies)	Robotics and automation replace repetitive labor, increasing the need for technical skills.	Robotics, Automation in Manufacturing
Frey & Osborne (2017)	Quantitative Analysis (Job Automation Risk)	Manufacturing jobs are highly susceptible to automation; routine tasks at high risk.	Automation Risk, Labor Displacement
Xu et al. (2018); Li et al. (2020)	Empirical (Smart Manufacturing Analysis)	Industry 4.0 drives skill-biased employment changes in developed nations.	Industry 4.0, Smart Manufacturing
Khouja et al. (2020)	Empirical Study (EU)	Adoption of digital tech leads to displacement of low-skilled workers, more high-skill jobs.	EU Industry 4.0, Employment Shifts

Author(s)/ References	Methodology	Main Findings	Important Components
World Bank (2020)	Global Development Report	Automation to heavily impact low-skilled jobs in developing countries.	Global Automation Risk, Inequality
ILO (2021)	Global Labor Trends Analysis	AI and automation exacerbate inequality unless social protections and training improve.	Labor Market Inequality, Skills Investment
Acemoglu & Restrepo (2021)	Econometric Modeling	Automation linked to decreased employment and wage shares for low-education workers.	Displacement Effect, Inequality
ILO & ADB (2021)	Regional Report (Asia-Pacific)	Southeast Asia faces skill gaps, but automation also opens up regional outsourcing and tech jobs.	Reskilling, Tech Job Creation
Bughin et al. (2021)	Forecast Modeling	Automation is likely to impact routine-intensive sectors first; proactive workforce planning essential.	Routine Work, Transition Management
Bessen et al. (2022)	Longitudinal Firm-Level Data	Automation complements some tasks while displacing others; net employment depends on firm response.	Task Substitution, Firm Strategy
OECD (2023)	Cross-Country Analysis	Countries with stronger vocational education systems face less labor disruption from digitalization.	TVET Systems, Labor Resilience
Manyika et al. (2023)	McKinsey Global Institute Study	By 2030, 375 million workers may need to switch jobs due to AI and digital disruption.	Job Transitions, Future of Work

Table 2.1: Summary of Global Studies on Digitalization and Employment

Table 2.1 summarizes key global studies highlighting the impact of digitalization on employment.

2.7.2 Bangladesh-Focused Studies

While global trends provide essential benchmarks, the realities of digitalization in Bangladesh's manufacturing sector diverge significantly due to structural, economic, and institutional factors. Table 2.2 consolidates key empirical studies focusing specifically on Bangladesh, offering insights into the country's digital readiness, skill mismatches, and vulnerabilities within the labor market.

Author(s)/ References	Methodology	Main Findings	Important Components
Ahmed & Sultana (2018)	Survey on Industrial Workers	Limited awareness of digital tools among workers in medium-scale enterprises.	Digital Literacy, Awareness Barriers
Sarkar & Kundu (2019)	Survey Research	Digital adoption faces training gaps, infrastructure deficits.	Tech Adoption Barriers, Skill Gaps
Mollah et al. (2020)	Case Study (Bangladesh Manufacturing)	Early digitalization hindered by financial, skills, and technological gaps.	Digital Divide, Early-stage Adoption
Khan & Mollah (2020)	Empirical (Survey on Skills)	Major mismatch between worker skills and digital job demands.	Workforce Digital Skills Gap
World Bank (2020)	Macro-level Analysis	Bangladesh risks job polarization due to automation and uneven digital integration.	Structural Change, Automation Risks
ITU (2021)	Global ICT Index Analysis	Bangladesh ranked low in ICT infrastructure and digital skills development.	ICT Development Index, Global Benchmark
Islam et al. (2021)	Mixed Methods (Field Interviews + Firm-level Data)	Digital technology adoption is limited by resistance to change and lack of top-level commitment.	Organizational Readiness, Leadership Resistance
Chowdhury & Mahmud (2022)	Policy Analysis	Industrial policy does not sufficiently align with the needs of digital transformation.	Policy-Industry Misalignment
Rahman & Bhattacharya (2022)	Sector Review	Larger firms are more likely to adopt tech, SMEs lagging.	Firm Size and Digital Adoption
Hossain & Rahman (2023)	Survey	Readiness for digital adoption uneven across manufacturing.	Digital Readiness Disparities
Hasan & Karim (2023)	Sectoral Comparative Study	RMG and textile industries face unique automation challenges due to labor dependency.	Sector-specific Vulnerabilities
Uddin & Islam (2024)	Quantitative (Employment Impact Projection)	Productivity gains could result in 1.8 million job losses in manufacturing.	Job Loss Risk, RMG Sector Threats
Daily Star (2025)	Policy Review	Govt. initiatives for digital literacy, upskilling, and infrastructure growth.	Digital Bangladesh Vision, Policy Programs

Table 2.2: Summary of Bangladesh-Focused Studies

Table 2.2 presents key Bangladesh-focused studies examining digitalization and its implications for employment, skills, and industrial transformation in the manufacturing sector.

2.7.3 Theoretical Models Applied

The exploration of digitalization's employment effects is anchored in several well-established theoretical frameworks. These models help explain how firms and workers respond to technological change and provide a structured lens through which to interpret empirical findings. Table 2.3 outlines the primary theories and models guiding this study's conceptual framework

Author(s)/References	Theory	Main Findings	Important Components	Relevance to This Study	Implications
Schumpeter (1942)	Creative Destruction Theory	Economic development is driven by creative destruction, where new technologies and innovations replace outdated systems, leading to structural transformation in industries and employment.	Innovation-driven disruption, Replacement of old industries, Dynamic capitalist evolution, Employment shifts due to technology	Explains how digitalization disrupts traditional manufacturing practices in Bangladesh, creating new opportunities while displacing certain job categories.	Firms should anticipate structural changes, invest in innovation, and design strategies for workforce transition to mitigate job displacement.
Doeringer & Piore (1971)	Labor Market Segmentation Theory (LMST)	Labor markets split into stable (primary) vs. unstable (secondary) sectors, leading to unequal employment opportunities and segmented workforce outcomes.	Labor Market Dualism, Primary vs. Secondary Segments	Helps analyze how digitalization widens gaps between secure skilled jobs and insecure unskilled roles in Bangladesh's manufacturing sector.	Policymakers should design inclusive labor policies; firms should develop programs for skill enhancement to reduce workforce inequality.
Davis (1989)	Technology Acceptance Model (TAM)	Technology acceptance is driven by perceived ease of use and perceived usefulness, influencing adoption behavior.	Technology Adoption Intentions, Innovation Diffusion Factors	Provides a framework to understand how managers and employees in Bangladeshi manufacturing adopt or resist digital technologies.	Training programs and awareness campaigns can increase perceived usefulness and ease of use, facilitating smoother technology adoption.

Author(s)/ References	Theory	Main Findings	Important Components	Relevance to This Study	Implications
Rogers (2003)	Diffusion of Innovation (DOI) Theory	Adoption of innovation depends on perceived benefits, compatibility with existing systems, complexity, trialability, and observability.	Relative Advantage, Compatibility, Complexity	Useful to study how digital tools spread across manufacturing firms in Bangladesh, highlighting adoption barriers and enablers.	Firms should focus on compatibility, demonstration projects, and trial opportunities to accelerate technology diffusion and reduce resistance.
Becker (1964)	Human Capital Theory	Investment in education, training, and skills enhances worker productivity, employability, and adaptability in changing labor markets.	Education & Training, Skill Development, Productivity Enhancement, Workforce Adaptability	Explains the importance of upskilling and reskilling workers to cope with digital transformation in manufacturing employment.	Policymakers and firms should prioritize continuous training and skill development programs to maintain workforce competitiveness.
Autor, Katz & Krueger (1998); Acemoglu (2002)	Skill-Biased Technological Change (SBTC) Model	Technological progress disproportionately increases demand for skilled labor, leading to wage inequality and polarization in labor markets.	- Demand for Skilled vs. Unskilled Labor, Wage Inequality, Labor Market Polarization, Technology-Skill Complementarity	Explains how digitalization in Bangladesh's manufacturing creates higher demand for digitally skilled workers, while low-skilled workers face job displacement.	Firms should implement targeted recruitment, upskilling, and retention strategies for skilled workers; governments should consider retraining programs to prevent labor market polarization.

Table 2.3: Summary of Theoretical Models Applied

Table 2.3 summarizes the key theoretical models applied in this study, drawing from established literature to explain the relationship between digitalization, technological change, and employment dynamics in the manufacturing sector (Schumpeter, 1942; Nelson & Phelps, 1966; Becker, 1964; Cirera et al., 2021).

2.7.4 Policy Implications and Gaps

As digital transformation advances, managing its labor market implications requires thoughtful and proactive policy responses. Table 2.4 highlights key policy directions and institutional efforts recommended in the literature, especially those pertinent to developing economies like Bangladesh, where workforce vulnerabilities are pronounced.

Author(s)/References	Methodology	Main Findings	Important Components
McKinsey Global Institute (2019)	Global Labor Market Study	Digital jobs are growing but unevenly distributed; need for adaptive labor laws.	Future of Work and Labor Law Reforms
CPD (2020)	National Policy Analysis	Weak industrial policy coherence: informal sector left out of digitization plans	Formalization and Industrial Policy Integration
Planning Commission (2021)	Policy Documents	Vision 2041 outlines digital manufacturing but lacks SME focus	Digital Bangladesh Plans
ILO (2021)	Global Policy Report	Bangladesh must urgently align training programs with Industry 4.0 skills	Workforce Reskilling Strategies
ADB (2021)	Regional Policy Brief	Digital divide threatens equitable growth; calls for targeted upskilling for women	Inclusive Digital Growth Strategies
ITU (2021)	ICT Development Index Report	Bangladesh ranks low in ICT access and skills readiness	ICT Infrastructure & Skills Gap
UNCTAD (2021)	Global Digital Economy Report	Developing countries lag in digital governance, infrastructure, and taxation	Regulatory Frameworks for Digital Economy
World Bank (2022)	Country Diagnostic Report	Limited digital skills among labor force; weak links between education and industry	Human Capital Development, TVET modernization
BIDA (2023)	National Investment Guidelines	Digital investment is critical but missing inclusive strategies	Investment in Digital Infrastructure
Rahman & Sattar (2023)	Empirical Study (Bangladesh)	Automation affecting garment workers; need for sector-specific digital strategy	Sector-Specific Workforce Strategies
Daily Star (2025)	Policy Review	Need for reskilling, social protection programs, digital literacy campaigns	Policy Interventions for Digital Inclusion

Table 2.4: Summary of Policy Implications and Gaps

Table 2.4 summarizes the key policy implications and research gaps in the literature on digitalization and employment in manufacturing, highlighting that while digital transformation enhances productivity and competitiveness, it also creates challenges related to skills mismatch, labor displacement, and policy readiness in developing economies such as Bangladesh

Conclusion

The review of the literature, organized across four thematic areas, provides a comprehensive understanding of digitalization's impact on employment within the manufacturing sector. Global studies emphasize how automation, Industry 4.0 technologies, and smart manufacturing practices are reshaping labor markets, displacing routine manual jobs while creating demand for highly skilled technical roles. These trends establish a global benchmark for understanding the broader impacts of technological disruption on employment structures.

Bangladesh-specific studies reveal a contrasting landscape, where limited digital infrastructure, skill mismatches, and heavy reliance on low-cost, labor-intensive production models slow down the pace and inclusiveness of digital transformation. The digital divide across firms based on size, sector, and resource access further exacerbates vulnerabilities among low-skilled workers.

The theoretical frameworks reviewed—particularly the Creative Destruction Theory, Diffusion of Innovation Theory, Technology Acceptance Model, Labor Market Segmentation Theory, and Task-Based Model of Technological Change—provide robust explanations for the differential adoption of digital technologies and their uneven impacts on employment. These theories highlight that Technology Acceptance Model is not merely a technical issue but is deeply embedded within organizational, institutional, and socio-economic contexts.

Finally, the emerging policy literature underscores the urgent need for coordinated interventions focusing on workforce reskilling, digital literacy, inclusive infrastructure development, and institutional readiness. Without targeted and proactive measures, digitalization risks amplifying socio-economic inequalities, particularly in labor-intensive economies like Bangladesh. Collectively, these insights establish a strong conceptual foundation for developing the research model and hypotheses that explore the specific mechanisms through which digitalization impacts employment dynamics in Bangladesh's manufacturing industries.

Chapter 3: Theoretical Framework and Model Development

3.1 Introduction

This study draws upon multiple theoretical perspectives to develop a comprehensive framework for examining the impact of digitalization on employment in the manufacturing industries, with a particular focus on Bangladesh. Theoretical approaches such as Creative Destruction Theory, Labor Market Segmentation Theory (LMST), the Skill-Biased Technological Change (SBTC) Model, the Technology Acceptance Model (TAM), the Diffusion of Innovation (DOI) Theory, and the Human Capital Theory (HCT) provide a foundation for analyzing the complex and multifaceted interactions between technological advancements, organizational strategies, policy interventions, and labor market outcomes. The proposed conceptual model incorporates key variables including technological advancements, IT investments, digital skills, strategic organizational responses, and policy interventions, all within the broader context of digital transformation in manufacturing. The model also considers how organizational characteristics—specifically firm size and type of organization—mediate and shape the employment effects of digitalization by influencing production processes, managerial practices, and skill requirements. By integrating these factors, the framework not only grounds the hypotheses of this study but also offers a structured basis for empirical investigation into how digital transformation is reshaping employment patterns in Bangladesh's manufacturing sector.

3.2 Theoretical Foundations and Conceptual Framework

This research is anchored in a set of complementary theoretical frameworks that collectively explain how digitalization influences employment outcomes, Labor Market Dynamics, and organizational strategies within the manufacturing context. The theories employed include the Creative Destruction Theory, Labor Market Segmentation Theory (LMST), the Skill-Biased Technological Change (SBTC) Model, the Technology Acceptance Model (TAM), the Diffusion of Innovation (DOI) Theory, and the Human Capital Theory (HCT).

Each of these frameworks contributes a distinct perspective:

- ***Creative Destruction*** explains the disruptive yet regenerative nature of technological innovation.
- ***Labor Market Segmentation*** highlights inequalities and divides in access to labor opportunities.
- ***SBTC*** emphasizes the tendency of digitalization to favor skilled over unskilled labor.
- ***TAM and DoI*** illuminate how individuals and organizations adopt and adapt to new technologies.
- ***HCT*** underscores the role of education, training, and skills in determining labor market adaptability.

All these perspectives underpin the conceptual model of this study, which examines how the drivers of digitalization—Technological Advancement (TA), Digital Skills (DS), IT Investment (ITI), Research & Development (R&D), and Strategy and Policy (SP)—affect Labor Market Dynamics (LMD). Moderating factors such as firm Size (SZ) and organizational Type (TY) are incorporated to capture contextual variations within Bangladesh’s manufacturing sector. The framework developed for this study offers both conceptual rigor and contextual relevance. It also provides the analytical foundation for hypothesis development and interpretation of empirical findings.

3.2.1 Creative Destruction Theory

Creative Destruction, introduced by Joseph Schumpeter (1942), describes technological innovation as a disruptive force that dismantles existing industries and job structures while simultaneously creating new ones. This cyclical process of destruction and renewal is considered fundamental to long-term productivity growth and economic development. In the beginning of digital era, Brynjolfsson and McAfee (2014) expanded on this theory, illustrating how automation, artificial intelligence (AI), and advanced digital technologies simultaneously accelerate job displacement and generate new opportunities in emerging sectors.

- **Global Insights**

Acemoglu and Restrepo (2019) demonstrate that while automation reduces employment in routine and low-skilled occupations, it also stimulates demand for

new roles in technology-driven industries. This reflects the central tenet of creative destruction: short-term disruption offset by long-term growth and transformation.

- **Bangladesh Context**

In Bangladesh's manufacturing sector, the process of creative destruction is increasingly visible. Ahmed and Rahman (2018) show that automation in garments and textiles has displaced traditional roles such as hand-embroiderers and manual cutters. At the same time, it has generated demand for technicians and operators skilled in managing digital sewing machines, AI-driven quality control systems, and automated logistics solutions. This transition reflects the coexistence of job loss and job creation that defines the digital era

3.2.2 *Labor Market Segmentation Theory (LMST)*

The Labor Market Segmentation Theory, first articulated by Doeringer and Piore (1971), argues that labor markets are not homogeneous but segmented into distinct sectors—commonly categorized as *primary* (stable, well-paid, with career mobility) and *secondary* (unstable, low-paid, with limited mobility). Precarious employment and labor market insecurity have become increasingly prominent in contemporary capitalist economies (Kalleberg & Vallas, 2022). Access to these segments is often shaped less by individual ability than by structural, institutional, and organizational factors.

- **Global Insights**

Autor et al. (2015) highlights that digitalization has contributed to growing job polarization, whereby routine, middle-skill jobs are increasingly automated, pushing workers into either high-skill, high-wage positions or low-skill, precarious ones. Howell & Kalleberg, (2022) further argue that digital transformation deepens inequalities, reinforcing divides between primary and secondary labor markets. The benefits of digitalization are often distributed unevenly, favoring highly skilled workers while increasing job insecurity and precarious employment among lower-skilled workers (Arewa, 2022; Charles et al., 2022). Moreover, technological change and platform-based employment models have contributed to labor market polarization, widening disparities in wages, job quality, and employment opportunities (Qureshi, 2022; Vallas & Prener, 2012).

- **Bangladesh Context**

In Bangladesh, this segmentation is evident in the manufacturing sector. Khatun et al. (2022) observe that larger enterprises adopting advanced digital tools retain high-skilled professionals such as engineers, designers, and IT specialists within stable, primary labor markets. By contrast, low-skilled manual workers, especially those concentrated in small and medium-sized enterprises (SMEs), face heightened risks of job displacement and instability. This uneven distribution of opportunities underscores how digitalization can reinforce structural inequalities in developing economies unless counterbalanced by policy interventions.

3.2.3 Skill-Biased Technological Change (SBTC) Model

The SBTC model explains how technological progress disproportionately benefits skilled over unskilled workers, reshaping employment structures (Acemoglu, 2002; Autor, Levy & Murnane, 2003).

- **Global Insights**

Recent evidence confirms that automation and AI intensify job polarization, reducing routine and middle-skill employment while expanding high-skill, technology-complementary jobs. This process has also contributed to rising wage inequality, as high-skill workers benefit disproportionately from digital technologies (Steinmetz, 2025).

- **Bangladesh Context**

In Bangladesh, manufacturing traditionally relies on low-skilled labor, especially in garments. However, as firms adopt automation, routine-intensive jobs shrink while demand grows for digitally competent workers, such as data analysts and machine technicians. (The Business Standard, 2024)

3.2.4 Technology Acceptance Model (TAM)

Developed by Davis (1986, 1989), TAM explains technology adoption based on perceived usefulness and perceived ease of use. Later extensions, such as UTAUT (Venkatesh et al., 2003), add constructs like performance expectancy, effort expectancy, and social influence.

- **Global Insights**

Recent research confirms that perceptions of usefulness and organizational readiness remain key determinants of digital technology adoption in industrial and organizational contexts. Studies show that employees' performance expectancy and perceived benefits strongly influence acceptance of AI and digital systems, while organizational readiness—such as leadership support, infrastructure, and culture—shapes adoption success (Mutambik & Almuqrin, 2024). These findings extend earlier acceptance models by demonstrating that both individual perceptions and organizational conditions are central to successful digital transformation in contemporary workplaces.

- **Bangladesh Context**

Hossain et al. (2020) found that leadership support, training availability, and government subsidies influence technology adoption in Bangladeshi manufacturing firms. SMEs, however, face barriers such as financing constraints and resistance to change.

3.2.5 Diffusion of Innovation (DoI) Theory

The DoI Theory (Rogers, 1962) explains how new technologies spread through populations, emphasizing adoption categories (innovators, early adopters, early majority, late majority, laggards) and innovation attributes (relative advantage, compatibility, complexity, trialability, observability).

- **Global Insights:** DoI has been applied to explain heterogeneous adoption rates of industrial technologies, showing that organizational capacity and leadership determine early adoption.
- **Bangladesh Context:** In Bangladesh, large firms often act as early adopters due to greater resources, while SMEs lag due to infrastructure and capacity constraints. This variation affects employment restructuring across firm types.

3.2.6 Human Capital Theory (HCT)

Human Capital Theory (Becker, 1964) posits that investments in education, training, and skill development increase workers' productivity and employability. In the context of digital transformation, human capital determines the capacity of workers and firms to adapt

to new technologies. Employees with higher levels of education, digital competencies, and continuous training are generally better positioned to utilize advanced technologies and respond effectively to technological change (Autor, 2015; Acemoglu & Restrepo, 2019). At the organizational level, investments in human capital facilitate technology adoption, innovation, and productivity enhancement, thereby improving firms' competitiveness in increasingly digitalized environments (Brynjolfsson & McAfee, 2014; OECD, 2023). Furthermore, the development of digital skills and lifelong learning has become essential for ensuring workforce adaptability and resilience amid rapid technological transformation (World Economic Forum, 2023; European Commission, 2023).

- **Global Insights** Nelson and Phelps (1966) argue that countries with higher levels of human capital adapt more effectively to technological change. More recently, the OECD (2019) emphasizes the importance of continuous reskilling and upskilling to ensure inclusive digital transitions and sustained employability.
- **Bangladesh Context** Bangladesh faces a paradox: while manufacturing generates millions of jobs, most workers possess limited digital literacy or technical training (Rahman & Rahman, 2021). This skill gap reduces adaptability to digitalization. Firms that invest in workforce training, however, report smoother transitions and productivity gains.

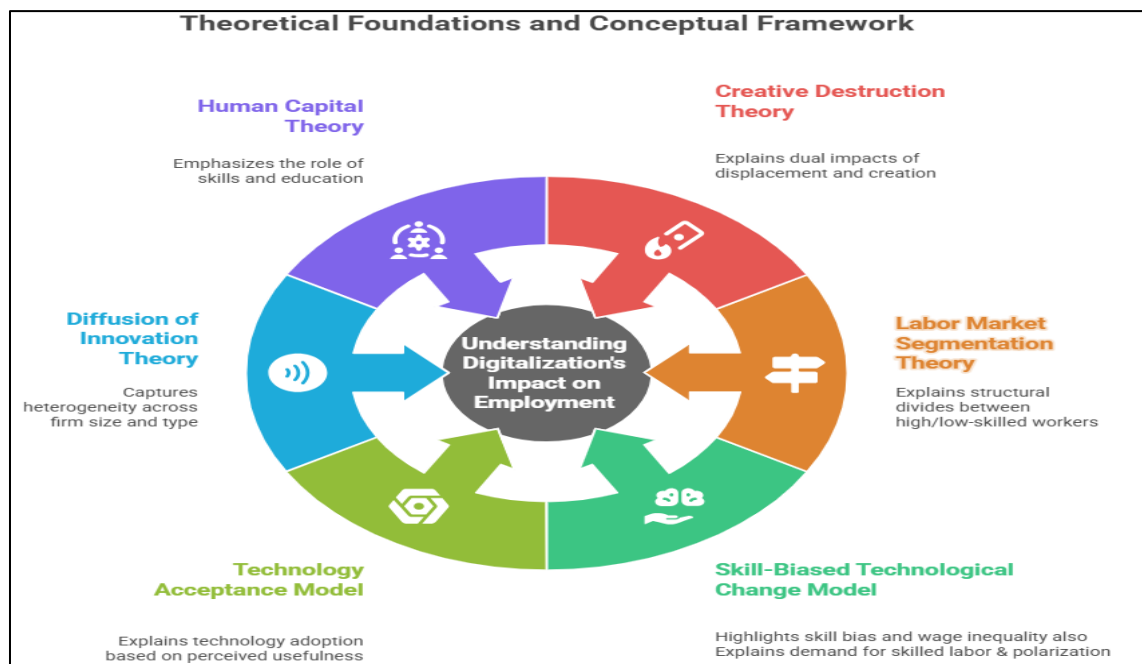


Figure 3.1: Theoretical Foundation and Conceptual Framework

The theoretical foundation and conceptual framework of this study are presented in *Figure 3.1*. The figure illustrates the relationships among digitalization, employment, organizational strategy, and policy dimensions within the manufacturing industries of Bangladesh. It also demonstrates how the underpinning theories and constructs are integrated to explain the impact of digital transformation on employment outcomes in the manufacturing sector.

3.3 Model Development

The conceptual model developed in this study is based on key theoretical frameworks to analyze and assess the impact of digitalization on employment in Bangladesh's manufacturing industry. The proposed model established key ideas derived from Creative Destruction, Labor Market Segmentation, Diffusion of Innovation, Human Capital Theory, Skill-Biased Technological Change (SBTC) Model, and Technology Adoption Models to identify the complex relationships between technological advancement, industrial changes, and Labor Market Dynamics.

The model incorporates key variables, including technological advancements, workforce digital skills, organizational strategies, and policy interventions. It suggests that digitalization reshapes employment by transforming production and management processes, altering skill requirements, and shifting Labor Market Dynamics. Strategy and policy are identified as critical factors, while industry type and size serve as moderating variables that influence the extent and direction of these changes in Bangladesh's manufacturing industry. All together these established theories and applying them to the specific context of Bangladesh's manufacturing sector, the model provides a solid framework and ground for conceptual model. This conceptual model serves as the foundation for formulating hypotheses and conducting empirical analysis to examine the impact of digitalization on employment in Bangladesh's manufacturing industry.

3.3.1 Independent Variables of the Proposed Model

In examining the impact of digitalization on employment in Bangladesh's manufacturing sector, this study identifies key independent variables that drive this transformation

3.3.1.1 Technological Advancements

Technological advancements refer to the continuous development, refinement, and application of tools, systems, and processes aimed at improving efficiency, productivity, and innovation across various industries. These advancements play a crucial role in transforming traditional methods of production and service delivery by introducing new technologies and optimizing existing practices. As Nielsen (2012) describes, technological advancements integrate innovative approaches into existing systems, leading to significant changes in how tasks are performed, and services are delivered. The same echo by Freeman and Soete (1997) earlier emphasized that such improvements and advancement foster industrial innovation by enhancing the abilities to compete in a dynamic global market.

ILO, in 2009 expressed that Technological advancements can reshape economic activities, creating opportunities for new industries and redefining existing ones as and the introduction of automation and artificial intelligence in manufacturing has revolutionized production processes, reduced costs and increased precision. (International Labor Organization, 2009).

While identifying the relationship between Employment Dynamic and Technological advancements, such as automation, IoT, robotics, and artificial intelligence, are central to reshaping labor markets by driving operational efficiency and redefining labor demands. Deloitte (2022) describes Industry 4.0 technologies as transformational forces within manufacturing, fostering innovation and displacing low-skilled labor. One hand Automation and robotics are reforming production lines, which increases output but often at the cost of routine, manual routine jobs. Bessen (2020) argues that while automation reduces costs and increases productivity, it also forces significant workforce adaptation. Syverson et al. (2020) emphasize that AI adoption leads to task restructuring, where humans and machines collaborate in newly defined roles, reshaping employment structures (Autor, 2015; Acemoglu & Restrepo, 2019).

Studies by Acemoglu and Restrepo (2022) show that automation's effects on employment vary significantly across industries, with skill-biased changes creating challenges in labor-intensive sectors like textiles and garments. These advancements

highlight the need for workers to acquire new, higher-order skills to remain relevant in the workforce.

3.3.1.2 Digital Skills

Digital skills are one kind of ability to use digital devices, automated applications, and networks effectively to access, manage, evaluate, and initiate information (UNESCO, 2018). These skills are critical in navigating technology-rich environments and are essential for participating in modern workplaces and societies. According to the Organization for Economic Co-operation and Development (OECD, 2023), digital skills encompass a range of competencies, including basic computer literacy, internet navigation, digital communication, and problem-solving using digital tools. The U.S. Department of Education (2020) enlarges on this definition by introducing the perception of digital resilience, which emphasizes the ability to adjust and thrive in technology-driven environments, particularly in the face of rapid technological advancement.

Digital skills include data analysis, cybersecurity, and proficiency in various digital platforms, and are essential for adapting to the demands of the digital workplace which recently we have found in the manufacturing Industries along with service industries. Van Deursen and Van Dijk (2019) argue that digital skills significantly determine both access to employment and career progression across sectors. Brown et al. (2021) emphasizes the role of digital literacy in improving organizational performance, while recent studies highlight the importance of digital competencies for employability, workforce adaptability, and firm competitiveness (Van Laar et al., 2020; OECD, 2023; World Economic Forum, 2023). Most importantly, these relationships are reflected in the theoretical model of this study.

PwC (2023) found that nearly 74% of organizations identified workforce digital skills as the most critical factor for maintaining competitiveness in the rapidly evolving manufacturing industry. This research conducted in the developed countries that's why this study will try to find the result in the developing country like Bangladesh.

Schlogl et al. (2022) also note the importance of public-private partnerships in addressing skill gaps, particularly in sectors like manufacturing, where the adoption of digital tools is essential for maintaining productivity.

In summary, digital skills are multi-faceted, extending beyond basic technical abilities as the reliance on digital tools increases in industries such as manufacturing, the development of digital skills has become a crucial factor in fostering workforce readiness and competitiveness.

3.3.1.3 IT Investment

Bresnahan et al. (2002) specify comprehensive evidence linking IT Investment to labor productivity and demand for skilled workers. Research conducted by Gartner (2022) noticed that IT investments have reached \$4.5 trillion, where manufacturing industries being one of the highest-spending sectors. Autor (2019) claims that integration of IT adoption fosters job specialization while reshaping traditional roles, particularly in industries undergoing digital transformation.

There is report by IDC (2023) projected that cloud and AI-driven IT investments will create over 1.2 million new jobs globally by 2025. Most Recently, US president Donald trump (2025) announced The Stargate Project which intends to invest \$500 billion over the next four years building new AI infrastructure for OpenAI in the United States. According to Trump, this infrastructure will create hundreds of thousands of American jobs and generate massive economic benefit for the entire world. This project will not only support the re-industrialization of the United States but also provide a strategic capability to protect the national security of America and its allies.

3.3.1.4 Strategy and Policy

Most research shows that strategic alignment with organization and government policies is vital to deal with the challenges and opportunities presented by digital transformation and advancement. Earlier Mintzberg et al. (1998) conceptualize strategy as a structured response to competitive pressures, emphasizing the importance of policy frameworks in facilitating Technology Acceptance Model. The OECD (2023) highlights the need for national digital strategies that focus on comprehensive growth and workforce reskilling, which are essential for supporting labor market transformation. Institutional theories by Scott (2014) suggest that well-designed policy frameworks can shape employment outcomes during periods of technological turmoil. Research highlights that appropriate strategies and policies are crucial for SMEs to engage with global digitalization trends,

which create both opportunities and risks for competitiveness and sustainability (OECD, 2021; World Bank, 2020; Lu et al., 2022).

3.3.1.5 Research and Development (R&D)

Numerous literatures support the argument that Investments in R&D are pivotal for driving technological innovation that enhance productivity and create new employment opportunities. The Global Innovation Index (2023) ranks countries based on R&D expenditure, showing its strong positive correlation with economic resilience, more R&D expenditure more progress.

Pavitt (1998) highlights R&D's role in confirming industrial competitiveness and improvements through integration of advanced innovative technologies. Brynjolfsson and McAfee (2014) emphasize that economies prioritizing R&D in automation technologies experience job creation in high-skill domains, demonstrating the potential of R&D to facilitate positive employment outcomes.

Another research by Nambisan et al. (2021) shows that R&D investments in digital technologies not only introduce innovation in the process but also generate scalable business models that create and offer jobs opportunities. All these analyses highlight the role and impact of R&D in shaping Labor Market Dynamics that enhance both productivity and employment opportunities.

3.3.2 *Moderating Variables of the Proposed Model*

This study considers organizational type and size as moderating variables influencing the relationship between digitalization and employment. Larger firms tend to adopt technology more readily, whereas SMEs often face resource constraints. Additionally, firm size affects automation adoption and workforce adjustments, ultimately shaping employment outcomes in Bangladesh's manufacturing industry.

3.3.2.1 Type of the Manufacturing Industry

In this study, the Type of Manufacturing Industry is conceptualized as a moderating variable to explore whether the effects of digitalization on employment vary across different industrial sectors. This approach acknowledges that sectoral characteristics—particularly the degree of technological intensity—influence how digital technologies are adopted, integrated, and ultimately impact labor market outcomes.

To establish a meaningful classification of manufacturing sectors, the study draws upon both international and national frameworks. Internationally, the study employs the OECD (2011) technology intensity-based classification, which categorizes manufacturing industries based on their research and development (R&D) intensity. This framework includes four major categories: low-technology industries (e.g., textiles, food processing, wood), medium-low technology industries (e.g., rubber, plastics, basic metals), medium-high technology industries (e.g., machinery, motor vehicles), and high-technology industries (e.g., electronics, pharmaceuticals). The classification allows for a comparative analysis of digitalization's effects in industries with varying capacities for innovation and technological absorption.

In parallel, national classifications by the Bangladesh Bureau of Statistics (BBS) and the Ministry of Industries offer a locally grounded taxonomy of manufacturing sectors. These include categories such as Food and Beverage, Textile and Garments, Leather, Chemicals, Electrical and Electronics, Machinery, and Pharmaceuticals. These classifications reflect Bangladesh's industrial policy focus and economic structure, and they provide context-specific insights into how digitalization is operationalized across sectors (BBS, 2023; Ministry of Industries, 2022).

Classification by BBS (2023) and the Ministry of Industries (2020), Textile and Garments sector—a low-technology industry by OECD standards—is a major employment generator in Bangladesh, it is also increasingly adopting automation and digital supply chain tools, which may have mixed implications for job creation and displacement (ADB, 2021; ILO, 2020). On the other hand, high-tech sectors such as pharmaceuticals and electronics, though relatively smaller in scale, may demonstrate more sophisticated integration of digital technologies and greater demand for high-skilled labor (UNIDO, 2022).

By examining the role of industry type as a moderating factor, the study aims to capture sector-specific dynamics in the relationship between digital transformation and employment. This dual-framework approach enhances the theoretical and empirical rigor of the analysis, allowing for targeted policy recommendations tailored to the varying needs and capacities of different industrial segments in Bangladesh.

3.3.2.2 Size of the Manufacturing Industry

In this study, the size of the manufacturing industry is considered a moderating variable to assess whether digitalization's impact on employment differs across firms of varying scales. Firm size influences digital adoption capacity, workforce structure, and resource availability—factors that shape how technology affects labor dynamics (OECD, 2017; UNCTAD, 2021).

Following the classification guidelines of the Bangladesh Bureau of Statistics (BBS) and the SME Foundation, firms are categorized as:

- Micro (1–9 employees)
- Small (10–49 employees)
- Medium (50–99 employees)
- Large (100+ employees)

Larger firms typically have greater resources to invest in advanced technologies, while smaller firms often face limitations in infrastructure and skills (ADB, 2021; UNIDO, 2022). However, even minimal digital adoption in smaller firms can significantly affect employment, making firm size a crucial lens for analysis. This classification allows for a more nuanced understanding of the digitalization–employment relationship across different organizational scales within Bangladesh's manufacturing sector.

3.3.3 *Dependent Variables of the Proposed Model*

This study identifies Labor Market Dynamics as the dependent variable, focusing on employment shifts, job creation, and workforce transitions influenced by digitalization.

3.3.3.1 Labor Market Dynamics

Labor Market Dynamics refer to the complex interactions that determine employment levels, occupational demand, wage distribution, and worker mobility. Shimer (2005) explores equilibrium unemployment and vacancy rates under cyclical economic conditions, emphasizing how labor market fluctuations are linked to economic cycles. Davis and Haltiwanger (1992) pointed out that both job creation and destruction play a pivotal role in the process of employment restructuring. They explore that the entry and exit of jobs are significant factors that shape Labor Market Dynamics.

According to Mortensen & Pissarides (1999) Labor Market Dynamics refer to the continuous changes and adjustments within the labor market, encompassing employment, unemployment, labor force participation, wage levels, and job mobility. These dynamics are influenced by economic, technological, institutional, and demographic factors, reflecting the interplay between labor supply and demand over time.

Another explanation published in Employment Outlook in 2010 "Labor Market Dynamics are the processes and interactions that determine employment outcomes, wage adjustments, and the allocation of labor resources over time." (OECD, 2010, *Employment Outlook*). In the *Regional Economic Outlook*, the International Monetary Fund (IMF, 2019) defines Labor Market Dynamics as "the continuous changes in employment patterns, including transitions between formal and informal sectors, driven by economic cycles, technological advancements, and labor policies."

Labor Market Dynamics also involve measuring, over time, changes in individuals' activity status—employed, unemployed, or inactive—and changes in job situations, reflecting the fluid nature of labor markets (ILO, 2009).

Donovan & Schoellman (2022) found that Labor Market Dynamics as the processes of job creation and destruction, worker mobility across employment states, and labor reallocation across sectors—shaped by economic development, technological change, and policy. This definition is crucial for this study, as it frames Labor Market Dynamics as the dependent variable, allowing an analysis of how digitalization influences employment patterns in Bangladesh's manufacturing sector.

3.4 Key Components of the Model

This section outlines the key components of the conceptual model, focusing on the factors driving digitalization in Bangladesh's manufacturing sector. These components include digitalization factors, contextualize factors and moderating factors. Each component plays a crucial role in shaping employment patterns, productivity, and workforce adaptation to digital transformation. The model examines how these components interact to influence job creation, displacement, and the overall Labor Market Dynamics within the sector

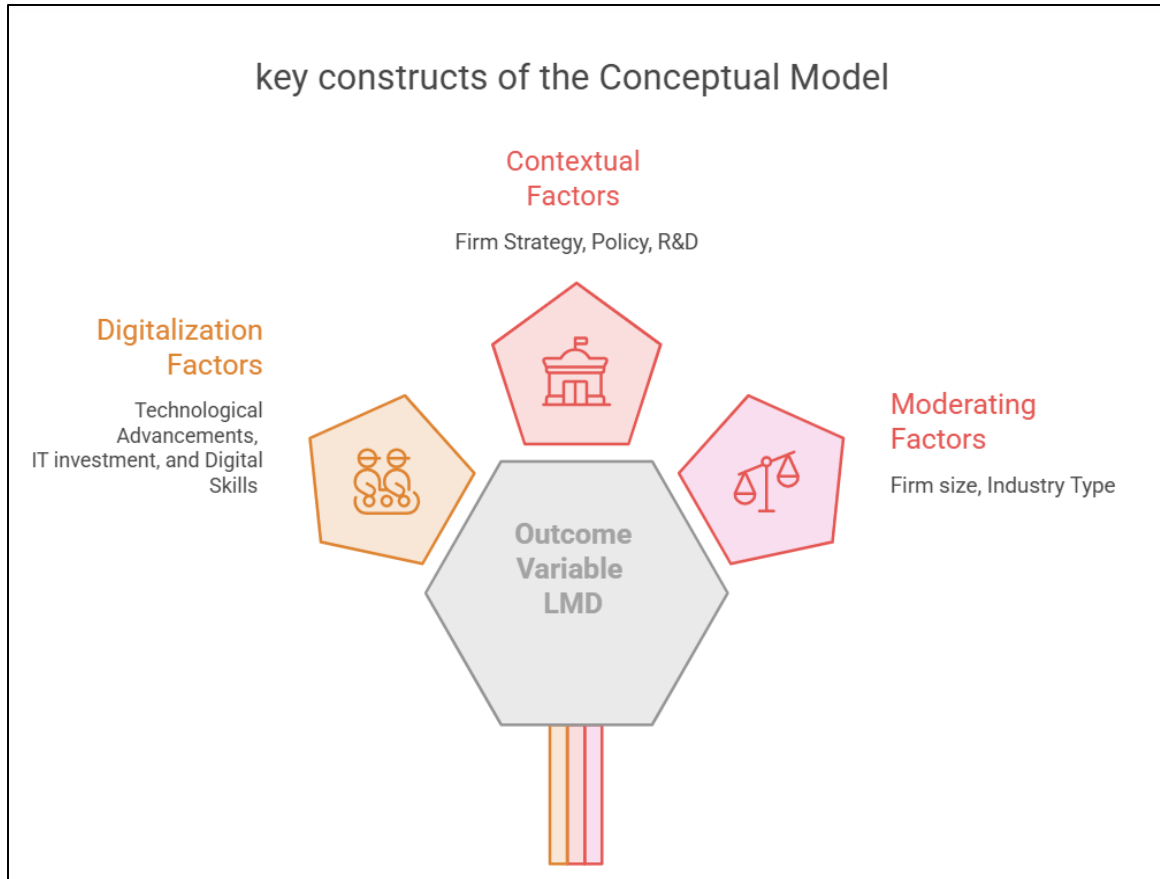


Figure 3.2: Key Components of the Proposed Conceptual Model

Figure 3.2 presents the key components of the proposed conceptual model employed in this study. The figure illustrates the interrelationships among digitalization, employment, organizational strategy, and policy factors within the manufacturing industries of Bangladesh. It further demonstrates the structural alignment of the study variables and the overall analytical direction of the research framework.

3.5 Integrated Theoretical Justification of the Proposed Model

By combining these six theories, this study builds a comprehensive framework to explain the multifaceted relationship between digitalization and employment:

❖ **Creative Destruction Theory:**

This theory justifies hypotheses linking Technological Advancement (TA), IT Investment (ITI), and R&D with LMD, as digitalization simultaneously eliminates outdated roles and generates demand for new skill sets.

✓ ***Explains dual impacts of displacement and creation (TA, ITI, R&D → LMD).***

❖ **Labor Market Segmentation Theory:**

Labor Market Segmentation Theory (LMST) supports hypotheses related to Digital Skills (DS), Strategy (ST), and Policy (PL) in shaping LMD, as it explains why structural inequalities influence employment outcomes in digitally transforming sectors.

- ✓ *Explains structural divides between high/low-skilled workers. (DS, ST, PL → LMD).*

❖ **Skill-Biased Technological Change:**

SBTC directly underpins hypotheses linking Digital Skills (DS) and Technological Advancement (TA) with LMD, highlighting how digitalization increases the premium on skilled labor while marginalizing unskilled workers.

- ✓ *Highlights skill bias and wage inequality also Explains demand for skilled labor & polarization. (DS, TA → LMD).*

❖ **Technology Acceptance Model:**

TAM supports hypotheses where IT investment (ITI), Strategy (ST), and Policy (PL) influence LMD via their impact on digital adoption, thereby reshaping employment structures.

- ✓ *Explains adoption pathways for digital technologies. (ITI, ST, PL → Digital Adoption → LMD).*

❖ **Diffusion of Innovation Theory:**

DoI provides justification for hypotheses incorporating firm Size (SZ) and organizational Type (TY) as moderators in the relationship between digitalization drivers and LMD.

- ✓ *Captures heterogeneity across firm size and type (SZ, TY as moderators).*

❖ **Human Capital Theory:**

Human Capital Theory (HCT) provides theoretical grounding for hypotheses emphasizing the role of Digital Skills (DS), Policy (PL), and Strategy (ST) in shaping LMD, highlighting that investments in human capital mediate the benefits of digitalization.

✓ ***Justifies skill development as a key enabler (DS, ST, PL → LMD).***

This theoretical foundation strengthens the study's conceptual model and provides a solid justification for the hypotheses. It ensures that the analysis of Bangladesh's manufacturing sector is grounded in globally recognized theories while addressing context-specific challenges of a developing economy.

3.6 The Proposed Conceptual Model

A detailed conceptual model is proposed to operationalize the key constructs and hypothesized relationships for this study.

The proposed model captures the dynamic interactions between digitalization, organizational strategies, firm characteristics, and employment outcomes within the context of Bangladesh's manufacturing sector. It is informed by theoretical frameworks such as the Diffusion of Innovation Theory, Technology Acceptance Model, Labor Market Segmentation Theory, Human Capital Theory, Skill-Biased Technological Change and the concept of Creative Destruction.

In this framework, the moderating variables—Firm Size and Type of organization—are posited to both moderate the relationships between the independent variables (e.g., IT Investment, R&D, Digital Skills, Technological Advancement, and firm Strategy) and the dependent variable (Labor Market Dynamics) and exert Direct Effects on the dependent variable itself. This modeling approach acknowledges that organizational characteristics such as size and type may not only influence how digitalization impacts employment but may independently shape labor outcomes due to inherent structural or strategic differences. This modeling approach follows the “Moderated plus direct effect model”, this dual-role conceptualization is well-supported in the literature (Baron & Kenny, 1986; Aiken & West, 1991; Preacher et al., 2007; Memon et al., 2019; Hair et al., 2017). Incorporating direct effects of moderators is particularly relevant in complex management and social research, such as this study on digitalization and employment in Bangladesh's manufacturing sector. Given this strong theoretical and empirical grounding, incorporating a moderated plus direct effect structure enhances the robustness and realism of the proposed conceptual model in this research.

This study develops a dynamic capability-based conceptual framework for digital transformation, emphasizing three core capabilities: seizing, and reconfiguring—and their role in enabling organizational digital transformation through structural, strategic, and cultural mechanisms. (Ghosh et al. 2022)

This conceptual model forms the foundation for the formulation of the study's hypotheses and the design of the empirical analysis.

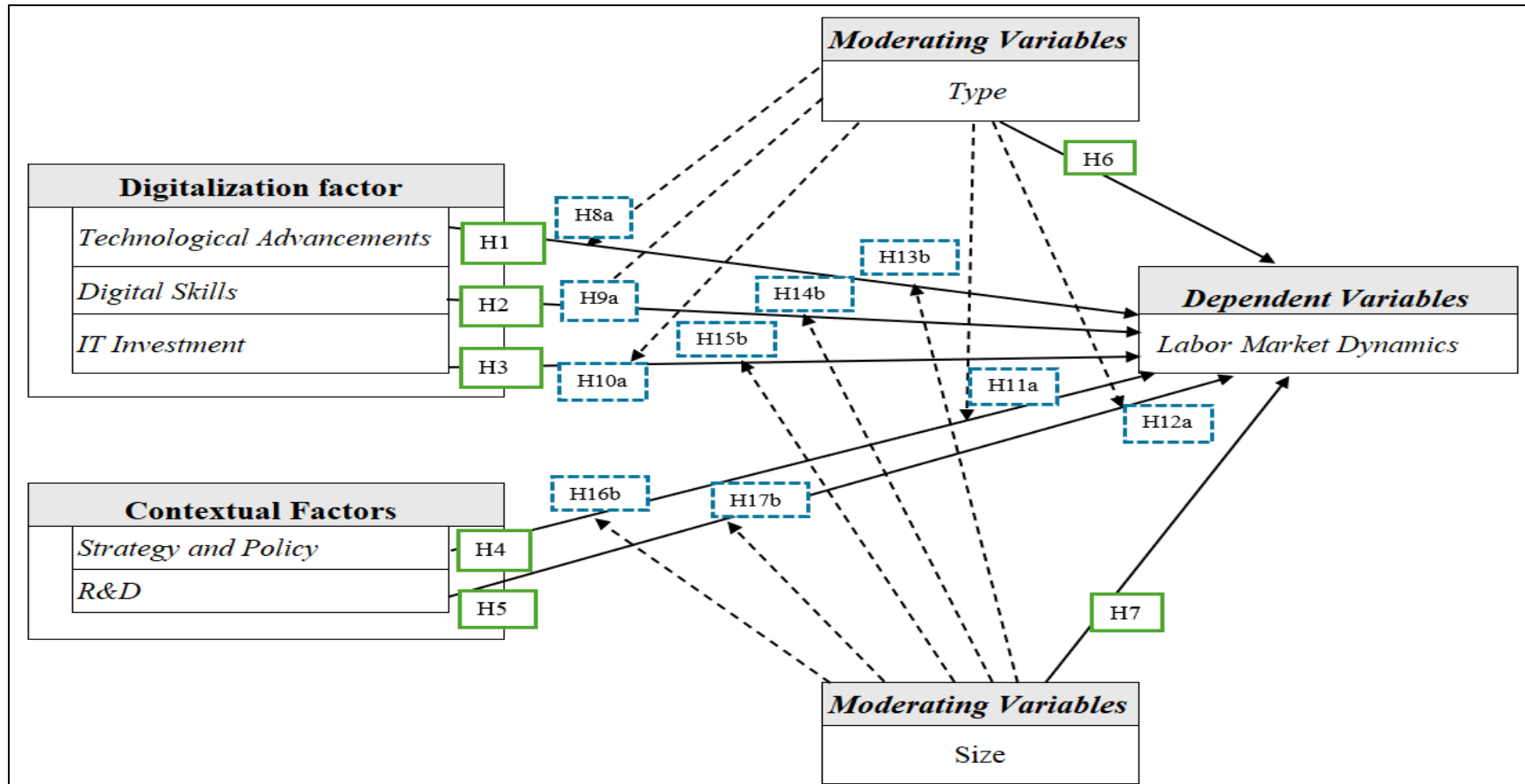


Figure 3.3: Proposed Conceptual Model for Examining the Impact of Digitalization on Employment

Figure 3.3 illustrates the proposed conceptual model developed for examining the impact of digitalization on employment in the manufacturing industries of Bangladesh. The model demonstrates the hypothesized relationships among digitalization, employment outcomes, organizational strategy, and policy-related factors, thereby providing the analytical foundation for the empirical investigation of the study.

3.7 Construct Development and Measurement Items

Attribute	Items	Statement	References
Technology Advancement	TA-1	Technological Advancements such as Robotics, Artificial Intelligence (AI), and machine learning have led to automation of various tasks and jobs.	Brynjolfsson & McAfee (2011). Race against the machine. Bhargava & Bolton (2021). Employees' perceptions of robotics
	TA-2	Technological Advancements have increased the demand for high-skilled workers	Shi (2025). Evaluating impacts of ICT development on wages of workers. Technological and Economic Development of Economy.
	TA-3	Technological Advancements created new industries and job opportunities, particularly in sectors related to information technology, biotechnology, renewable energy, and advanced manufacturing.	World Economic Forum. (2025). Transformations in employment and skills by 2030. World Economic Forum.
	TA-4	Workers need to adapt to new technologies and acquire new skills to fill emerging job roles.	Brynjolfsson & McAfee (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies
	TA-5	Technological Advancements have contributed to widening income inequality, as high-skilled workers benefit from increased demand and higher wages, while low-skilled workers face stagnant or declining wages due to job displacement and competition.	Hémous, D., & Olsen, M. (2022). Automation, skill bias, and wage inequality. Technological Change and Labor Markets Journal
	TA-6	Policymakers and industry leaders should address the challenges caused by technological advancement through introducing or initiatives like education and training programs, labor market policies, and social safety nets to support workers affected by job displacement.	OECD. (2023). OECD employment outlook 2023: Skill needs and policies in the age of artificial intelligence.
Digital skills	DS-1	Growing demands of technical and upskill creates a significant digital skills gap in the manufacturing sector.	OECD. (2020). Digital skills for jobs and inclusive growth: Breaking the link between digital skills and economic disparities.

Attribute	Items	Statement	References
	DS-2	Digital Skills are now considered fundamental for various job roles, from entry-level positions to executive roles.	WEF. (2020). The future of jobs report 2020.
	DS-3	There is often a gap between the demand for digital skills and the available talent pool, leading to skill shortages in certain industries and regions.	European Commission. (2021). Digital Skills and Jobs Coalition. European Commission
	DS-4	Individuals with strong digital skills have a competitive advantage in the job market, with higher employability and opportunities for career advancement.	Acemoglu & Restrepo. (2020). Robots and jobs, Journal of Political Economy, 128(6), 2188–2244.
	DS-5	Employers prioritize candidates with digital literacy and proficiency in using technology to streamline processes and drive innovation.	Acemoglu & Restrepo. (2020). Robots and jobs, Journal of Political Economy, 128(6), 2188–2244.
	DS-6	Gap of digital skills exacerbates inequality, as individuals from disadvantaged backgrounds may face barriers to accessing quality education and training in technology-related fields.	OECD. (2025). Digital divide in education. OECD iLibrary
	DS-7	Manufacturing companies that invest in digital skills development for their workforce demonstrate improved operational efficiency, innovation capability, and competitiveness in the global market.	Deloitte Insights. (2021). Skills for the digital manufacturing revolution: Upskilling, reskilling and bridging the gap.
	DS-8	While Technical Digital Skills are essential, soft skills such as problem-solving, teamwork, and communication are equally important for successful digital transformation initiatives in manufacturing.	World Economic Forum. (2020). The future of jobs report 2020.
	DS-9	Introduction and initiative of Vocational training programs and apprenticeships that incorporate digital skills training modules are critically important and essential for preparing the next generation of manufacturing workers to meet the demands of Industry 4.0.	European Commission. (2021). Digital skills and green competences. European Commission.
	DS-10	Lifelong learning initiatives and continuous professional development opportunities are essential for maintaining and upgrading digital skills among manufacturing professionals amidst rapid technological advancements.	ManpowerGroup. (2021). Upskilling 2025: Enterprise leaders need to plan for the long game.

Attribute	Items	Statement	References
IT Investment	ITI-1	Investment in IT often leads to the creation of new job opportunities, particularly in technology-related fields such as software development, data analysis, cybersecurity, and IT support.	Heller. (2025). Big shift in IT employment shows new skills are needed.
	ITI-2	IT investment facilitates the transformation of existing jobs by automating routine tasks, increasing efficiency, and creating demand for workers with digital skills.	McKinsey & Company. (2025). Automation and the future of the workforce: Skill shifts and job transformation
	ITI-3	Investment in IT infrastructure and systems drives demand for workers with specialized IT skills, such as programming, network administration, database management, and cybersecurity.	World Economic Forum. (2025). The Future of Jobs Report 2025.
	ITI-4	IT investment enables remote work opportunities and digital collaboration.	Wu & Lee. (2019). The effects of IT investments on firm performance. Information & Management, 56(5), 102–113
	ITI-5	IT-driven innovation often leads to the creation of high-value-added jobs and contributes to overall economic growth.	The impact of innovation on economic growth, foreign direct investment, and self-employment: A global perspective. (2025). Economies, 11(7).
	ITI-6	While IT investment has the potential to create opportunities for economic advancement, there are concerns about widening inequality due to disparities in access to technology and digital skills.	Martini & Sgambato. (2025). Digital inequalities and access to technology: Analyzing how digital tools exacerbate or mitigate social inequalities. Societies, 15(11)
	ITI-7	Strategic planning by businesses to align IT investments with organizational goals and workforce development strategies is critical for maximizing the positive impacts on Labor Market Dynamics.	World Economic Forum. (2025). The Future of Jobs Report 2025

Attribute	Items	Statement	References
Strategy and Policy	SP-1	Effective government and training policies are essential for equipping workers with the skills needed to succeed in the labor market.	OECD. (2024). Skills for the digital age: OECD Digital Economy Outlook 2024 (Vol. 2). OECD Publishing.
	SP-2	Labor market regulations, such as employment protection laws and minimum wage policies, impact job creation, worker mobility, and wage levels are crucial for fostering innovation and entrepreneurship.	Liebrechts. (2019). Employment protection legislation and entrepreneurial activity. ResearchGate/SAGE Publications
	SP-3	Trade agreements and globalization policies influence Labor Market Dynamics by affecting outsourcing, offshoring, and the movement of goods and services across borders.	Autor, Dorn, & Hanson. (2013). The China syndrome: Local labor market effects of import competition in the United States. American Economic Review, 103(6), 2121–2168.
	SP-4	Innovation and industrial policies can stimulate economic growth and job creation by fostering innovation ecosystems, supporting Research and Development (R&D), and promoting entrepreneurship.	Ding & Hesary. (2025). Can government R&D expenditure promote innovation? New evidence from 37 OECD countries
	SP-5	Social protection policies, including unemployment benefits, healthcare coverage, and social assistance programs, play a crucial role in supporting workers during periods of economic transition and job loss.	Bischler (2024). Social protection and active labour market policies for employment transitions. ILO Research

Attribute	Items	Statement	References
R&D	R&D-1	R&D activities stimulate job creation by fostering innovation and driving technological advancements in various sectors of the economy.	Investment, innovation activities and employment across European regions. (2023). Structural Change and Economic Dynamics, 65, 474-490
	R&D-2	Investments in R&D lead to the development of new products, processes, and services, which often require skilled workers for research, design, engineering, and implementation.	Investment, innovation activities and employment across European regions. (2023). Structural Change and Economic Dynamics, 65, 474-490
	R&D-3	R&D-intensive industries tend to have a higher demand for workers with specialized skills in science, technology, engineering, and mathematics (STEM).	Belenzon, Pataconi & Ziegler (2018). Acquiring human capital through the acquisition of external technologies: Evidence from software patents. Management Science, 64(11), 5151–5170
	R&D-4	R&D activities facilitate knowledge spillovers and collaboration between firms, universities, and research institutions, leading to cross-fertilization of ideas and skills often collaborate with external partners, contributing to the diffusion of knowledge and expertise across the economy.	Audretsch, Belitski & Chowdhury. (2024). Knowledge investment and search for innovation: Evidence from UK firms. Journal of Technology Transfer, 49(4), 1387–1410
	R&D-5	R&D plays a crucial role in developing new technologies and business models, creating opportunities for job creation and economic growth.	Danta & Rath. (2024). A conceptual framework linking innovation and economic growth. International Journal of Research and Innovation in Social Science
	R&D-6	Government policies and funding support for R&D, such as tax incentives, grants, and public-private partnerships, play a crucial role in promoting innovation and job creation.	OECD. (2025). Public support to R&D and innovation. Organization for Economic Co-operation and Development.
	R&D-7	Manufacturing firms are adopting new R&D management strategies and methodologies, such as agile development, design thinking, and lean innovation, to accelerate the pace of digital transformation and Industry 4.0 adoption.	Cooper et al. (2021). Accelerating innovation: Some lessons from the pandemic. Journal of Product Innovation Management, 38(2), 221–232

Attribute	Items	Statement	References
Type	TY-1	Advanced manufacturing industries, characterized by the adoption of cutting-edge technologies such as 3D printing, robotics, and automation often lead to the creation of high-value products and services, contributing to economic growth and job creation.	Deloitte Insights. (2021). Skills for the digital manufacturing revolution: Upskilling, reskilling, and bridging the gap. Deloitte.
	TY-2	Startups often drive innovation and job creation by introducing new products, services, and business models to the market.	Yaşar. (2025). Role of startups in economic growth: Evaluating how new business ventures contribute to job creation, innovation, and regional development. Next Generation Journal for The Young Researchers.
	TY-3	SMEs play a significant role in job creation and employment, particularly in sectors such as retail, hospitality, and manufacturing.	Aidis & Mickiewicz. (2012). Size matters: Entrepreneurial entry and government. Small Business Economics, 39(1), 119-139.
	TY-4	MNCs have a global footprint and can influence Labor Market Dynamics in multiple countries through their investments, operations, and supply chains.	Impact of Multinational Corporations on Globalization and Labour Markets. (2025). Number Analytics. Impact of MNCs on globalization and labour markets
	TY-5	MNC often provide opportunities for skilled employment, technology transfer, and knowledge spillovers in host countries.	Impact of Multinational Corporations on Globalization and Labour Markets. (2025). Number Analytics. Impact of MNCs on globalization and labour markets
	TY-6	Government-Owned Enterprises (GOEs);, such as state-owned enterprises (SOEs), can influence Labor Market Dynamics through their role in providing essential services and infrastructure.	OECD. (2025). State-Owned Enterprises and Sustainability

Attribute	Items	Statement	References
Size	SI-1	Large-scale manufacturing industries, characterized by extensive production capacities and market presence, play a significant role in driving economic growth, job creation, and innovation.	OECD. (2021) Large firms and economic resilience: The case of OECD countries. OECD Publishing, Paris.
	SI-2	Large corporations in the digital sector, such as tech giants like Google, Facebook, and Amazon, have a significant impact on Labor Market Dynamics.	Osman. (2024). Big Tech's overpowering influence: Risks to markets and your money
	SI-3	SMEs may offer opportunities for entrepreneurial individuals, freelancers, and remote workers to participate in the digital economy.	OECD. (2017). Enhancing the Contributions of SMEs in a Global and Digitalized Economy
	SI-4	Small-scale and micro manufacturing enterprises contribute to job creation, poverty alleviation, and local economic development, particularly in rural and underserved areas.	UNIDO. (2021). Micro, Small and Medium-sized Enterprises Day 2021
	SI-5	Emerging and start-up manufacturing companies may offer flexible employment opportunities, attract young talent, and contribute to skills development through hands-on experience.	Critical success factors affecting the performance of high-tech startups: A flexible learning perspective. (2025). Global Journal of Flexible Systems Management, 26, 359–380
Labor market Dynamic	LMD-1	To what extent do you agree that digitalization of the manufacturing sector led to significant structural changes in employment, such as job displacement or the creation of new roles.	Bilateral Effects of the Digital Economy on Manufacturing Employment: Substitution Effect or Creation Effect? (2024). Sustainability, 15(19)
	LMD-2	Current workforce training and reskilling programs addressing the skill gaps created by digital technologies in the manufacturing sector.	Bilateral Effects of the Digital Economy on Manufacturing Employment: Substitution Effect or Creation Effect? (2024). Sustainability, 15(19)
	LMD-3	To what extent do you agree that Labor Market Dynamics are influenced by public policies, such as minimum wage laws, unemployment benefits, labor market regulations, and education policies.	Huan. (2025). An analytical study of Labor Market Dynamics and employment trends. Journal of Socialomics, 14(1), 262.
	LMD-4	To what extent do you agree that Labor Market Dynamics influence the Variations in wages and compensation	Huan. (2025). An analytical study of Labor Market Dynamics and employment trends. Journal of Socialomics, 14(1), 262.

Table 3.1: Summary table of Items and construct development

As shown in Table 3.1, the study's constructs and measurement items were developed based on established scales and relevant literature.

3.8 Summary of Literature Synthesis on Key Constructs

Attribute	Definition	Attribute and its Impact	Reference
Technology advancement	Technology Advancement can be defined as the iterative process of innovation and improvement in technological systems, encompassing the creation of novel technologies, enhancements to existing ones, and their widespread adoption to address societal needs and challenges	IT investment can lead to long-term productivity improvements and employment growth through various mechanisms	OECD. (2025). OECD Science, Technology and Innovation Outlook 2025: Driving Change in a Shifting Landscape. OECD Publishing
Digital skills	Digital Skills encompass the range of competencies necessary for individuals to effectively utilize digital technologies, including but not limited to proficiency in computer use, internet navigation, information literacy, digital communication, data management, and cybersecurity	Van Deursen and van Dijk (2019) highlight and address the importance of digital skills in facilitating doors for job opportunities and for career advancement. Digital skills and digital proficiency are more likely to be employed, earn higher wages, and engage in lifelong learning to adapt to technological changes (European Commission, 2017).	International Journal of Innovative Research and Scientific Studies. (2025). Contemporary definitions and competencies of digital literacy and digital skills, 8(5), 1645–1650
IT Investment	IT investment refers to the allocation of financial resources, time, and effort towards acquiring, implementing, maintaining, or upgrading information technology infrastructure, systems, and applications within an organization.	Research by Autor et al. (2003) suggests that IT-intensive industries exhibit a higher demand for workers with advanced technical and analytical skills	Putritama, & Khamainy. (2024). Future research directions of information technology investment: A systematic literature review. Journal of Accounting and Investment, 25(2), 601–620.

Attribute	Definition	Attribute and its Impact	Reference
Strategy and Policy	Strategy and Policy refer to a comprehensive plan of action designed to achieve specific goals or objectives. It involves assessing current conditions, setting goals, making decisions about resource allocation, and outlining the steps necessary to achieve desired outcomes while adapting to changing circumstances.	Institutional theory posits that organizations' strategies and Policy are shaped by institutional pressures, including governmental policies affecting employment practices	Huan. (2025). An analytical study of Labor Market Dynamics and employment trends. <i>Journal of Socialomics</i> , 14(1), 262–273.
R&D	Research and Development (R&D) refers to systematic activities undertaken by the organizations or individuals with the primary objective of discovering new knowledge, creating innovative technologies, or improving existing products, processes, or services. R&D typically involves experimentation, analysis, and exploration of new ideas or concepts, aimed at advancing scientific or technological understanding and fostering innovation.	Investments in R&D aimed at enhancing labor productivity can lead to overall job creation and improved living standards (Brynjolfsson & McAfee, 2014).	UNESCO Institute for Statistics. (2025). Research and experimental development (R&D). UNESCO Institute for Statistics.
Types	Types of manufacturing Industries can be categorized based on different dimensions. Technology intensity-based classification (OECD/UNIDO), which groups industries into low, medium-low, medium-high, and high-technology categories—reflecting their capacity for digital adoption. The national policy-based classification (BBS/MoI), which aligns with Bangladesh’s industrial strategies and includes sectors like textiles, food, electronics, and pharmaceuticals.	Types of manufacturing Industries and their impact would provide valuable insights into the complexities of industrial structure, dynamics, and their implications for economic development and policy formulation	BBS. (2025). Bangladesh Standard Industrial Classification (BSIC) 2020. Statistics Division, Ministry of Planning, Government of Bangladesh

Attribute	Definition	Attribute and its Impact	Reference
Size	Based on the classification standards of the Bangladesh Bureau of Statistics (BBS) and the SME Foundation, manufacturing firms are categorized as micro (1–9 employees), small (10–49), medium (50–99), and large (100+).	Size of manufacturing Industries can significantly influence on economic performance, industry dynamics, and competitiveness	BBS. (2025). Bangladesh Standard Industrial Classification (BSIC) 2020. Statistics Division, Ministry of Planning, Government of Bangladesh
Labor Market Dynamics	Labor Market Dynamics refer to the complex interplay of forces and phenomena that govern the functioning and evolution of the labor market over time. These dynamics encompass a wide range of factors, including changes in employment levels, fluctuations in job availability, shifts in occupational demand, variations in wages and compensation, and movements of workers between different sectors and industries.		Huan. (2025). An analytical study of Labor Market Dynamics and employment trends. Journal of Socialomics, 14(1), 262

Table 3.2: Summary of Literature synthesis on key Constructs

Table 3.2 presents a synthesis of the literature on the key constructs examined in this study. The table summarizes the definitions, theoretical foundations, and empirical findings associated with the major constructs used in the research framework

3.9 Hypotheses Development

This section presents and describes the development of the constructs and hypotheses that examine the relationship between various factors—such as technological advancements, digital skills, IT investments, strategies and policies, and R&D—and Labor Market Dynamics (LMD) in the context of digitalization. It also explores how organization type and size act as moderating factors, influencing how these variables impact employment trends in the manufacturing sector. Through these hypotheses, the study aims to provide insights into the complex interactions between these elements and their effects on labor markets.

3.9.1 Direct Effects on Labor Market Dynamics (LMD)

This study examines the direct impact of key digitalization and contextualization related factors like Technological Advancements, Digital Skills, IT investments, Strategies and Policies, and R&D on Labor Market Dynamics (LMD) in Bangladesh's manufacturing industry. The hypotheses are formulated based on established theoretical foundations such as Schumpeter's Creative Destruction Theory, Labor Market Segmentation Theory, Human Capital theory, Skill – Biased technological Change and Diffusion of Innovation Theory, alongside empirical evidence.

3.9.1.1 Technological Advancement and Labor Market Dynamics

Technological Advancements have unarguably reshaped and transformed labor markets globally, driving both opportunities and challenges. Technological advancement redesign and automated many manual tasks by eliminating manual intervention with precision and efficiency. Brynjolfsson and McAfee (2014) highlighted in their research how automation technologies, such as robotics and AI, significantly streamline operations across industries, reducing costs and enhancing productivity and efficiency. Further analysis by Frey and Osborne (2017) explored that automation threatens up to 47% of current jobs, particularly those involving routine, predictable tasks.

The wave of advanced innovative technologies has escalated the demand for highly skilled workers adept at managing, maintaining, and innovating within automated systems. In support of that statement Acemoglu and Restrepo (2020) note that Technology Acceptance

Model creates a skill-biased shift in labor demand, favoring individuals with expertise in AI, data science, and system integration. Similarly, Susskind (2020) argues that as machines handle routine tasks, workers must develop complementary skills to remain relevant and can sustain in this transformation.

However, there are additional arguments suggesting that technological advancements have not been universally beneficial. Dasgupta and Gupta (2021) document a growing pay gap, where low-skilled workers, unable to transition into technology-based or tech-handled roles, face a rising unemployment crisis. This underscores the need for comprehensive study and needful strategies that balance the benefits of technology with its socioeconomic implications. Ahmed et al. (2021) Thus, we hypothesized that

- ✓ ***H1: Technological Advancements (TA) have a significant impact on Labor Market Dynamics (LMD).***

3.9.1.2 Digital Skills and Labor Market Dynamics

Demand for Digital Skills is increasing exponentially in the modern labor market, as one of the key determinants of employability, economic growth and sustainability. The manufacturing sector all over the world, especially in the developing countries, faces a significant digital skills gap. Ali & Khan (2022) report that the adoption of Industry 4.0 technologies creating a huge gap between demand and supply of Digital Skill workforce, it's more relevant in Bangladesh because, the country outpaced the availability of workers with requisite digital competencies, particularly in developing regions.

Still Digital skills are not confined to specialized roles but are essential across job levels, from entry-level positions to executive roles. Müller et al. (2021) and Katz & Krueger (2019) highlight those digital skills and literacy enhances employability, as workers need to be proficient in using software, technology driven machines, mobile technology, data analysis tools, and digital communication platforms are to meet organizational demands.

Now a days employers are prioritizing digital skills and proficiency as a critical employment hiring criterion. NASSCOM (2020) highlights that digital skills are a primary factor in recruitment decisions across industries, not only in technology-intensive sectors but also traditional manufacturing industries. The same opinion echoed by Nguyen et al.

(2021), they found that digital literacy is linked to higher productivity and innovation within organizations.

Habib et al. (2022) identify cost, infrastructure limitations, and geographic disparities as the main obstacles to adopting and accessing digital skills. UNESCO (2021) warns that this digital divide exacerbates socioeconomic inequalities, leaving vulnerable populations in the job market. Li et al. (2020) and the World Bank (2020) advocate that Investment and initiatives in vocational training programs, and lifelong learning initiatives will help to mitigate or handle these challenges also suggested that for integrating digital skills modules into primary, secondary and tertiary education systems and promoting continuous professional development to equip workers for the demands of Industry 4.0. Thus, we proposed the following hypothesis:

- ✓ ***H2: Digital Skills (DS) have a significant impact on Labor Market Dynamics (LMD).***

3.9.1.3 IT Investment and Labor Market Dynamics

Autor et al. (2020) and Gupta and Sharma (2020) identify some key areas such as cybersecurity, data analytics, AI, and software development as key beneficiaries of IT-driven job creation. Automation simplified the routine tasks, allowing workers to focus on higher-value activities. Arntz et al. (2017) and OECD (2021) highlight how IT investment has increased productivity across sectors including Manufacturing Industries. IT also allows workers to work from home, facilitated remote work and digital collaboration, expanding access to employment opportunities irrespective of geographic constraints (Li et al., 2021; Santos et al., 2021). Kumar, N., & Kumar, R. (2021), Examines how IT innovations drive the gig economy and impact traditional employment structures. Considering all the literature, we hypothesized that:

- ✓ ***H3: IT Investment (ITI) has a significant impact on Labor Market Dynamics (LMD).***

3.9.1.4 Strategy and Policy Impact on Labor Market Dynamics

Strategies and Policies are crucial for directing the complexities of Labor Market Dynamics. Andersen and Holm (2018), examine how Denmark's active labor market policies have successfully reduced unemployment and enhanced workforce adaptability.

His study found that the policies adopted in Denmark focus on continuous training and skill development, enabling workers to transition seamlessly into emerging sectors.

Another research by Jørgensen (2020) highlights Norway's labor laws, that balance flexibility and safeguard for employers with protections for workers, promoting a stable employment environment. Rodríguez et al. (2019) discuss how Mexico's trade policies have expanded job opportunities in export-oriented industries. Similarly, Chatterjee et al. (2020) highlight India's experience with globalization, on one side it has created jobs while also exposing vulnerabilities in traditional sectors. It's also noted that globalization and different trade agreements have significantly influenced employment trends all over the world.

Bhorat et al. (2021) and Wagner et al. (2020) underscore the proper strategy and policy of unemployment benefits, healthcare, and retraining programs mitigating the effects of job displacement and fostering long-term workforce resilience. Unfortunately, there is very few or no literature on such important matter in Bangladesh, Thus, we hypothesized that:

- ✓ ***H4: Strategy and Policy (SP) have a significant impact on Labor Market Dynamics (LMD).***

3.9.1.5 R&D and Labor Market Dynamics

Research and Development (R&D) are one of the fundamental drivers of innovation and employment growth. Lee et al. (2020) and Sakamoto and Tsujimoto (2019) illustrate how R&D investments stimulate the creation of high-value jobs in fields such as engineering, design, and technology development. The National Science Foundation (2020) and Li (2019) report that workers with expertise in science, technology, engineering, and mathematics are critical for advancing innovation and this affects the workforce productivity.

Müller et al. (2020) highlight the importance of Collaboration between academia and industry as a key mechanism for adopting R&D. Müller et al. (2020) also highlight Germany's success in leveraging university-industry partnerships was key to drive innovation. In support of that study, OECD (2021) and Smith et al. (2021) document how tax breaks, grants, and public-private partnerships have bolstered R&D activities, creating a ripple effect on job creation and economic growth. Similar findings have been reported

by the World Bank (2023) and International Labour Organization (2023), which highlight the role of innovation policies and collaborative ecosystems in fostering technological advancement, productivity growth, and employment generation. Thus, we hypothesized that:

- ✓ ***H5: Research & Development (RD) have a significant impact on Labor Market Dynamics (LMD).***

3.9.1.6 Types of the Manufacturing industries and Labor Market Dynamics

Many Studies found that different types of companies contribute uniquely to employment dynamics. Advanced manufacturing industries in Germany and Japan drive high-value job creation through innovation (Wagner et al., 2020; Sakamoto & Tsujimoto, 2019). Startups, such as those in Silicon Valley and Bangalore, foster entrepreneurship and introduce novel business models (Katz & Krueger, 2019; NASSCOM, 2020). SMEs are crucial, especially in the developing regions because they provide large number of jobs and drive local economic growth (Bhorat et al., 2021; Nguyen et al., 2021). Another research by Ahmed addressed, Meanwhile, MNCs contribute to workforce stability through global investments and technology transfer (Ahmed et al., 2021; Santos et al., 2021). Thus, we hypothesized that:

- ✓ ***H6: Types of the industry (TY) have a significant impact on Labor Market Dynamics (LMD).***

3.9.1.7 Size of the Manufacturing industry and Labor Market Dynamics

Some research found that, even size of the industries deeply impacts labor markets. Large corporations, with rich resources and global reach, drive innovation and create high-value jobs (National Science Foundation, 2020; Xu et al., 2018). SMEs, on the other hand, advance local economic growth and offer flexible employment opportunities (Müller et al., 2021; Bhorat et al., 2021). Startups provide dynamic work environments and attract young talent, contributing to skill development through hands-on experiences (Gupta & Sharma, 2020; Santos et al., 2021). Thus, we hypothesized that:

- ✓ ***H7: Sizes (SZ) of the industry have a significant impact on Labor Market Dynamics (LMD).***

3.9.2 Moderating Effects of Type and Size on LMD

Moderation occurs when the strength or direction of a relationship between an independent and dependent variable is influenced by a third variable (Baron & Kenny, 1986). The type and size of organizations can act as moderators, altering the impact of technological advancements, digital skills, strategies, R&D, and IT investments on Labor Market Dynamics (LMD).

3.9.2.1 Moderating Role of Industry Type (TY)

➤ **Type of industry → Technological Advancement → Labor Market Dynamics**

The type of organization (e.g., manufacturing, IT, service, government, private) plays a critical role in determining how technological changes impact employment. Different industries adopt, implement, and respond to digital transformation in diverse ways: Manufacturing firms focus on automation, robotics, and process efficiency, leading to job displacement for routine workers but an increased demand for engineers and robotics specialists (Acemoglu & Restrepo, 2020). IT and service firms prioritize cloud computing, AI, and digital platforms, increasing demand for data scientists, programmers, and cybersecurity professionals (Brynjolfsson & McAfee, 2014). Public-sector organizations often face bureaucratic constraints, limiting rapid digital adoption, whereas private-sector firms are more flexible in workforce restructuring (OECD, 2021). The type of organization significantly affects how technological advancements, digital skills strategies, and R&D translate into labor market changes. IT-intensive organizations invest in automation and AI, leading to job restructuring (Brynjolfsson & McAfee, 2014). Manufacturing firms focus on robotics and process automation, displacing low-skilled workers but increasing demand for engineers (Autor et al., 2003). Service industries leverage cloud computing and AI-driven analytics, altering workforce demand (Bessen, 2019). Thus, we hypothesized

✓ ***H8a: Industry Type moderates the relationship between Technological Advancements and Labor Market Dynamics (LMD).***

➤ **Type of industry → Digital Skills → Labor Market Dynamics**

The demand for Digital Skills is highly dependent on the type of organization. Traditional industries like manufacturing industries still focus on basic digital literacy

and automation control skills. Research indicates that financial and IT companies invest more in digital skill training, leading to labor market segmentation but manufacturing industries way behind the adoption of Innovative technology (World Economic Forum, 2020). The variation in digital skill adoption across industries significantly affects workforce employability and job transitions. Thus, we hypothesized that:

✓ ***H9a: Industry Type moderates the relationship between Digital Skills and Labor Market Dynamics (LMD).***

➤ **Type of industry → IT Investment → Labor Market Dynamics**

The impact of IT investment on Labor Market Dynamics varies depending on the type of organization. IT firms and multinational corporations (MNCs) tend to lead in digital transformation, investing heavily in cloud computing, big data analytics, and AI integration, which drive employment growth in tech-related job sectors (OECD, 2021). Meanwhile, small and medium enterprises (SMEs) and traditional industries often struggle with digital adoption due to financial constraints and skill shortages, leading to slower job creation and technological adaptation (World Economic Forum, 2020). The variation in IT investment strategies across different organization types results in uneven employment outcomes. Thus, we hypothesized that:

✓ ***H10a: Industry Type moderates the relationship between IT Investment and Labor Market Dynamics (LMD).***

➤ **Type of industry → Strategy and Policy → Labor Market Dynamics**

Large corporations implement structured HR policies, such as reskilling programs and remote work options, to mitigate technological disruptions (McKinsey, 2020). Conversely, manufacturing and traditional sectors often struggle with policy adaptation, leading to greater job displacement risks. Firms that proactively develop innovation-driven policies and invest in continuous learning initiatives experience smoother transitions in workforce adaptation (OECD, 2021). Success depends on the right strategy, organization's type, size, and sectoral characteristics. Thus, we hypothesized that:

✓ ***H11a: Industry Type moderates the relationship between Strategy and Policy and Labor Market Dynamics (LMD).***

➤ **Type of industry → Research and Development → Labor Market Dynamics**

Investment in Research and Development (R&D) plays a significant role in shaping labor market trends across different organization types. From last few years tech-based companies allocate substantial resources in R&D, driving innovation-led employment opportunities in emerging fields such as artificial intelligence, biotechnology, and automation (Autor et al., 2003). In contrast, traditional industries with lower R&D investments experience slower workforce adaptation to technological changes, leading to employment stagnation or job displacement. Empirical studies indicate that firms with strong R&D capabilities create high-skilled job opportunities and foster knowledge-intensive employment growth (Deloitte, 2021). Thus, we hypothesized that:

- ✓ ***H12a: Industry Type moderates the relationship between R&D and Labor Market Dynamics (LMD).***

3.9.2.2 Moderating Role of Industry Size (SZ)

➤ **Size of industry → Technological Advancements → Labor Market Dynamics**

The relationship between Research and Development and Labor Market Dynamics is moderated by Industry Size. Larger firms with dedicated R&D divisions drive technological innovation and create high-value job opportunities (Acemoglu & Restrepo, 2020). Meanwhile, SMEs rely more on external partnerships for innovation, leading to a different employment structure and slower job market transitions (European Commission, 2020). The scale of R&D investment influences how organizations respond to technological disruptions and workforce transformation. Thus, we hypothesized that:

- ✓ ***H13b: Industry Size moderates the relationship between Technological Advancements and Labor Market Dynamics (LMD)***

➤ **Size of industry → Digital Skills → Labor Market Dynamics**

Organization size (e.g., small, medium, or large enterprises) influences how firms invest in technology, workforce training, and innovation, thereby affecting employment outcomes. Larger firms often have more financial and technological resources to implement advanced digital transformation strategies, whereas SMEs face

barriers in adopting AI and advanced technology. Large corporations invest heavily in reskilling programs, AI-driven automation, and global workforce restructuring (Deloitte, 2021). Small and Medium Enterprises (SMEs) struggle with digital transformation costs, often leading to slow adoption and workforce downsizing (OECD, 2020). MNCs with strong R&D divisions drive job creation in emerging technology sectors, whereas small firms rely on external innovation. Thus, we hypothesized that:

✓ ***H14b: Industry Size moderates the relationship between Digital Skills and Labor Market Dynamics (LMD)***

➤ **Size of industry → IT Investment → Labor Market Dynamics**

IT investment strategies differ significantly based on organizational size, influencing employment trends and workforce digitalization. Large corporations and MNCs allocate substantial budgets for IT infrastructure, AI-driven automation, and cloud computing, driving employment growth in tech-related fields (Deloitte, 2021). In contrast, SMEs face financial and technical barriers in adopting digital technologies, leading to slower job transformation and limited employment growth in digital sectors (OECD, 2021). The scale of IT investment plays a crucial role in shaping Labor Market Dynamics and workforce restructuring. Thus, we hypothesized that:

✓ ***H15b: Industry Size moderates the relationship between IT Investment and Labor Market Dynamics (LMD).***

➤ **Size of industry → Strategy and Policy → Labor Market Dynamics**

Size of the organization affects the formulation and execution of strategies and policies related to workforce management and Technology Acceptance Model. Large firms typically implement structured policies, such as employee retraining programs, automation integration plans, and flexible work arrangements, to manage labor market transitions effectively (Acemoglu & Restrepo, 2020). On the other hand, SMEs may struggle with resource constraints, leading to slower policy adaptation and higher employment uncertainty (OECD, 2021). The difference in strategic approaches between large and small firms creates disparities in job security and employment trends. Thus, we hypothesized that:

- ✓ *H16b: Industry Size moderates the relationship between Strategy and Policy and Labor Market Dynamics (LMD).*

➤ **Size of industry → Research and Development → Labor Market Dynamics**

From the very outset, it is evident that large organizations are typically better positioned to invest substantially in research and development (R&D), which in turn fosters innovation-driven employment growth. Firms with higher R&D budgets are more likely to generate high-skilled employment opportunities and enable their workforce to adapt to technological advancements (Brynjolfsson & McAfee, 2014). In contrast, small and medium-sized enterprises (SMEs) often face resource constraints—both financial and structural—that restrict their ability to make significant investments in R&D. As a result, their potential to drive innovation-led job creation remains limited (World Economic Forum, 2020). These disparities in R&D investment, shaped by the size of the organization, directly influence Labor Market Dynamics and the evolving demand for skills within the sector. Based on this reasoning, the following hypothesis has been developed:

- ✓ *H17b: Industry Size moderates the relationship between Research and Development (R&D) and Labor Market Dynamics (LMD).*

Both organizational type and size are therefore critical in shaping how technological advancements, digital skills, strategies, policies, R&D efforts, and IT investments affect labor market outcomes. Large and technology-driven firms often act as engines of job creation through digital transformation, whereas SMEs and traditional industries may encounter significant adaptation challenges. These challenges frequently manifest in workforce restructuring, skill mismatches, or even job displacement. Accordingly, the study underscores the importance of treating firm size and type as key moderating variables when analyzing employment trends in the context of digital transformation within the manufacturing sector.

The hypotheses developed in this study offers a structured framework for exploring how digitalization impacted the Labor Market Dynamics specially in Bangladesh's manufacturing industry. By applying Structural Equation Modeling (SEM) and conducting

empirical validation, the research aims to deliver evidence-based insights that can assist policymakers, guide industry leaders, and support workforce planners for sustainable labor market outcome.

3.10 Visual Illustration of the Conceptual Model

A graphical and visual representation of the conceptual model illustrates hypothesized relationships, showing a systematic pathway for hypothesis testing and comprehensive analysis. The conceptual model developed in this study provides a graphical roadmap of the key relationships of the relevant constructs. It brings together the key constructs—technological advancements, digital skills, IT investments, strategies and policies, and R&D illustrates how they interact to shape Labor Market Dynamics in Bangladesh’s manufacturing sector. In particular, the model positions digitalization and its contextual factors as the independent variables, while Labor Market Dynamics serve as the Dependent variable.

The model also incorporates the moderating effects of firm type and firm size, recognizing that organizational characteristics significantly influence how digital transformation translates into employment outcomes. Inclusion of these moderators, the model reflects the heterogeneous nature of Bangladesh’s manufacturing sector and provides a more concrete and closer lens for analyzing digitalization effects on employment.

The graphical representation of this model depicts variable linkages; it functions as a blueprint for the empirical phase of the study. Through Structural Equation Modeling (SEM), the relationships outlined in the conceptual model will be tested and validated, ensuring both statistical rigor and theoretical coherence. In this way, the visual model bridges the gap between theoretical assumptions and empirical analysis, providing a structured pathway for hypothesis testing and deeper exploration of digitalization’s impact on employment in Bangladesh’s manufacturing sector.

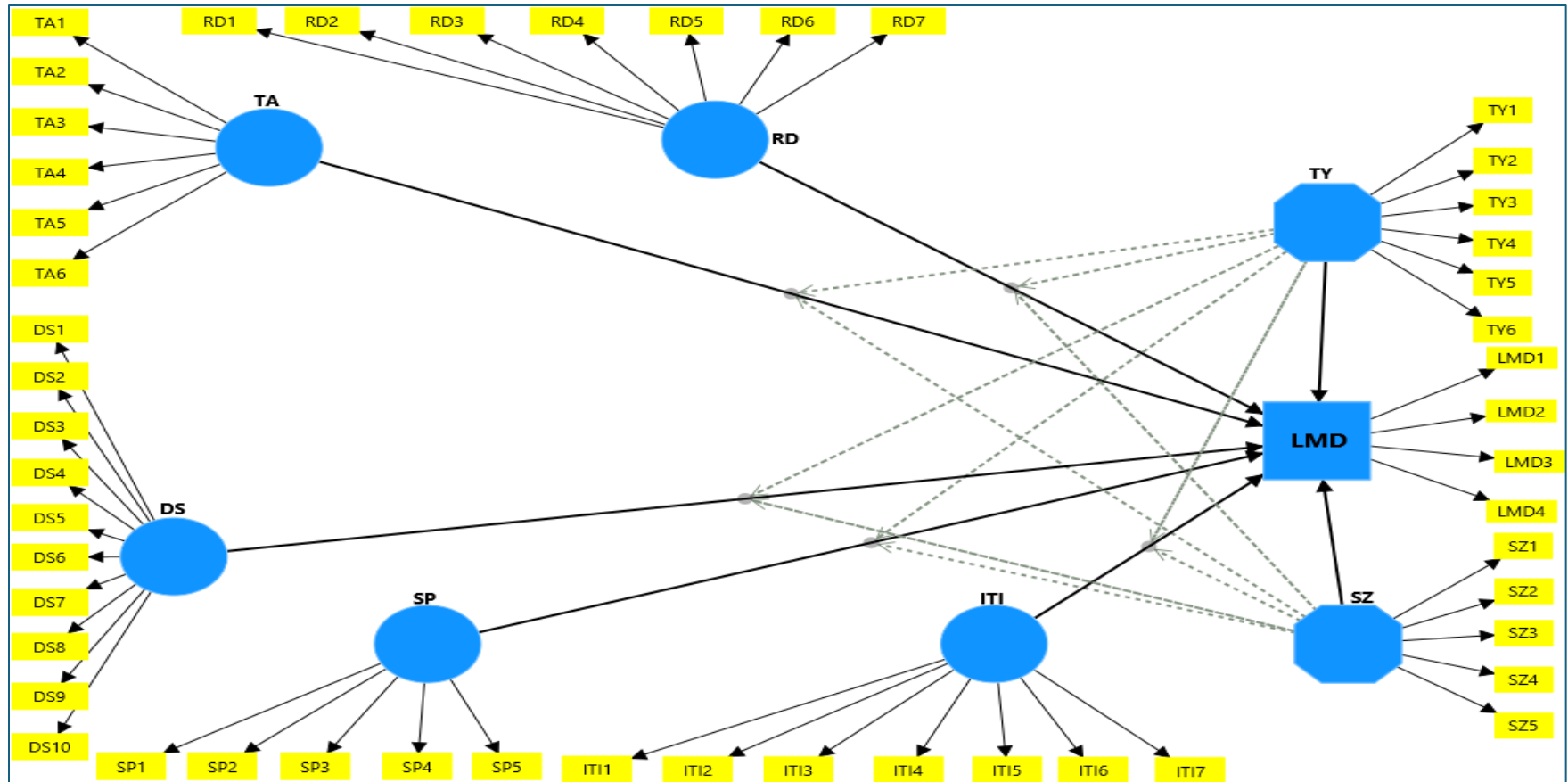


Figure 3.4: Pre - Conceptual framework

Figure 3.4 presents the pre-conceptual framework of the study, developed based on the integration of established theories and prior empirical literature on digital transformation, technological change, and employment dynamics in manufacturing industries (Schumpeter, 1942; Nelson & Phelps, 1966; Acemoglu & Restrepo, 2018; Cirera et al., 2021).

3.11 Justification of the Model

The conceptual model developed in this study has been carefully considered to capture the complex relationship between digitalization and employment within the context of Bangladesh's manufacturing sector. Each construct included in the model has been selected based on both theoretical relevancy and empirical support from prior studies, theoretical models, global and local studies. Technological Advancements, Digital Skills, IT Investments, Strategies and Policies, and R&D are considered essential drivers of labor market transformation, as they directly shape how industries adopt and integrate technological advancements. At the same time, Labor Market Dynamics are positioned as the key outcome variable, reflecting changes in employment patterns, job quality, wage inequality, job disparities, and skill demand resulting from digital transformation.

The inclusion of moderators—firm Type and firm Size—further strengthens the model by acknowledging the heterogeneous nature of Bangladesh's manufacturing sector. Large firms with substantial resources often lead innovation and create high-skilled employment opportunities, whereas small and medium-sized enterprises (SMEs) may struggle to adapt due to financial and structural limitations. By integrating these organizational characteristics, the model provides a more realistic and context-sensitive understanding of how digitalization influences employment outcomes.

This framework also addresses critical gaps in existing literature. Much of the global research on digitalization and employment has been conducted in advanced economies, with relatively little attention given to developing countries like Bangladesh. By situating the analysis within Bangladesh's socio-economic and industrial context, the model captures factors such as policy challenges, defocus on R&D, Digital Skills gaps, and the dominance of labor-intensive industries. These contextual considerations make the model particularly relevant for exploring the unique opportunities, threats and challenges those digital technologies present for employment in Bangladesh.

Considering and inclusion of these dimensions, the model not only draws from established theoretical foundations and international evidence but also adapts these insights to the realities of Bangladesh's manufacturing sector. It therefore provides a comprehensive and

contextually grounded framework for analyzing the effects of digitalization on employment, bridging the gap between theory, global trends, and local industrial dynamics.

- **Rationale for Including Specific Constructs**

The constructs are chosen based on relevant theories, prior studies to understanding the complex relationship between digitalization and employment in Bangladesh. These constructs align with the theoretical frameworks discussed earlier and are supported by empirical evidence from both global and local contexts.

- **Addressing Identified Gaps**

The model addresses gaps in the literature by contextualizing digitalization's impact within Bangladesh's manufacturing sector. It considers the unique socio-economic and industrial characteristics of Bangladesh, providing a broad outline for analyzing the effects of digital technologies on employment

3.12 Application of the Model

The proposed model carries both theoretical and practical implications for policymakers, academia, industry leaders, and other stakeholders engaged in Bangladesh's manufacturing sector.

- ✓ **Policymakers:**

The model will give insights that can guide the Policy maker and strategist to design and formulate strategies and policies to facilitate digital adoption while minimizing negative impact on employment. By emphasizing workforce reskilling and digital skills development, the findings will help create an enabling environment that balances technological progress with employment sustainability.

- ✓ **Academia:**

In the academic domain, the model contributes to theoretical advancement by offering a structured framework for analyzing the intersection of digitalization and Labor Market Dynamics. It enhances scholarly understanding and serves as a reference point for future studies, enabling knowledge generation and comparative research across disciplines and contexts.

✓ **Industry Leaders:**

The model functions as a strategic tool for evaluating the implications of digitalization on workforce structures for the industry leaders. It will assist the leaders to develop effective upskilling initiatives, strengthen competitiveness, and manage organizational transitions more effectively. By adopting such a framework, firms can mitigate risks, enhance efficiency, and achieve long-term growth in a rapidly digitalizing environment.

Finally, for all stakeholders, including investors, employees, and customers, the model offers a systematic perspective for navigating the uncertainties of technological transformation. It supports informed decision-making, alignment with industry trends, and the optimization of outcomes in the evolving employment landscape.

3.13 Limitations and Assumptions

Like other studies, this study has also certain limitations and relies on some assumptions. Lack of comprehensive and disaggregated information across regions and industries, restrict the ability to capture the full diversity of Bangladesh's manufacturing sector, while regional variations in technological adoption may limit generalizability. The model also assumes linear relationships and continuous technological progress, which may oversimplify complex dynamics, and relies on frameworks such as the Technology Acceptance Model (TAM), Creative destruction or labor market segmentation theory that may not fully reflect local socio-cultural contexts. These boundaries, while necessary for the current analysis, highlight important avenues for future research through longitudinal studies, cross-regional comparisons, and alternative theoretical perspectives.

3.13.1 Limitations of the Study

While this study aims to provide a comprehensive analysis of the impact of digitalization on employment in Bangladesh's manufacturing sector, several constraints must be acknowledged.

- **Data Availability and Quality**

In Bangladesh the Data available and ensuring reliable sources are in great challenge. Data needed for the study might be limited and inconsistent, may not be authentic that might affect the model's accuracy and robustness.

- **Scope of Industry**

Models focus primarily on manufacturing industries, and the results may not fully apply to all sub-sectors, backward and forward linkages industries that are also undergoing digital transformation.

- **Regional Differences**

The impact of digitalization may vary across different regions even within Bangladesh due to different infrastructure, and socioeconomic differences, which could limit the generalizability of the model.

- **Technology Acceptance Model Variability**

The adoption of digitalization differs from industries to industries, type to type, area to area this disparity could create challenges in creating a unified model that captures all relevant cases.

- **External Factors**

Factors such as political instability, changes of rules and act, reform of the regulatory, or global economic shifts could impact on the employment landscape in ways that the model may not fully account for, affecting the results.

3.13.2 Assumptions

This study is based on several key assumptions that shape the analysis of digitalization's impact on employment in Bangladesh's manufacturing sector.

- **Linear Relationship Between Digitalization and Employment**

The model assumes a direct, linear relationship between the adoption of digital technologies and its effect on dynamic employment, but realistically it's more complex and dynamic.

- **Homogeneous Impact Across Sectors**

For the study another assumption is made that digitalization has the same effect on employment across all manufacturing sub-sectors might oversimplify the variation in Technology Acceptance Model and workforce impact.

- **Constant Technological Progress**

One of the assumptions of the model is that technological progress in manufacturing will continue at the same rate, although this could vary due to economic, policy, or global supply chain disruptions.

- **Availability of a Skilled Workforce**

Another assumption is that there is an adequate supply of skilled workers to complement the digital tools being introduced, but there may be gaps in skills and training that hinder the effectiveness of digitalization.

- **Rational Responses to Digitalization**

The model assumes that companies and employees will make rational decisions based on the digital tools available to them, though real-world decision-making can be influenced by external pressures, biases, or misalignment between employee skillsets and technology needs.

By addressing the scope and constraints of the model, this study provides a foundation for future research that can offer a more comprehensive understanding of how digitalization impacts employment in developing economies like Bangladesh.

Chapter 4: Research Design and Methodology

4.1 Introduction and Overview of Research Methodology

This study employs a mixed-methods research design that integrates qualitative and quantitative approaches to provide a comprehensive understanding of the research problem. According to Creswell and Plano Clark (2018), mixed-methods research is particularly effective when a study requires both numerical evidence and contextual understanding to address complex social and economic issues. In this study, dual approach is used for capturing not only key statistical patterns of employment dynamics as well as the practical experiences, insights, and perspectives of employers, policymakers, and industry stakeholders who are directly or indirectly engaged or influenced in the process of digital transformation. The strength of the mixed-methods design lies in its capacity to combine descriptive, exploratory, and explanatory analyses. This dual approach is very much relevant in the context of Bangladesh's manufacturing industry, which is characterized by firm-level diversity, varying technological capabilities, and a workforce with significant differences in Skills, Policy & Strategy, IT Investment and adaptability.

Quantitative evidence alone cannot discover the deep realities of how digitalization affects employment across different types of organizations. Conversely, focusing only on qualitative narratives could limit the ability to generalize findings and establish broader sectoral trends. Blending the two approaches ensures a holistic and balanced understanding of the problem (Tashakkori & Teddlie, 2010; Saunders, Lewis & Thornhill, 2019). Specifically, the exploratory qualitative phase draws on in-depth insights from policymakers, industry leaders, employers, and employees.

Qualitative analysis highlights contextual challenges, emerging strategies, and workforce experiences that may not be visible in statistical datasets. In parallel, the descriptive and explanatory quantitative phases provide robust data to identify employment trends, validate relationships, and examine dependencies among critical indicators. Shen et al. (2024) develop a conceptual framework based on ecosystem orchestration practices using a systematic literature review and qualitative meta-synthesis approach. Their study integrates existing research on digital industrial ecosystems to identify key themes such as

coordination mechanisms, capability development, and value co-creation among interconnected actors. Methodologically, the study demonstrates how secondary data can be systematically synthesized to build a robust theoretical model, moving from fragmented evidence to an integrated conceptual framework.

Combining these two methodologies complement each other: qualitative findings enrich the interpretation of quantitative data, while quantitative analysis grounds qualitative insights in broader sectoral realities (Creswell, 2014). Ultimately, the mixed-methods design ensures that the study not only addresses the research gap but also provides a rich, context-specific understanding of how digitalization is transforming employment in the country's manufacturing sector.

4.2 Research Design and Research Approach for Qualitative Analysis

The qualitative approach adopted in this study is intended to capture in-depth insights and key themes from individuals who are directly or indirectly influenced by, engaged in, or interacting with the process of digitalization within the manufacturing sector. Qualitative research is particularly appropriate for examining digital transformation and Labor Market Dynamics, as these phenomena involve complex social, organizational, and technological interactions that cannot be fully explained through quantitative measures alone. This approach enables meanings, patterns, and themes to emerge organically from participants' narratives rather than being constrained by rigid, predefined variables or hypotheses.

Recent studies highlight that qualitative methods are especially effective in uncovering workers' perceptions, managerial decision-making, and organizational responses to digital transformation, which are often overlooked in large-scale quantitative analyses (Hanelt et al., 2021; Van der Schaft et al., 2024; Viljoen et al., 2024). Moreover, qualitative research has been widely used to explore the human and institutional dimensions of Industry 4.0, including skill transitions, algorithmic management, and the socio-technical implications of advanced manufacturing technologies (Hanelt et al., 2021; Orlikowski & Scott, 2021; OECD, 2023; ILO, 2023).

In this context, the qualitative design employed in this study ensures that the findings reflect the practical realities, challenges, and opportunities experienced by stakeholders within the manufacturing sector. By complementing quantitative analysis, this approach strengthens the overall research design and underscores the importance of capturing both

measurable outcomes and the human experiences underpinning the process of digital transformation.

4.2.1 Population and Sectoral Representation for Qualitative Analysis

The qualitative phase of this study focused on individuals who are directly or indirectly involved in the digital transformation of Bangladesh's manufacturing sector. A purposive sampling strategy was employed to include a carefully selected mix of stakeholders, ensuring the collection of rich, diverse, and contextually grounded insights. Such an approach is widely recommended for qualitative research examining complex socio-technical transformations, including digitalization and workforce change (Creswell & Poth, 2018; Hanelt et al., 2021).

To ensure a diverse and representative qualitative sample, participants were selected using purposive and stratified judgmental sampling from multiple stakeholder groups involved in or affected by digitalization in the manufacturing sector of Bangladesh. The study includes respondents from different hierarchical positions, industries, educational backgrounds, and levels of digital exposure to capture a comprehensive understanding of digital transformation and its implications for employment.

The sample includes executives and senior managers, mid-level managers, frontline employees, policymakers, industry experts, and academics/researchers.

The target population comprised multiple stakeholder groups representing different hierarchical and institutional perspectives:

- **Executives and senior managers**, responsible for formulating and overseeing digital strategies, process automation, and innovation initiatives within manufacturing firms.
- **Mid-level and frontline employees**, who experience firsthand the implications of digitalization for daily work practices, job roles, and evolving skill requirements.
- **Policymakers and industry experts**, engaged in designing and implementing regulatory frameworks, industrial policies, and workforce development programs related to digital technologies.
- **Academics and researchers**, involved in industry-focused research, skills development initiatives, and policy advisory roles connected to manufacturing digitalization.

Category	Sub-Category	Number of Participants	Percentage (%)
Industry Stakeholders	Senior Executives / Managers	13	25%
	Mid-Level Managers	11	21%
	Frontline Employees / Workers	8	15%
Policy & Institutional Actors	Policymakers / Government Officials	6	11%
Experts & Academics	Industry Experts / Consultants	8	15%
	Academics / Researchers	7	13%
Total		53	100%

Table 4.1: Profile of Qualitative Respondents by Stakeholder Category

As shown in Table 4.1 (Field Survey, 2025), respondents are distributed across key stakeholder categories. To ensure broad sectoral representation, participants were drawn from key manufacturing sub-sectors, including pharmaceuticals, leather and footwear, cement and ceramics, textiles and garments, food processing, light engineering, and engineering and electronics. These sub-sectors were purposefully selected due to their economic importance, heterogeneous levels of digital maturity, and distinct labor structures. Prior studies emphasize that such sectoral diversity is critical for understanding how digital transformation affects employment dynamics differently across industries (ILO, 2021; UNIDO, 2023; World Bank, 2022).

Location Type	Area	Number of Participants	Percentage (%)
Urban Industrial Hubs	Dhaka	26	49.10%
	Chittagong	12	22.60%
Semi-Urban Areas	Gazipur / Narayanganj	8	15.10%
Rural Manufacturing Zones	Outside major cities	7	13.20%
Total		53	100%

Table 4.2: Distribution of Qualitative Respondents by Location Type and Industrial Area

The geographic distribution of qualitative respondents is presented in Table 4.2, Geographic coverage includes urban industrial hubs (Dhaka and Chittagong) as well as

semi-urban and rural manufacturing zones, ensuring variation in digital infrastructure and exposure levels. (Field Survey, 2025).

Manufacturing Sector	Number of Participants	Percentage (%)
Pharmaceuticals / Chemicals	11	21%
Cement Industry	5	9%
Food Processing & Beverages	9	17%
Leather & Footwear	6	11%
Electronics	8	15%
Ceramics	3	6%
Light Engineering	6	11%
Others	5	9%
Total	53	100%

Table 4.3: Distribution of Qualitative Respondents by Manufacturing Sector

The sector-wise distribution of qualitative respondents is presented in Table 4.3, indicating that participants were drawn from a diverse range of manufacturing industries, with a higher concentration from pharmaceuticals/chemicals and food processing sectors (Field Survey, 2025).

By incorporating perspectives from multiple organizational levels and diverse industrial segments, the qualitative research design facilitated the collection of nuanced and multi-dimensional data. This inclusive approach was essential for capturing how digitalization is perceived, implemented, and responded to across Bangladesh’s manufacturing landscape, thereby providing deeper insights into both the opportunities and challenges associated with digital transformation in a developing-country context (UNCTAD, 2021; World Bank, 2019; ILO, 2023; OECD, 2023).

4.2.2 Sampling Technique for Qualitative Analysis

A purposive non-probability sampling technique was adopted to select participants based on their knowledge, insights, perceptions, experience, and relevance to the study objectives (Palinkas et al., 2015; Patton, 2002). To ensure diversity, maximum variation sampling was also employed. Participants were drawn from:

- Firms of various sizes (small, medium, and large),

- Both local and multinational organizations,
- A range of geographic locations include Dhaka, Gazipur, Narayanganj, Chittagong, Narsindhi and Savar.

The inclusion of perspectives from firms with varying degrees from different locations ensures proper representation of the data.

4.2.3 Sample Size Determination and Rationale for Qualitative Analysis

A total of 53 participants participated in the qualitative study, selected through purposive sampling based on their relevance to the research objectives. The qualitative sample included:

- 30 in-depth semi-structured interviews conducted with key stakeholders such Mid-level to Senior level managers, employers, policymakers and Academics also. These participants were chosen for their strategic and operational roles in shaping and responding to digitalization within the manufacturing sector.
- 4 focus group discussions involving a total of 23 employees from various departments and organizational levels within manufacturing firms. These discussions provided rich, collective insights into how digitalization is experienced at the operational level, particularly in terms of job roles, skill requirements, and workplace transformation.

The chosen sample size aligns with qualitative research standards and was deemed sufficient to achieve thematic saturation, where no new themes or significant insights emerged from subsequent data collection. This ensured a comprehensive and balanced exploration of digitalization's impact across different organizational roles and perspectives within Bangladesh's manufacturing industry.

4.2.4 Sample Size Justification for Qualitative Analysis

The sample size of 53 participants in the qualitative phase of this study is consistent with established principles of qualitative research, particularly the concept of thematic saturation. Thematic saturation refers to the point at which no new information, insights, or themes emerge from additional data collection, indicating that the dataset is sufficiently rich for analysis (Guest, Bunce, & Johnson, 2006; Fusch & Ness, 2015; Saunders et al., 2018). Thematic saturation was detected after 40th participants after 41st participant,

subsequent responses primarily reinforcing previously identified themes and patterns. This suggests that the sample size was not only sufficient but also provided the necessary depth, breadth, and diversity to ensure conceptual robustness and analytical rigor.

Qualitative research literature suggests that 12 to 30 interviews are generally adequate for saturation, especially when the participants share common experiences or when the research questions are clearly defined (Guest et al., 2006; Mason, 2010; Marshall, Cardon, Poddar, & Fontenot, 2013). For focus groups, studies recommend conducting 3 to 6 groups with 6–8 participants each to adequately explore variation and uncover dominant themes (Krueger & Casey, 2015; Morgan, 1997). The composition of this study includes 30 interviews and 4 focus groups involving 23 employees—thus falls well within the accepted qualitative methodological standards.

Moreover, the use of maximum variation sampling across firm sizes, industry types, and stakeholder roles helped ensure that the findings reflect the heterogeneity of experiences and perspectives within Bangladesh's manufacturing sector. This further enhances the credibility and transferability of the results.

When questions were raised on ethical consideration, this study strictly followed the Ethical issues, all participants were selected based on informed consent and briefed in advance regarding the purpose, scope, and voluntary nature of their participation. Ethical protocols and guidelines were strictly adhered throughout the research process, including assurances of confidentiality, anonymity, and the right to withdraw at any time without consequence. Formal ethical clearance was obtained from the institutional authority prior to data collection, and all interviews and focus groups were conducted in a respectful and non-coercive manner.

4.3 Research Design and Research Approach for Quantitative Analysis

The determination of the population size is crucial for this study. To confirm representative data, for quantitative analysis this study followed a stratified random sampling technique, a probability-based method designed to ensure that specific subgroups (strata) within the target population are adequately represented in the sample.

4.3.1 Population and Sample Size Determination for Quantitative Analysis

To confirm the accurate number of registered manufacturing industries currently operating in Bangladesh was difficult and challenging due to data inconsistencies across different sources. However, a recent authentic report by the Bangladesh Bureau of Statistics (BBS) that is supported by publications from the Ministry of Industries (2023), Estimates that there are approximately 7,000 registered manufacturing firms across the country. These firms span multiple sub-sectors, including pharmaceuticals, cement, ceramics, leather and footwear, textiles, electronics, and food processing (BBS, 2023).

The selection of population comprises key organizational personnel involved in digital transformation processes. This includes senior management, operational managers, and technical staff who are either directly implementing or adapting digital technologies within their respective firms. Focusing on these groups allows the research to capture a comprehensive range of insights into how digitalization is influencing employment structures, job roles, and workforce strategies across different hierarchical levels. Their diverse experiences and responsibilities contribute to a holistic understanding of the impact of digital technologies on labor dynamics within Bangladesh's evolving manufacturing landscape.

Several established techniques applied to determine the proper sample size for this study. Cochran's (1977) formula was applied because this method ensures selected sample is adequately representative of the target population. The use of Cochran's formula aligns with best practices in survey-based research, providing a statistically robust foundation for hypothesis testing and ensuring analytical rigor.

The formula for **Cochran's** sample size determination for finite populations is expressed

$$\text{as: } n = \frac{N \cdot Z^2 \cdot p \cdot (1-p)}{e^2 \cdot (N-1) + Z^2 \cdot p \cdot (1-p)}$$

Where:

- **n:** Required sample size
- **N:** Population size (7,000 registered firms)
- **Z:** Z-score for a 95% confidence level (Z=1.96)
- **p:** Estimated proportion of the population exhibiting the characteristic of interest (assume $p = 0.5$ for maximum variability).
- **e:** Chosen margin of error (7.5% or 0.075).

Substituting the values:

$$n = \frac{7000 \cdot 1.96^2 \cdot 0.5 \cdot (1-0.5)}{(0.075)^2 \cdot (7000-1) + 1.96^2 \cdot 0.5 \cdot (1-0.5)}$$

$$n = \frac{7000 \cdot 3.8416 \cdot 0.25}{0.005625 \cdot 6999 + 3.8416 \cdot 0.25}$$

$$n = \frac{6722.8}{39.369375 + 0.9604}$$

$$n = \frac{6722.8}{40.3298} \approx 166.0$$

This formula is particularly suitable for research involving finite populations, such as the 7,000 registered firms in this study. By substituting the relevant values—Population (N)=7,000, Z=1.96, p=0.5 and Marginal Error (e)=0.075, the calculated sample size 166 ensures both precision and representativeness.

The required sample size of 166 ensures both precision and representativeness (population size of 7,000, margin of error of 7.5%, and desired confidence level), increasing the sample size to 213 allows more representation of dataset that applied in the study. This reduces the potential for bias and ensures that variations across different subgroups (e.g., firm size, industry type) are better captured, enhancing the reliability of the findings.

4.3.2 PLS-SEM Sample Size Justification

When using Partial Least Squares Structural Equation Modeling (PLS-SEM), determining an appropriate sample size is crucial for achieving reliable and valid results. A sample size of 213 respondents is well-justified for the research on digitalization and employment in Bangladesh's manufacturing industries, considering the following reasons:

I. Meets the "10 Times Rule" in PLS-SEM

- The "10 times rule" is a widely used heuristic in PLS-SEM, which suggests that the minimum sample size should be at least 10 times the largest number of structural paths pointing to a single latent variable in the model.
- The model includes a latent variable with seven predictors; the minimum sample size should be $10 \times 7 = 70$. With 213 respondents, the sample size significantly exceeds this threshold, ensuring adequate statistical power.

II. Ensures Adequate Statistical Power

- Another approach to determine the Sample size is Statistical power that refers to the ability to detect significant relationships among variables. A power level of 0.80 or higher is recommended in research.
- According to Hair et al. (2011) and Kock & Hadaya (2018), for models with
 - *Effect sizes $f^2 = 0.15$*
 - *Alpha $\alpha =$ significant level of 5%,*
 - *Power $1 - \beta = 0.80$*
 - *Number of predictors = 7*

For 7 predictors with a medium effect size (0.15), the required sample size is 103 participants

Since survey-based research typically experiences a 10-20% non-response rate, consider increasing the sample size by at least 20% to account for incomplete responses. If G*Power suggests 103, collect at least (120% of 103) 123 responses to ensure a robust analysis. a sample size of approximately 120–180 is required for sufficient power. With 213 respondents, the study achieves even higher power, enabling reliable detection of smaller effect sizes in complex models.

Using a sample size of 213 respondents in PLS-SEM study exceeds the commonly required thresholds, ensuring robust and reliable results. This larger sample size enhances statistical power, supports complex model structures, reduces biases, and allows for meaningful subgroup analyses. As a result, the findings on the impact of digitalization on employment in Bangladesh's manufacturing industries will be more generalizable, credible, and impactful.

4.4 Data Sources

Primary and secondary sources used to support the study. Primary data is collected through surveys and interviews with key stakeholders in Bangladesh's manufacturing sector, while secondary data is sourced from industry reports, academic articles, and government publications to provide a comprehensive view of digitalization's impact on employment.

4.4.1 Primary Data Sources

Primary data is collected through:

- **Surveys** Targeting employees, managers, industry leaders, academics and industry stakeholders who are directly or indirectly involved in manufacturing sectors.
- **Interviews** with industry management, experts and policymakers to gain insights into digitalization trends and their implications for employment.

4.4.2 Secondary Data Sources

Secondary data is gathered from:

- Studies published by reputable and authoritative organizations, such as the Bangladesh Bureau of Statistics (BBS), World Bank, IDB, IMF, and ADB, as well as government reports, peer-reviewed journal articles, and credible news sources. These sources were selected due to their authenticity, reliability, and relevance in providing accurate data, insights, and analyses on industrial digitalization in Bangladesh, including related policies, frameworks, and strategic initiatives. This approach ensures that the study is grounded in credible evidence and contemporary perspectives relevant to the research context.

Manufacturing Sector	Number of Respondents	Percentage (%)
Pharmaceuticals / Chemicals	43	20%
Cement Industry	19	9%
Food Processing & Beverages	36	17%
Leather & Footwear	39	18%
Electronics	26	12%
Ceramics	19	9%
Light Engineering	12	6%
Others	19	9%
Total	213	100%

Table 4.4: Distribution of Quantitative Respondents by Manufacturing Sector

The distribution of respondents across different manufacturing sectors is presented in **Table 4.4**, which shows that the highest proportion of respondents came from pharmaceuticals/chemicals, followed by leather & footwear and food processing industries (Field Survey, 2025).

Region	Area Coverage	Number of Respondents	Percentage (%)
Dhaka Division (Urban Core)	Dhaka City Industrial Areas	88	41%
Outside Dhaka – Industrial Belt	Gazipur, Narayanganj, Savar	62	29%
Chittagong Division	Chittagong EPZ & Industrial Zones	34	16%
Other Regions (Semi-Urban/Rural Manufacturing Clusters)	Khulna, Rajshahi, etc.	29	14%
Total		213	100%

Table 4.5: Distribution of Quantitative Respondents by Regions and Area Coverage

The regional distribution of respondents across major industrial locations is presented in Table 4.5, indicating a concentration of respondents in Dhaka Division and surrounding industrial belts, followed by Chittagong Division and other semi-urban manufacturing clusters (Field Survey, 2025).

Category	Sub-Category	Number of Participants	Percentage (%)
Industry Stakeholders	Senior Executives / Managers	73	34%
	Mid-Level Managers	53	25%
	Frontline Employees / Workers	28	13%
Policy & Institutional Actors	Policymakers / Government Officials	13	6%
Experts & Academics	Industry Experts / Consultants	28	13%
	Academics / Researchers	18	8%
Total		213	100%

Table 4.6: Profile of Quantitative Respondents by Stakeholder Category

The composition of respondents based on stakeholder categories and sub-categories is presented in Table 4.6, showing that most participants were industry stakeholders, particularly senior and mid-level managers, followed by experts, academics, and policy actors (Field Survey, 2025).

4.5 Survey Design and Data Collection

A detailed survey instrument comprising of Fifty-One (51) Items, designed to capture data across seven (7) latent constructs. These constructs were sensibly selected to reflect the multifaceted relationship between digitalization and employment in Bangladesh's manufacturing sector. Three digitalization factors- Technological Advancement, Digital Skills, IT investment and two contextual factors - Strategy and Policy, R&D. These five factors directly influence the Labor Market Dynamics. Among seven constructs, two constructs Type and Size are identified as moderating variables, hypothesized to influence the relationships between independent and dependent variables. (Baron & Kenny, 1986).

The study applies a 5-point Likert scale, ranging from Strongly disagree (1) to strongly agree (5). This scaling method is widely recognized in social science research for its reliability, acceptability and effectiveness in presenting attitudes, perceptions, relationships and opinions (Joshi et al., 2015; Likert, 1932).

A structured questionnaire was administered through Google Forms, and additional responses were collected physically from individuals who are directly or indirectly associated with the manufacturing industry. Both methods were employed to maximize response rates, ensure wider coverage, and accommodate participants with varying levels of access to digital platforms, thereby enhancing the representativeness and reliability of the data collected. A mixed-methods approach has been widely recommended for improving data reliability, validity, and representativeness by integrating the strengths of both qualitative and quantitative research methods (Bryman, 2016; Creswell & Creswell, 2018). Online surveys were distributed via email using Google Forms, while in-person surveys and interviews were conducted at manufacturing facilities, factories, and corporate offices. Initially, the data collection process was planned for six months; but, due to lower-than-expected response rates, an additional four months were required to achieve the targeted sample size. During this period, follow-up reminders and requests were regularly

sent to non-respondents, also, maintained all sorts of practices to maintain integrity and confidentiality as an ethical consideration (Saunders, Lewis, & Thornhill, 2019).

A total of 213 responses were recorded, a sample size considered adequate established by rigorous different statistical sampling techniques like Conchran calculation, Statistical Power Calculation and 10-time rule in PLS-SEM.

This methodological approach strengthens the reliability and validity of the study's findings and that aligns with established best practices in survey research.

4.6 Data Analysis

Primary data is collected through surveys and interviews with key stakeholders in Bangladesh's manufacturing sector, while secondary data is sourced from industry reports, academic articles, and government publications to provide a comprehensive view of digitalization's impact on employment

4.6.1 *Method of Qualitative Analysis*

Qualitative analysis investigates insights, opinions, feedback and perceptions of the interviewer that provide context, background and foundation for the in-depth analysis for the study. Thematic analysis, key patterns and themes were identified to understand the impact of digitalization on employment in the manufacturing sector of Bangladesh. The analysis followed a systematic process, including research design, demographic profiling, theme identification, and interpretation of findings. Thematic analysis was used to interpret insights from interviews and policy documents, providing context for the quantitative findings. This process involves the following steps:

4.6.1.1 Qualitative Step 1: Interviews & Focus Groups

Interviews were conducted with executives and employees to gather diverse perspectives on digitalization's impact.

4.6.1.2 Qualitative Step 2: Coding & Thematic Analysis

Applied open and focused coding to identify key themes like technological advancement, job displacement, and skills development etc.

4.6.1.3 Qualitative Step 3: Categorization & Data Interpretation

Considered contextual factors, digitalization factors and moderating factors, and applied relevant theories (e.g., Creative Destruction, TAM) to interpret insights.

4.6.1.4 Qualitative Step 4: Key Themes Identified

Explored how digitalization affects employment, firm strategies, and government policies in Bangladesh's manufacturing sector.

4.6.1.5 Qualitative Step 5: Validation & Triangulation

Ensured credibility through member checking, peer reviews, and triangulation across multiple data sources.

4.6.1.6 Qualitative Step 6: Thematic Map for Conceptual Model

Thematic framework informed the construction of the conceptual model and guided hypothesis development for the quantitative phase.

4.6.2 *Quantitative Analysis*

The quantitative process of this study follows a structured approach to scrutinize and explore the impact of digitalization on employment in manufacturing industries in Bangladesh. First, the research adopts a survey-based quantitative design, employing a stratified random sampling technique, a probability-based sampling method to categorize firms based on size and type of organization. Data is collected through structured questionnaires, distributed via online and face-to-face surveys, targeting the employees, employers and stakeholders of manufacturing industries. The study measures key variables, with digitalization as the independent variable, employment dynamics as the dependent variable, firm size and type as potential mediators. Next, data analysis begins with descriptive statistics to summarize the sample characteristics, followed by reliability and validity tests (Exploratory Factor Analysis, Cronbach's alpha, and composite reliability). Correlation and covariance analysis helps examine relationships between variables, while structural equation modeling (SEM) is applied to test the conceptual model and hypotheses. Finally, the findings are interpreted considering relevant theories, including Creative Destruction and Innovation Diffusion, and the study concludes with discussions on policy and managerial implications. Below the steps of the quantitative analysis

4.6.2.1 Quantitative Step 1: Descriptive Statistics

Descriptive Statistics in research methodology refers to the process of summarizing and organizing data in a meaningful way. It is the first step in quantitative analysis and helps researchers understand the basic features of the data, including the central tendency (mean, median, mode), variability (range, variance, standard deviation), and distribution (skewness, kurtosis). Descriptive statistics provide a clear overview of the sample or population, enabling researchers to identify patterns, trends, and anomalies before further statistical analysis.

4.6.2.2 Quantitative Step 2: Exploratory Factor Analysis (EFA)

After Descriptive Statistics analysis, the Exploratory Factor Analysis (EFA) in this study is conducted to identify the underlying factor structure of the measurement items related to digitalization, employment impact, and firm strategies in Bangladesh's manufacturing sector.

For EFA First, Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity are conducted to evaluate and measure the sampling adequacy and data suitability for factor analysis. Next, for factor extraction Principal Axis Factoring (PAF) statistical technique employed in exploratory factor analysis (EFA) to identify the factors that explain the correlations among observed variables. Factor rotation used Promax Rotation to identify underlying relationships in the study by allowing factors to correlate and interpret complex relationship among variables. Dimensional reduction simplifies the dataset by reducing the number of variables, keeping and maintaining the principal patterns in digitalization and employment in the manufacturing industry, that confirming the analysis more manageable. This process ensures that the constructs used in the study are statistically sound and suitable for further analysis, such as Measurement Model and Structural Equation Modeling (SEM).

4.6.2.3 Quantitative Step 3: Measurement Model Validation and Evaluation

The measurement model is crucial for assessing the reliability and validity of the constructs that were defined in the theoretical framework. Measurement model evaluates whether the constructs and their indicators are Reliable and Valid. The Measurement Model Evaluation of this study checks the reliability and validity of the constructs before proceeding to Structural Equation Modeling (SEM) which is vital for the completeness of this study. To

confirm indicator's reliability outer loading, for internal consistency composite reliability and Cronbach's Alpha, for convergent validity (e.g., Average Variance Extracted - AVE) and discriminant validity (e.g., Fornell-Larcker criterion, HTMT) to verify that constructs are distinct from each other. A measurement model ensures that the study's findings are robust and that the relationships between variables in the structural model are meaningful and not influenced by measurement errors. A well-evaluated measurement model confirms that the constructs are statistically valid for further hypothesis testing in SEM.

4.6.2.3.1 Reliability Assessment

Reliability measures the consistency of the measurement items in representing the constructs. It is assessed using:

i. Indicator Reliability

Indicator Reliability Check if individual items (indicators) strongly measure their latent variables.

Metrics:

- **Outer loadings** > 0.70. (Retain indicators with loadings between 0.4 and 0.7 only if they contribute to AVE or Composite Reliability and Remove indicators with loadings below 0.4, unless theoretically necessary. (Hair et al. (2021)

ii. Internal Consistency Reliability

Assess whether the items collectively measure the same construct.

Metrics:

- **Composite Reliability (CR)** values greater than 0.70 are considered acceptable for confirmatory research, while values between 0.60 and 0.70 may be tolerated in exploratory studies (Hair et al., 2021; Fornell & Larcker, 1981).
- **Cronbach's Alpha** > 0.7 for established constructs.

A CR value above 0.70 indicates good construct reliability. CR is preferred over Cronbach's alpha as it considers indicator loadings.

4.6.2.3.2 Convergent and Discriminant Validity Assessment

Validity assessment ensures that the measurement items accurately reflect the theoretical constructs. It is assessed through convergent validity and discriminant validity.

a) Convergent Validity

Convergent validity verifies that indicators for a construct converge to measure the same concept.

It is measured using:

- **Average Variance Extracted (AVE):** AVE assesses the amount of variance captured by the construct versus the variance due to measurement error. It is calculated as:

$$AVE = \frac{(\sum Factor\ Loading)^2}{Number\ of\ items}$$

An AVE value above 0.50 indicates that more than 50% of the variance is explained by the construct, demonstrating good convergent validity.

b) Discriminant Validity

Discriminant validity ensures that a construct is distinct from other constructs in the model. It is assessed using:

- **Fornell-Larcker Criterion:** The AVE of each construct should be greater than the squared correlations between that construct and any other construct.

$$\sqrt{AVE} > correlation\ between\ constructs$$

- **Heterotrait-Monotrait Ratio (HTMT):** HTMT assesses the discriminant validity by comparing the relationships between constructs. An HTMT value **below 0.85** indicates acceptable discriminant validity.

4.6.2.4 Quantitative Step 4: Model Refinement (if needed)

If the initial model does not achieve satisfactory fit indices, model modifications may be necessary. Modifications should be theory-driven rather than solely based on statistical recommendations (Byrne, 2016). Common approaches include removing items with low factor loadings (< 0.50) and correlating error terms if supported by theoretical justifications (Brown, 2015). The Modification Indices (MI) provided by statistical software can guide adjustments to improve model fit.

4.6.2.5 Quantitative Step 5: Validation of the Final Measurement Model

Once modifications are completed and the model achieves a satisfactory fit, validation is necessary. Cross-validation using a different sample ensures the robustness of the

measurement model (Schumacker & Lomax, 2021). Researchers must thoroughly test the measurement model to confirm that the constructs accurately measured its reliability and validity, also theoretically sound. Once the measurement model is validated, the next step is to check for multicollinearity among the latent constructs. Multicollinearity ensure indicators are not highly correlated with each other. This is important because multicollinearity can distort the estimation of structural relationships. After addressing multicollinearity, the next phase involves testing the structural model, which focuses on assessing the hypothesized relationships between the latent constructs.

4.6.2.6 Quantitative Step 6: Assessment of Collinearity (VIF Analysis)

Collinearity evaluation ensures that predictor variables are not highly correlated, which could distort path coefficients and weaken or undermine model accuracy. The Variance Inflation Factor (VIF) is used to detect multicollinearity, where a VIF value below 5 indicates acceptable collinearity levels.

As an example, if in the study, found Digitalization and IT Investment have a VIF of 2.3, it suggests no collinearity concerns. However, if $VIF > 5$, one of the predictor variables may need to be removed or adjusted to avoid redundancy in explaining Employment Impact.

4.6.2.7 Quantitative Step 7: Structural Model Assessment

After conducting the Variance Inflation Factor (VIF) analysis to ensure multicollinearity is within acceptable limits, the next step involves assessing the structural model. In Partial Least Squares Structural Equation Modeling (PLS-SEM), the structural model represents the hypothesized relationships between the latent variables (constructs) and evaluates how effectively the theoretical framework explains the dependent variables. In the context of this study, the structural model was assessed through the following steps:

- a) Evaluating the direct impact of digitalization on employment outcomes by analyzing the path coefficients.
- b) Examining whether firm size moderates the relationship between digitalization and employment through moderation analysis.

- c) Assessing the model's explanatory and predictive power by evaluating key indicators such as R^2 (coefficient of determination), Q^2 (predictive relevance), and SRMR (Standardized Root Mean Square Residual) to ensure a good model fit.

4.6.2.7.1 Path Coefficients and Hypothesis Testing

Path coefficients (β) show how strongly and in what direction of one construct influences another in the model. A positive β means the relationship moves in the same direction (e.g., digitalization increases with employment), while a negative β reflects an opposite effect (e.g., digitalization reduces employment).

To test whether these relationships are meaningful, t-values and p-values are used. A t-value above 1.96 ($p < 0.05$) indicates a significant effect, while lower values suggest the relationship is not statistically supported. Confidence intervals from bootstrapping further confirm reliability by ensuring the estimated effect does not cross zero.

4.6.2.7.2 Coefficient of Determination (R^2 Analysis)

The coefficient of determination (R^2) measures the variance explained by independent variables in the dependent variable. It indicates the explanatory power of the structural model. The R^2 value ranges from 0 to 1, with thresholds:

- **0.75 (Substantial explanatory power)**
- **0.50 (Moderate explanatory power)**
- **0.25 (Weak explanatory power)**

For example, in the study, if R^2 for Employment Impact is 0.52, it means 52% of the variance in employment changes can be explained by digitalization and firm strategies, demonstrating moderate explanatory power.

4.6.2.7.3 f-square (f^2) statistic

In addition to the path coefficients and R^2 values, the effect size (f^2) was calculated to assess the contribution of each exogenous construct to the explanatory power of the endogenous constructs. The f^2 values were obtained by examining the change in R^2 when a predictor construct was included versus excluded from the model. Following Cohen's (1988) guidelines, f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. Values below 0.02 are considered negligible.

4.6.2.7.4 Predictive Relevance (Q^2 Analysis)

Predictive relevance (Q^2) assesses how well the structural model predicts out-of-sample observations. Q^2 values were obtained using the blindfolding procedure in PLS-SEM. A Q^2 value greater than zero for the endogenous constructs confirms that the model has sufficient predictive relevance.

The interpretation of Q^2 values follows similar thresholds as R^2 :

- $Q^2 > 0.35$ (*Strong predictive relevance*)
- $Q^2 > 0.15$ (*Moderate predictive relevance*)
- $Q^2 > 0.02$ (*Weak predictive relevance*)

4.6.2.8 Quantitative Step 8: Model Fit Evaluation

Model fit assessment confirms that the structural model adequately represents the data. For PLS-SEM, Model fit is assessed using the Standardized Root Mean Square Residual (SRMR < 0.08).

4.7 Rationale for Employing PLS-SEM

For Quantitative analysis, Partial Least Squares Structural Equation Modeling (PLS-SEM) was chosen because PLS-SEM is suitable for exploratory research, it has powerful measurement tools for predictive power analysis and could address complex models that incorporate multiple latent constructs and indicators (Hair et al., 2022; Sarstedt et al., 2021) which is relevant for this study.

PLS-SEM can manage models with numerous interdependencies, can handle high-dimensional data and generate path coefficients with strong effect size, predictive relevance (f^2 , Q^2 , and R^2 values) further enhances the reliability of the findings (Cepeda-Carrion et al., 2019).

Considering these strengths, PLS-SEM stands out as the most fitting analytical tool for this research, providing the necessary methodological strength to capture the complex and evolving relationship between digitalization and employment in the manufacturing industry.

4.8 Pilot Study

The pilot study assists as a primary foundation for the main research, a base foundation for refining the research design and evaluating the measurement model through established reliability and validity assessments (Hair et al., 2019; Henseler et al., 2015).

For this study a total of twenty-one (21) interviews were collected as a pilot study then the results were analyzed to examine the adequacy of the measurement instruments. The findings provided important methodological insights that informed necessary adjustments, thereby ensuring that the instruments employed in the full-scale study would yield accurate, reliable, and valid data for subsequent analysis.

4.8.1 Pilot Study Results: Demographic Insights

Valuable demographic insights from Pilot study that help to contextualize the findings of the study.

Name	Mean	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
Respondent	21				
Age frequency	2.429	0.495	-2.115	0.311	0
Gender	0.952	0.213	21	-4.583	0
Education	3.952	0.575	0.351	-0.001	0
Organization Type	3.81	1.096	-1.353	-0.29	0.004
Designation	3.429	1.003	-0.876	0.517	0
Duration of Job	2.619	1.253	-0.762	0.335	0.072

Table 4.7: Descriptive Demographic Statistics of Pilot Study

The demographic profile of the pilot study respondents is presented in Table 4.7

Variable Group	Key Observations
Demographics	Respondents' age frequency (Mean = 2.429) suggests a young to middle-aged workforce. Gender distribution (Mean = 0.952) is skewed, indicating a male-dominated sample. Education level (Mean = 3.952) suggests most respondents have a bachelor's or higher degree.

Variable Group	Key Observations
Organizational Factors	Organization Type (Mean = 3.81) is diverse, ranging from SMEs to large firms. Designation (Mean = 3.429) and Job Duration (Mean = 2.619) indicate that respondents hold mid-level positions with moderate job tenure.

Table 4.8: Demographic and Organizational Profile of Pilot Study Respondents

As shown in Table 4.8, the pilot study respondents exhibit a relatively young to middle-aged workforce profile, with a strong male dominance and a high proportion of respondents holding at least a bachelor's degree. In terms of organizational characteristics, the sample reflects diversity across firm types, while most respondents hold mid-level positions and possess moderate levels of job experience.

4.8.2 Pilot Study Results: Descriptive Insights of the Construct

Items	Mean	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
TA 1	4.571	0.583	0.348	-1.078	0
TA 2	4.238	0.921	-0.254	-0.921	0
TA 3	4.238	0.811	1.145	-1.074	0
TA 4	4.524	0.663	0.26	-1.15	0
TA 5	3.619	0.785	0.055	-0.428	0
TA 6	4.333	0.642	-0.551	-0.474	0
DS 1	4.143	0.888	1.233	-1.184	0
DS 2	4.286	0.825	1.18	-1.166	0
DS 3	3.857	0.71	1.128	-0.634	0
DS 4	4.619	0.486	-1.913	-0.529	0
DS 5	4.429	0.66	-0.35	-0.788	0
DS 6	3.381	0.898	-0.456	0.387	0.001
DS 7	4.524	0.732	0.17	-1.27	0
DS 8	4.571	0.583	0.348	-1.078	0
DS 9	4.476	0.663	-0.102	-0.962	0
DS 10	4.571	0.583	0.348	-1.078	0
ITI 1	4.143	0.774	-1.312	-0.272	0.001
ITI 2	4.429	0.583	-0.56	-0.476	0
ITI 3	4.19	0.906	-0.294	-0.828	0
ITI 4	4.667	0.471	-1.579	-0.763	0
ITI 5	4.238	0.811	-1.364	-0.496	0
ITI 6	3.667	1.208	-0.725	-0.511	0.022
ITI 7	4.238	0.811	-1.364	-0.496	0
SP 1	4.571	0.583	0.348	-1.078	0
SP 2	4.571	0.583	0.348	-1.078	0
SP 3	4.19	0.906	-0.294	-0.828	0
SP 4	4.476	0.794	3.218	-1.763	0
SP 5	4.095	0.75	-1.206	-0.17	0.001
RD 1	4.238	0.868	0.332	-0.989	0
RD 2	4.429	0.849	1.754	-1.52	0
RD 3	4.476	0.794	-0.394	-1.147	0

Items	Mean	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
RD 4	4.476	0.732	-0.197	-1.092	0
RD 5	4.619	0.575	0.989	-1.319	0
RD 6	4.238	0.921	1.255	-1.316	0
RD 7	4.238	0.868	0.332	-0.989	0
TY 1	4.667	0.563	1.895	-1.595	0
TY 2	4.714	0.547	3.182	-1.92	0
TY 3	4.333	0.713	-0.765	-0.631	0
TY 4	4.524	0.906	10.617	-2.977	0
TY 5	4.571	0.904	11.544	-3.155	0
TY 6	4.238	0.921	-0.254	-0.921	0
SZ 1	4.667	0.471	-1.579	-0.763	0
SZ 2	4.381	0.898	0.726	-1.313	0
SZ 3	4.571	0.495	-2.115	-0.311	0
SZ 4	4.238	0.921	6.317	-2.105	0
SZ 5	4.381	0.722	-0.654	-0.774	0
LMD 1	4.143	0.774	-1.312	-0.272	0.001
LMD 2	4.429	0.583	-0.56	-0.476	0
LMD 3	4.19	0.906	-0.294	-0.828	0
LMD 4	4.667	0.471	-1.579	-0.763	0

Table 4.9: Descriptive Statistics for the construct of Pilot Study

Table 4.9 presents the descriptive statistics of the constructs used in the pilot study (Field Survey, 2025).

Interpretation of the Descriptive Statistics:

Variable Group	Key Observations
Technological Advancement (TA)	TA items show high mean value (3.619 - 4.571) , indicating strong technological Advancement across firms. Negative skewness suggests more responses at the higher scale (agree/strongly agree).
Digital Skills (DS)	Most DS items have high mean value (3.381 - 4.619), suggesting digital literacy is prevalent. Some items show excess kurtosis and negative skewness, indicating responses are concentrated at higher levels.
IT Investment (ITI)	ITI 1 – ITI 7 have means from 3.667 - 4.667 , reflecting consistent IT adoption, with some variations in investment levels (e.g., ITI6 shows lower mean = 3.667).
Strategy & Policy (SP)	SP variables have mean value above 4.0 , reflecting strong alignment with digitalization strategies, but SP4 (kurtosis = 3.218) suggests varied responses.
R&D Investment (RD)	RD indicators show high means (4.238 - 4.619) with moderate skewness, indicating firms invest in R&D but with some variations.
Industry Type (TY)	TY items show very high means (4.238 - 4.714) , indicating firms highly recognize technology's importance, but TY4 & TY5 show extreme kurtosis (>10) , suggesting outlier effects.
Industry Size (SZ)	SZ variables show strong agreement (Mean = 4.238 - 4.667) , indicating firm size plays a role in digital adoption, with slight variations.

Variable Group	Key Observations
Labor Market Dynamics (LMD)	LMD variables have high mean value (4.143 - 4.667) , supporting the model's predictive power. The skewness and kurtosis suggest that respondents perceive a strong digital influence on labor markets.

Table 10: Descriptive Statistics and Distributional Properties of Study Variables

The descriptive statistics of the study variables are presented in Table 10. The results indicate that all key constructs exhibit relatively high mean values, generally ranging above the mid-point of the scale, suggesting strong agreement among respondents regarding the presence and influence of the studied factors.

Technological Advancement (TA) items show high mean values (3.619–4.571), indicating a strong level of technological adoption across firms. The negative skewness suggests that responses are concentrated toward higher agreement categories. Similarly, Digital Skills (DS) demonstrate high mean scores (3.381–4.619), indicating widespread digital literacy among employees, although the presence of skewness and kurtosis suggests clustering of responses at higher levels.

IT Investment (ITI) variables (3.667–4.667) reflect consistent adoption of IT infrastructure, with minor variations across items, particularly ITI6, which shows comparatively lower investment intensity. Strategy and Policy (SP) constructs exhibit mean values above 4.0, indicating strong organizational alignment with digitalization strategies, although SP4 shows relatively higher kurtosis, suggesting response heterogeneity.

R&D Investment (RD) indicators also report high mean values (4.238–4.619), suggesting sustained innovation-related spending with moderate variability. Industry Type (TY) variables show very high mean scores (4.238–4.714), reflecting strong recognition of technological importance; however, TY4 and TY5 exhibit very high kurtosis values (>10), indicating potential outlier influence or response concentration.

Industry Size (SZ) variables indicate strong agreement (4.238–4.667), suggesting that firm size plays a significant role in digital adoption, with slight variations across firms. Finally, Labor Market Dynamics (LMD) variables show high mean values (4.143–4.667), supporting the model's assumption that digitalization significantly influences labor market

outcomes. Overall, skewness and kurtosis values indicate acceptable distributional properties with minor deviations in selected items.

All these insights provide a strong empirical basis and foundation for further research, reinforcing the need for a comprehensive in-depth analysis of this area.

4.8.3 Pilot Study Results: Reliability & Validity for the Measurement Model

Reliability and Validity Matrix Result Table

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
TA	0.671	0.723	0.805	0.516
DS	0.804	0.819	0.861	0.520
ITI	0.869	0.886	0.902	0.607
SP	0.773	0.832	0.849	0.539
RD	0.858	0.892	0.891	0.548
SZ	0.777	0.795	0.846	0.530
TY	0.593	0.675	0.778	0.549
LMD	0.830	0.838	0.889	0.668

Table 4.11: Reliability and Validity Matrix Result for Pilot Study

Table 4.11 presents the reliability and validity matrix results for the pilot study, confirming the internal consistency and construct validity of the measurement model (Field Survey, 2025).

The result from pilot study confirms the reliability and validity of the measurement model, ensuring that constructs are both internally consistent and capable of accurately capturing the underlying concepts.

- **Reliability Assessment:** Cronbach's Alpha values indicating construct are acceptable to strong internal consistency. Most constructs exceed the **0.7 threshold**, suggesting reliable measurement.
- **Composite Reliability (CR):** Values for rho_a and rho_c across all constructs are above 0.7, reinforcing the model's reliability and consistency. The highest reliability is observed in ITI (0.902) and LMD (0.889), reflecting strong construct coherence.
- **Convergent Validity:** The Average Variance Extracted (AVE) for all constructs surpasses 0.50, confirming that each construct explains a sufficient portion of its

variance. LMD (0.668) and ITI (0.607) exhibit the strongest convergent validity, while TA (0.516) and TY (0.549) remain above the required threshold.

4.8.4 Implications for the Study

The findings of AVE, CR denote that the measurement model is statistically robust, allowing for in-depth hypothesis testing in the main study. Strong reliability and validity affirm that the constructs are well-defined, reinforcing the credibility and strong foundations of digitalization's impact on employment in Bangladesh's manufacturing sector.

4.9 Limitations of Methodology

Despite employing a comprehensive Research Methodology, it is not without certain limitations that are acknowledged and addressed.

4.9.1 Cross-Sectional Design

This study employs a cross-sectional design, collecting data at a single point in time. As such, it is unable to establish causal relationships between digitalization and employment outcomes. Correlations between digitalization and employment trends are observed, but other external factors may also influence these changes (Hair et al., 2019).

4.9.2 Self-Reported Data

This research relies on self-reported survey data, which, while useful for capturing perceptions and experiences, is not without limitations. Responses may be influenced by biases such as social desirability, where participants provide answers, they believe are more acceptable or align with the expectations of the researcher (Podsakoff et al., 2003). Such biases can affect the accuracy and objectivity of the data.

4.9.3 Context-Specific Limitation

This study is rooted in the Bangladeshi context, where challenges such as unequal access to technology, large Informal labor market, limited infrastructure across different areas, and disparities in education and skills training strongly influences employment (Schwab, 2016). So, the findings from this study may not directly apply to countries with more advanced technological infrastructures or different labor market structures.

4.9.4 Limited Generalizability

As this study focusing on Bangladesh's manufacturing sector the results may not be fully generalized to other industries or countries that operate in different economic and technological environments (Frey & Osborne, 2017).

4.9.5 Lack of Longitudinal Data

Another limitation is the absence of longitudinal data. Interview and survey data provides a useful snapshot, but it cannot completely draw the picture of long-term effects of digitalization on employment, skills development, and job quality in the manufacturing sector. Longitudinal studies would allow researchers to trace how Digitalization affect Labor Market Dynamics over time—an especially important consideration in fast-changing industries (Brynjolfsson & McAfee, 2014). Future research could benefit from panel data or repeated surveys to gain deeper insight into these dynamics.

4.9.6 Potential Non-Response Bias

Although all possible caution and guidelines followed and applied to ensure a diverse representative sample, this study may be subject to non-response bias, which occurs when individuals who do not respond differ systematically from those who do, potentially affecting the generalizability of the findings (Groves et al., 2002; Bethlehem, 2010).

The limitations addressed in the study exposed new avenues and opportunities for future research, including longitudinal studies, cross industry analysis, and comparative cross-country analyses, which can provide a more comprehensive and globally relevant understanding of how digitalization is reshaping workforce dynamics and organizational strategies.

4.10 Methodological Reflection and Future Research Pathway

While this study offers important insights, it also leaves room for further inquiry. Future research can build on these findings by exploring the following directions:

4.10.1 Longitudinal Studies

Longitudinal studies can offer a greater understanding of how technological transformations influence employment over time and provide clearer insights into causal relationships (Brynjolfsson & McAfee, 2014).

4.10.2 Sectoral and Cross-Country Comparisons

Looking beyond manufacturing, future studies could also explore how digitalization is influencing other important sectors in Bangladesh, such as agriculture and services. This would help build a fuller picture of how technology is shaping jobs across the economy, not just in factories. At the same time, comparing Bangladesh with other countries could reveal how differences in economic conditions, policies, and levels of technological readiness shape the impact of digitalization on workers. Such comparisons would not only highlight what is unique about Bangladesh's experience but also show what lessons can be shared across borders. Sector-specific analyses could highlight unique challenges and opportunities, cross comparisons may reveal best practices and effective policy responses to digital labor transitions (Frey & Osborne, 2017).

4.10.3 Policy Interventions

Assessing the effectiveness of policies can ensure that digitalization increases productivity while safeguarding employment, particularly in labor-intensive sectors like manufacturing (Schwab, 2016). Future researchers should examine the role of policy measures, such as government-led reskilling programs, digital literacy initiatives, and labor regulations, in mitigating workforce displacement due to automation (Acemoglu & Restrepo, 2020).

Addressing these areas will provide a more inclusive broader understanding of the evolving relationship between digitalization and employment, both within manufacturing and across the broader labor market.

4.11 Ethical Considerations

Ethical standards followed throughout the research process, ensuring that participants were preserved with respect and maintained their privacy, confidentially, trying to protect all

rights at every stage. Ethical approval was obtained before data collection began, in line with established ethical research protocols (Resnik, 2020).

4.11.1 Informed Consent

Prior information of the objectives of the study, procedures, and potential use of the data were clearly explained to the participants. They were informed that participation was entirely voluntary, and they could withdraw from the study at any time without any negative consequences.

4.11.2 Data Security

All possible necessary preventive actions were taken to confirm the integrity, authenticity, privacy and confidentiality of the responses. Responses were stored securely through Google Forms, with access restricted only to authorized research team members. Personal, confidential and sensitive information was carefully protected against potential breaches, followed established data protection standards.

4.12 Methodological Summary

This study provides important insights into how digitalization is reshaping labor dynamics in Bangladesh's manufacturing sector. The research methodology of this study is guided by established methodological frameworks and boundaries (Angelova, 2025). At the same time, these limitations create opportunities for future research to build on this foundation. Further studies could examine the long-term effects of digitalization, extend the analysis to other industries, or explore cross-country comparisons to capture diverse experiences. Such work would not only strengthen the theoretical insights introduced in this thesis but also provide practical guidance for policymakers and business leaders. In this way, the study not only meets its stated objectives but also sets the stage for shaping strategies that can help workers and firms adapt to an increasingly digital future

Chapter 5: Qualitative Analysis

5.1 Introduction

While quantitative methods provide statistical evidence on the impact of digitalization on employment trends in Bangladesh's manufacturing sector, qualitative approaches offer deeper insights into workers' experiences, managerial perspectives, and industry-specific challenges (Creswell & Poth, 2018). Considering the mounting impact of digitalization on the manufacturing sector, qualitative research provides valuable insights into how employees perceive Technology Acceptance Model, the evolving skill requirements for digital integration, and the strategic responses of firms in managing labor market transitions (Yin, R. K. 2018).

In Bangladesh, where traditional workforce, poor organizational policies, and weak infrastructural realities all intersect, qualitative insights are especially illuminating (Schwab, 2016). Qualitative analysis combined with quantitative findings, offers a broader complete picture of digitalization's socio-economic impact on employment, not just in terms of trends and statistics, but through the practical experiences of those at the frontline of industrial transformation.

The following sections outline the qualitative pathway of this research, including participant selection, data collection methods, and the analytical approaches employed to capture and interpret the perceptions, themes, experiences of employees, managers, and policymakers navigating this wave of digital change.

5.2 Six-Step Thematic Analysis Framework

A purposive non-probability sampling strategy was adopted to ensure the inclusion of respondents with direct and relevant expertise. Semi-structured interviews and focus group discussions (FGDs) were conducted to gather rich, contextualized insights from individuals who actively experience or influence digital transformation within their organizations or the sector more broadly.

Sampling:

Participants were selected based on predetermined criteria, including experience with digital technologies, involvement in managerial or operational decision-making, and direct responsibility for workforce-related strategies. This purposive approach ensured that the

qualitative data captured the perspectives of individuals who are best positioned to comment on digitalization's implications for employment.

Data collected from interviews and FGDs were systematically analyzed using Thematic Analysis, following Braun and Clarke's (2006) six-step framework. This allowed for both deductive coding—informed by theoretical perspectives such as Creative Destruction, Labor Market Segmentation, Diffusion of Innovation, and Technological Adoption Models—and inductive coding, which emerged organically from participant narratives.

✓ **Steps 1: Familiarization with the data through Interview**

The first step involved immersing in the data by thoroughly reading interview transcripts and FGD notes. The interviews included senior executives, mid-level managers, production supervisors, HR officers, and employees whose roles were directly or indirectly affected by digitalization. These dialogues revealed nuanced insights into challenges, opportunities, workforce transformations, and strategic choices associated with digital technological adoption.

This familiarization phase ensured that the researcher gained an in-depth understanding of the context, tone, and implicit meanings present in the data.

✓ **Step 2: Themes from Coding & Thematic Analysis**

- **Initial Coding**

Open coding was conducted by reviewing transcripts line by line to identify recurring ideas, observations, and perceptions. Concepts such as technology adoption, job displacement, skill development, workflow redesign, R&D, and policy responses were captured. At this stage, the analysis remained open to unexpected insights to preserve the authenticity of participants' experiences.

- **Focused Coding**

Initial codes were refined and grouped into higher-order categories. For example, codes such as *digitalization*, *automation*, *robotics*, and *AI adoption* were consolidated under broader categories like technological advancement, IoT integration, and digital skills development. This step organized the data around core analytical categories and prepared the foundation for thematic development.

✓ **Step 3: Result of Categorization and Data Interpretation**

- **Contextual Factors**

During categorization, digitalization variable – Digital Skill, IT investment, technological advancement, contextual variables—such as Strategy, Policy, moderating variable - firm size, manufacturing subsector (e.g., RMG, leather, electronics), and geographical location—were considered, as they influence the nature and speed of digital adoption and its impact on employment.

- **Theoretical Framework Integration**

The emergent categories were interpreted using relevant theoretical lenses, including:

- Creative Destruction (technology-induced restructuring of jobs),
- Labor Market Segmentation (differences between skilled vs. semi-skilled workers),
- Diffusion of Innovation (adoption patterns within firms), and
- Technology Acceptance Models (perceptions influencing acceptance/resistance).

- **Perceptions of Technology**

The analysis also explored stakeholder perceptions regarding digital technologies. Some respondents expressed concerns about job insecurity and displacement, while others demonstrated optimism about emerging career pathways and capacity-building opportunities. These interpretations helped contextualize firm-level decision-making and policy implications.

✓ **Step 4: Themes and Insights**

Major themes were developed by clustering categories and codes that shared conceptual similarities. These themes included:

- **Impact on Employment**

The analysis revealed that digitalization is reshaping employment structures by:

- Replacing some routine, low-skilled positions through automation,
- Creating new technology-enabled roles requiring higher-level skills,
- Increasing demand for digital literacy and multi-skilled workers.

- **Strategic Responses of Firms**

Firms responded to digital transformation through strategies such as:

- Investing in employee reskilling and upskilling,
- Redesigning workflows and adopting lean digital processes,
- Integrating advanced technologies to enhance productivity and competitiveness.

- **Government and Policy Insights**

Participants highlighted the role of policy support in influencing digital adoption. Government initiatives related to industrial modernization, skill development, and technology financing were frequently cited as enablers—or constraints—of digital transformation.

✓ **Step 5: Validation and Triangulation**

To enhance the credibility and reliability of the qualitative findings, several validation techniques were employed:

- **Member Checking**

Selected participants were consulted to verify that the interpretations accurately reflected their experiences and perspectives.

- **Triangulation**

Findings were compared across multiple data sources—interviews, FGDs, secondary reports, and theoretical literature—to ensure consistency and robustness.

- **Peer Review**

Academic peers and colleagues reviewed the coding structure, thematic interpretations, and conceptual linkages to minimize bias and strengthen coherence with existing literature.

✓ **Step 6: Producing final Thematic Map for the Conceptual Model**

A final thematic map was developed to illustrate the relationships between major themes, categories, and theoretical concepts. This thematic framework informed the construction of the conceptual model and guided hypothesis development for the quantitative phase.

The thematic synthesis revealed actionable insights, such as the need for:

- Enhanced government-backed training and skill development programs,
- Organizational investments in digital capacity-building, and
- Cultivating an innovative-driven culture within manufacturing firms.

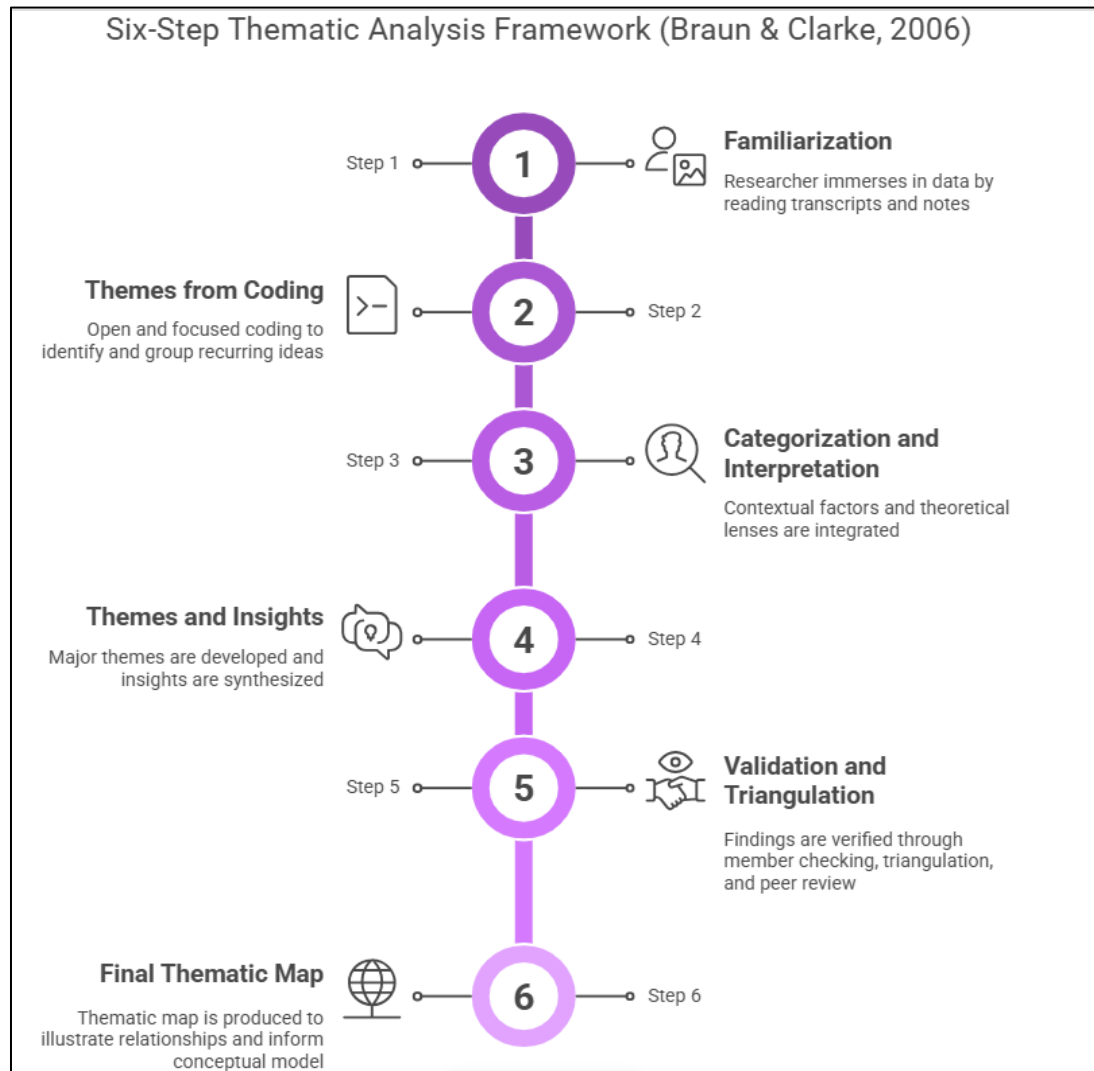


Figure 5.1: Thematic Analysis Framework

Figure 5.1 presents the thematic analysis framework adopted in this study, which was used to systematically guide the coding, theme development, and interpretation of qualitative data following established qualitative analysis procedures.

The thematic analysis framework was developed following the six-step approach to thematic analysis (Braun & Clarke, 2006).

5.3 Demographics for Qualitative Analysis

To ensure a diverse and representative sample, participants selected from different employment levels and positions, industry experts, policy makers and academics who provide insights into the research.

The study covers multiple manufacturing subsectors, including pharmaceuticals, cement, food processing, leather and footwear, textiles, food processing, electronics, and automobiles, recognizing that digital adoption varies across different types of industries. Participants are selected who have diverse work experiences, ranging from entry-level workers to senior professionals, to assess how career stages influence perceptions of job security and skill adaptation. Educational backgrounds are also considered, ranging from primary education to higher degrees, to evaluate how digitalization affects workers with different skill levels.

Participants are selected from both small and medium enterprises (SMEs) and large multinational corporations (MNCs) to compare differences in digital adoption and employment restructuring. Geographic representation includes urban hubs like Dhaka and Chittagong, as well as semi-urban and rural areas, where digitalization may be less advanced.

Finally, participants are selected who have varied levels of digital exposure, from traditional workers with minimal interaction with digital tools to tech-savvy employees and also selected the decision-makers who are engaged in automation and AI-driven processes. These demographic considerations will help provide a comprehensive analysis of digitalization's impact on employment, skill gaps, and workforce adaptation in Bangladesh's manufacturing industry.

5.4 Findings from the Thematic Analysis

Semi-structured focus group questionnaire designed criteria for a total of 53 interviews have been conducted and the result of the matrix given below. Sample size aligns with qualitative research standards, where 15 to 30 interviews are often sufficient to reach saturation in studies focusing on heterogeneous populations (Guest, Bunce, & Johnson, 2006; Marshall, Cardon, Poddar, & Fontenot, 2013). Furthermore, qualitative research

does not aim for statistical generalizability but rather seeks depth of understanding and thematic richness (Patton, 2015; Creswell & Poth, 2018)

Below is a matrix *Table 5.1* representing the thematic-wise percentage of responses from the qualitative analysis of the study. The table categorizes responses based on key themes identified during the focus group discussions. The percentage of responses indicates the proportion of participants who mentioned or agreed with each theme.

Thematic Category	Key Themes	Percentage of Responses (%)
Digitalization and Workplace Transformation	Adoption of automation, AI, ERP, IoT	85%
	Increased efficiency and productivity	78%
	Reduction in manual labor tasks	65%
Employment Impact of Digitalization	Job displacement due to automation	70%
	Creation of new job roles in technology fields	55%
	Increased demand for digital and technical skills	80%
	Inadequate training and skill development	68%
	Job insecurity and stress due to digital changes	60%
Firm Strategies and Policies	Digital adoption as a strategic vision	72%
	Resistance to digital transformation	58%
	High cost of digital implementation	66%
	Limited training opportunities provided by firms	63%
	Inadequate government policies for digitalization	75%
	Need for better industry-government collaboration	68%
	Lack of incentives for SMEs to adopt digital tech	62%
	Need for upskilling policies and labor protection	70%
Outlook and Recommendations	Continued shift toward AI-driven manufacturing	80%
	Importance of balancing digitalization and jobs	77%
	Need for a structured digital workforce roadmap	73%

Table 5.1: Thematic-wise percentage of responses

As presented in Table 5.1, the thematic analysis of the qualitative data identified several key themes emerging from the focus group discussions and interviews. The table

summarizes the percentage of participants who mentioned or agreed with each theme, providing an overview of the relative prominence of digitalization-related issues within Bangladesh's manufacturing sector.

5.4.1 Interpretation of Qualitative Results and Key Themes Identified

The qualitative results provide a comprehensive overview of the impact of digitalization on employment in Bangladesh's manufacturing industry. The data highlight key themes related to workplace transformation, employment impact, firm strategies, policies, and future recommendations. These insights align with existing literature on digitalization and its effects on labor markets, firm strategies, and policy needs (Hanelt et al., 2021).

For example, one senior Production manager from the Akij Beverage respondent that:

“Digital technologies have automated many routine processes, which has reduced the need for low-skill tasks, but it has also created opportunities for workers to move into higher-skilled roles requiring technical knowledge.”

Similarly, a mid-level employee in the Apex Footwear responded, *“While digitalization initially created uncertainty, training programs provided by the company allowed us to adapt and learn new digital tools, which made our work more efficient and meaningful.”*

These responses illustrate how digitalization is reshaping job roles, skill requirements, and workplace dynamics, reflecting both the challenges and opportunities identified in the broader literature on Industry 4.0 and employment (UNCTAD, 2021; OECD, 2023; Acemoglu & Restrepo, 2020)..

5.4.1.1 Digitalization and Workplace Transformation

The results show a significant adoption of automation, AI, ERP, and IoT technologies, reported by 85% of respondents, indicating that firms are embracing digital technologies to improve operations. This finding aligns with studies by Brynjolfsson and McAfee (2014), which suggest that digital technologies drive operational efficiency and transformation. The results also show increased efficiency and productivity (78%), confirming previous research that automation enhances output while reducing costs (Autor, 2015).

At the same time, 65% of respondents reported a shift away from manual labor tasks, indicating potential job displacement. This aligns with findings by Acemoglu & Restrepo (2020), who argue that automation reduces the demand for routine tasks, replacing manual labor with AI-driven processes. This observation is particularly relevant for Bangladesh, where a large portion of the manufacturing workforce is engaged in low-skilled manual tasks.

Respondents' perspectives provide further insight into these trends:

A senior manager in the RMG (Fakir Apparels Ltd.) sector stated: *"Implementing AI and ERP systems has streamlined many production processes. While it reduced some routine positions, overall efficiency and coordination across departments have improved significantly."*

A frontline employee from the leather and footwear industry (Apex footwear) noted: *"Some of the tasks we used to do manually are now automated (like SHOEMASTER software), which was challenging at first. However, we have received training to handle new digital tools, which has made our work more interesting and productive"*.

An operations executive in the Tiles & Ceramics (Akij Ceramics) engineering sector commented: *"IoT sensors and automation have allowed us to monitor production in real time. Although it replaced certain manual jobs, it also created new roles requiring technical skills, which encouraged skill development among staff"*.

These qualitative insights underscore how digitalization is transforming workplace practices, balancing increased productivity with challenges related to workforce displacement and skill adaptation, echoing broader international findings on technological change and labor market transformation (Acemoglu & Restrepo, 2020; OECD, 2023; UNCTAD, 2021).

5.4.1.2 Employment Impact of Digitalization

The qualitative findings indicate that digitalization has had both positive and negative impacts on employment in Bangladesh's manufacturing sector. While automation and AI have streamlined operations, improved productivity, and created higher-skilled roles, they have also displaced routine and low-skill jobs. These patterns mirror global trends observed

in Industry 4.0 contexts (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2014; UNCTAD, 2021).

Respondent insights highlight the direct and indirect effects on employment: A Top-level manager in the textile sector remarked: *“We have automated repetitive tasks in production, which reduced some low-skill positions. At the same time, new technical roles have emerged, requiring our staff to upskill”*

A mid-level employee in the leather and footwear industry shared: *“Initially, there was fear of losing jobs due to machines, but with reskilling programs, I learned to operate digital machinery, which improved my confidence and career prospects.”*

A policymaker also noted that, *“The challenge is ensuring that workforce policies keep pace with rapid digital adoption. Without adequate training and support, many workers may be left behind.”*

Another frontline worker in the food and beverage (Pran Group) sector stated, *“Some colleagues’ jobs were replaced by automation, but the company also introduced monitoring and data analysis roles that I could transition into with short training.”*

These findings highlight that employment effects of digitalization are multi-dimensional, combining job displacement for routine tasks with opportunities for skill upgrading and role diversification.

5.4.1.3 Firm Strategies and Policies

The qualitative data also reveal that firms are actively implementing strategies to leverage digitalization for competitiveness, operational efficiency, and workforce development. Firms employ a combination of technology adoption, employee reskilling, process redesign, and collaboration with government and educational institutions. These strategies align with the international literature, which emphasizes that successful digital transformation requires both technological investment and human capital adaptation (Hanelt et al., 2021; OECD, 2023; World Economic Forum, 2025; Warner & Wäger, 2019).

Key insights from respondents include:

A CEO in the light engineering sector commented: *“Our strategy focuses not only on introducing AI and ERP systems but also on ensuring employees are trained to work alongside these technologies. It’s about balancing efficiency and human capital development.”*

A top-level executive in the light engineering industry explained: *“We invested in digital tools and continuous learning programs. This has allowed us to improve productivity while retaining talent by offering career growth opportunities.”*

An industry expert stated: *“Collaboration with government and training institutes is essential. Firms that integrate workforce development into their digital strategy see better outcomes in both productivity and employee engagement.”*

A senior manager in the ceramics sector observed: *“Digital adoption is not just about technology; it’s about redesigning processes and aligning them with our strategic goals. This ensures that automation complements human work rather than replacing it entirely.”*

These responses demonstrate that firms in Bangladesh are adopting holistic digital strategies, emphasizing technology, people, and processes, to navigate the challenges and opportunities of Industry 4.0.

5.4.1.4 Outlook and Recommendations

Large proportion of respondents (**80%**) indicated that the manufacturing sector in Bangladesh is moving toward AI-driven operations, signaling that digital transformation is likely to accelerate in the near future. At the same time, **77% of respondents** emphasized the importance of balancing technological adoption with employment preservation. These findings align with Manyika et al. (2017), who emphasize the need for strategies that integrate advanced technologies while safeguarding employment opportunities.

Additionally, **73% of respondents** underscored the importance of establishing a structured digital workforce roadmap, echoing policy recommendations by the International Labour Organization (ILO, 2021), which advocate for skill development programs, social protection measures, and employment transition support to manage the workforce impacts of digitalization.

Respondent perspectives provide further insight into these themes:

A senior manager in the light engineering sector noted: *“We are rapidly adopting AI in our production lines, but we are also conscious about retraining staff to ensure that jobs are not lost. A clear roadmap for workforce transformation is essential.”*

A mid-level employee in the garments industry stated: *“Digital tools make work more efficient, but if training and reskilling are not provided, many colleagues may struggle to adapt. We need structured programs to help everyone transition.”*

An industry expert emphasized: *Policymakers should work with firms to design roadmaps that balance automation and employment. Skill development, social safety nets, and reskilling initiatives are critical to avoid negative social impacts.*

These responses reinforce the view that while digitalization promises increased efficiency and competitiveness, careful planning, workforce development, and policy interventions are essential to ensure a sustainable and inclusive transition in Bangladesh’s manufacturing sector (UNCTAD, 2021; ILO, 2021).

5.4.1.5 Policy Implications

The findings indicate that while digitalization enhances efficiency and creates new job opportunities, it also presents challenges related to job displacement, skill gaps, and gaps in existing policies. To facilitate a smooth transition, a multi-stakeholder approach is required, including firm-level initiatives, government interventions, and industry-academia collaborations:

- **Firms** are investing in training programs to equip employees with digital skills.
- **Government** is developing targeted policies, incentives, and regulatory frameworks.
- **Industry-academia collaborations** are aligning education and training programs with evolving workforce needs.

Respondents' insights reinforce these points:

A senior operations manager in the pharmaceuticals (*Incepta Pharmaceuticals*) sector stated: *"We have launched digital skills training across all departments to ensure that employees can adapt to new technologies. Without proper training, efficiency gains could backfire."*

A policymaker emphasized: *"The government must provide incentives and create clear regulations to encourage firms to adopt digital technologies while protecting jobs. Policy frameworks are critical to avoid negative social consequences."*

An academic involved in workforce development noted: *"Collaboration between universities and industries is essential. Curriculum and skill development programs must align with the digital needs of manufacturing firms."*

A mid-level employee in the textile sector commented: *"Upskilling and clear labor protections give us confidence that digitalization will not threaten our livelihoods but rather enhance our career prospects."*

These responses highlight the necessity of a structured digital workforce roadmap, combined with upskilling policies and labor protections, to ensure that Bangladesh fully harnesses the benefits of digitalization while mitigating its potential negative impacts (ILO, 2021; UNCTAD, 2021; Manyika et al., 2017).

5.5 Qualitative Findings and Theoretical Insights

Main findings from the qualitative analysis and connect them with the relevant theoretical frameworks.

5.5.1 Job Displacement vs. Creation

The findings align with the theory of creative destruction, which posits that while some traditional jobs become vulnerable due to technological change, digitalization simultaneously generates new opportunities requiring higher technical skills (Schumpeter, 1942; Acemoglu & Restrepo, 2020). In Bangladesh's manufacturing sector, this dynamic is evident as automation, AI, and digital tools replace routine,

low-skill tasks while creating roles in data management, process monitoring, and digital operations.

Labor market segmentation theory further highlights that high-skilled workers are more likely to benefit from these transformations, whereas low-skilled workers face a disproportionate risk of displacement (Doeringer & Piore, 1971; Autor, 2015). R Digitalization and artificial intelligence are reshaping labor demand by increasing employment in high-skill occupations while reducing routine and manual tasks through automation and restructuring of production systems (Acemoglu & Restrepo, 2020; Autor, 2015; Cheng, 2025; OECD, 2023).

These theoretical perspectives underscore the importance of targeted reskilling and upskilling programs, labor protections, and strategic workforce planning to ensure that the benefits of digitalization are equitably distributed across different skill groups in Bangladesh's manufacturing sector.

5.5.2 Firm Strategies in the Context of Innovation

The findings indicate that firms in Bangladesh's manufacturing sector are at different stages of digital adoption, with larger companies often leading the transformation while smaller firms face challenges in keeping pace. This pattern aligns with the Diffusion of Innovation Theory, which explains how new technologies are gradually adopted across organizations and industries (Rogers, 2003; Li et al., 2022). Larger firms tend to adopt innovations earlier due to greater financial resources, technical expertise, and organizational capabilities, whereas smaller firms often encounter barriers such as limited capital, lack of skilled personnel, and inadequate infrastructure.

In terms of strategic orientation, businesses are pursuing both cost-cutting and innovation-driven strategies. Automation and digitalization are used to improve efficiency and reduce operational costs, while firms simultaneously invest in process innovation, product development, and new business models to remain competitive. These strategic behaviors reflect principles from the Technology Acceptance Model (TAM) and strategic management theories, which emphasize the interplay between technological adoption, organizational capabilities, and

competitive advantage (Venkatesh et al., 2003; Hanelt et al., 2021; Warner & Wäger, 2019).

Recent studies reinforce that such differentiated strategies are critical for navigating Industry 4.0. For example, innovation-focused approaches allow firms to harness emerging digital technologies for productivity gains, while cost-efficiency strategies help maintain financial sustainability during the adoption phase (Zhang & Chen, 2024; Manyika et al., 2023). This dual approach underscores the importance of aligning technological adoption with firm-specific resources, workforce skills, and broader industry dynamics.

5.5.3 Policy Implications

The findings indicate that existing government policies in Bangladesh are currently insufficient to prepare workers for the rapid adoption of digital technologies. Displaced workers face limited access to training and upskilling programs, leaving a significant portion of the workforce vulnerable to skill obsolescence. Timely and targeted policy interventions are therefore essential to bridge this gap, ensuring that workers can adapt to the evolving demands of the digital economy.

Recent studies emphasize that digital transformation requires proactive government action, including skill development initiatives, social protection measures, and employment transition programs to mitigate the negative labor market impacts of automation and Industry 4.0 adoption (ILO, 2021; UNCTAD, 2021; Manyika et al., 2023). In particular, coordinated policies that align workforce development with technological adoption are critical for fostering an inclusive, resilient, and future-ready labor market, especially in the context of rapid automation and digital transformation (Bessen, 2022; OECD, 2023; World Bank, 2019; ILO, 2023)..

5.6 Summary of Qualitative Insights

Findings from the qualitative analysis confirm that digitalization is reshaping the workforce in a complex and multi-dimensional manner. On one hand, new technologies such as AI, IoT, ERP, and automation enhance efficiency, productivity, and competitiveness (Brynjolfsson & McAfee, 2014; Hanelt et al., 2021). In qualitative analysis of digital transformation and technology adoption, the Unified Theory of Acceptance and Use of Technology (UTAUT) framework remains one of the most widely used theoretical lenses

for understanding user acceptance of emerging digital technologies, including artificial intelligence and organizational digital tools (Venkatesh et al., 2022).

A senior manager from a pharmaceuticals sector noted: *“AI and automation have streamlined our production, allowing us to meet higher demand with fewer errors. Our processes are faster, and we can allocate human resources to more strategic tasks.”*

On the other hand, digitalization introduces pressing challenges, including job displacement, widening skill gaps, and unequal access to digital tools (Autor, 2015; Bessen, 2022).

A frontline employee in the leather and footwear industry reported: *“Many routine jobs were automated, and not everyone had the opportunity to learn new skills. It created anxiety among colleagues who were not digitally trained.”*

Another respondent, a mid-level manager in the Leather and Footwear sector, highlighted the importance of workforce adaptation: *“Digital transformation cannot succeed without reskilling programs. Employees must be prepared to handle new tools and processes; otherwise, efficiency gains will not be sustainable.”*

These qualitative insights, combined with theoretical perspectives such as creative destruction and labor market segmentation, illustrate the dual impact of digitalization in emerging economies: it creates high-skill opportunities while simultaneously challenging low-skill workers through task displacement, job polarization, and structural labor market shifts (Acemoglu & Restrepo, 2020; Autor, 2015; ILO, 2023; OECD, 2023).

By integrating lived experiences, perceptions, and organizational insights with existing theoretical knowledge, this study provides a nuanced understanding of how digitalization is shaping labor markets in Bangladesh and similar emerging economies. The findings lay a strong foundation for future research and policy design, emphasizing the need for inclusive reskilling programs, structured workforce adaptation strategies, and equitable access to digital technologies, ensuring that the shift toward digital manufacturing is both inclusive and sustainable (ILO, 2021; UNCTAD, 2021; Manyika et al., 2023).

Chapter 6: Quantitative Analysis

6.1 Introduction

This chapter explores into the quantitative analysis of how digitalization is reshaping employment in Bangladesh's manufacturing sector. Using robust statistical methods, it explores the links between Technology, Digital adoption, R &D, workforce changes, and organizational strategies. The analysis highlights key issues such as job displacement, emerging skill demands, and how firms adapt strategically, offering insights into both the human and organizational impacts of technological change (Brynjolfsson & McAfee, 2014; Autor, 2015).

As the previous chapter offered qualitative insights into workers' experiences and organizational realities, this chapter adopts a data-driven perspective. The integration of qualitative and quantitative findings allows for a more comprehensive understanding of digitalization's socio-economic implications—linking human experiences with observable employment trends and organizational practices (Creswell & Creswell, 2018; Yin, 2018).

6.2 Descriptive Statistics Results

Descriptive statistics provide a clear picture of the data structure and summarize participant demographics, helping validate the dataset's reliability and credibility (Field, 2018; Pallant, 2020). This initial analysis lays the groundwork for deeper modeling, enabling a precise exploration of how digitalization affects employment dynamics.

Name	Mean	Median	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
Age frequency	2.183	2	0.597	1.643	0.846	0
Gender	0.93	1	0.256	9.526	-3.382	0
Education	3.704	4	0.68	5.085	-1.721	0
Organization Type	4.07	4	0.909	-0.1	-0.669	0
Designation	3.023	3	0.981	-0.159	0.494	0
Duration of Job	1.962	1	1.202	0.091	1.069	0

Table 6.1: Demographics of Descriptive data

As shown in Table 6.1, the demographic profile of the respondents provides a descriptive overview of the sample used in this study.

Descriptive analysis presents insights and patterns of the demographic characteristics of respondents and their workplace attributes, measures of central tendency, dispersion, and distribution characteristics, which help to evaluate data normality, consistency and variability (Hair et al., 2019).

6.2.1 Interpretation of Descriptive Demographic Statistical Results

This section presents the interpretation of key demographic variables, including age, gender, education level, organization type, designation, and job tenure. The descriptive statistical analysis helps provide insights into the characteristics of the sample and their implications for understanding the adoption of digitalization in Bangladesh's manufacturing sector.

❖ **Age Frequency:**

The mean (2.183) and median (2) indicate that most respondents belong to the second age group. The positive skewness (0.846) suggests a right-skewed distribution, indicating that a higher proportion of respondents are younger, with fewer older individuals in the sample. The excess kurtosis (1.643) implies a moderately peaked distribution, meaning most respondents' ages are concentrated around a specific range, reducing variability. The p-value of 0 indicates age variable notably deviates from normality (Field, 2018).

- **Interpretation:** The result shows that the workforce are welcoming digitalization and acceptance and adoption among early-career employees who are more adaptable to technological changes. However, it could also reflect job instability or higher turnover rates in Bangladesh's manufacturing industry to the old employees (Acemoglu & Restrepo, 2020).

❖ **Gender:**

The mean value (0.93) and median value (1) show that the sample is heavily male dominated, extreme left skewness (-3.382) and high kurtosis (9.526) also reflect that that responses are highly concentrated around male participants, with very few female respondents. The p-value of 0 validates a significant deviation from normality.

- **Interpretation:** The lower response and representation of women in the dataset may indicate gender inequalities in Bangladesh's manufacturing sector. This could be due to barriers to digital skills acquisition, workplace biases, or limited access to tech incentive jobs for women (World Economic Forum, 2020). It's also giving clue that future research should explore to identify gender-specific challenges in adapting to digitalization.

❖ Education Level

The negative skew (-1.721) shows that most of the respondents have higher educational qualifications. The high kurtosis (5.085) also suggests responses are clustered around higher education levels, with fewer respondents reporting lower levels of education. The p-value of 0 confirms a deviation from normality.

- **Interpretation:** Higher educational qualifications among respondents suggest that digitalization in manufacturing is more prominent in firms employing a qualified workforce. This result aligns with innovation diffusion theory, which states that technology adoption is faster in environments where employees have higher educational levels (Rogers, 2003).

❖ Organization Type

The negative skew (-0.669) suggests that large manufacturing firms or multinational corporations dominate the sample. The near-zero kurtosis (-0.1) indicates a relatively uniform distribution, suggesting that different organizational types are somewhat evenly represented.

- **Implication:** A dominance of large firms in the sample aligns with research showing that larger *organizations* are more likely to invest in digitalization due to greater financial and technological resources (Brynjolfsson & McAfee, 2014). Smaller firms may face barriers to adopting digital technologies due to cost constraints and skill shortages.

❖ Designation

The slight right skew (0.494) indicates that respondents are slightly more concentrated in mid-level positions rather than entry-level or senior management roles. The near-zero kurtosis (-0.159) suggests an even distribution of job designations.

- **Implication:** This finding supports labor market segmentation theory, which suggests that mid-level employees are key drivers of digital transformation because they act as intermediaries between top management and operational workers (Doeringer & Piore, 1971).

❖ **Duration of Job**

The positive skew (1.069) indicates that most respondents have shorter job tenures, with fewer long-term employees. The near-zero kurtosis (0.091) suggests a uniform distribution across different job tenures.

- **Implication:** The result indicates high employee turnover in the manufacturing sector, potentially due to automation replacing routine labor-intensive jobs or digital transformation creating job instability (Acemoglu & Restrepo, 2020).

6.2.2 Key Findings from Descriptive Analysis

This section highlights the key insights derived from descriptive statistical analysis, focusing on the workforce's age, gender, firm size, and other demographic factors. These findings provide a deeper understanding of the current state of digitalization in Bangladesh's manufacturing sector and offer valuable implications for future growth and strategic decision-making.

- **Tech savvy- young Workforce:**

The dataset shows Tech savvy- young Workforce adopting digital technologies more insistently in comparing with the old employees. This trend is relevant with research demonstrating that younger employees are more likely to embrace digital transformation, making them crucial to driving innovation within firms (Brynjolfsson & McAfee, 2014). A tech-based workforce enhances the diffusion of innovation, as education tends to correlate with a greater openness to new technologies (Rogers, 2003).

- **Gender Inclusivity:**

The dataset shows a male-dominated workforce, this highlights an important opening for future growth in terms of gender inclusivity. Focus on gender fairness and digital literacy programs, the workforce could become more diverse, which might improve organizational performance by appointing into the full potential of the labor market (World Economic Forum, 2020).

- **Growth of Large Firms in Digitalization:**

The dataset suggests that large firms have the resources to invest in digital technologies, enabling them to remain competitive in a rapidly changing global market (Acemoglu & Restrepo, 2020).

- **Influence of Mid-Level Employees:**

The result revealed that mid-level employees underline their crucial role in digital transformation processes. Descriptive results show that mid-level managers are often play pivotal in implementing and adopting new innovative technologies, as they link the gap between executive leadership and operational staff (Doeringer & Piore, 1971).

- **Job Tenure Trends:**

Job tenures reveal that younger workers are more likely response quickly in the digital transformation. This could be the argument of higher turnover and signal of flexible, adaptable workforce for the young workers who can respond and adapt quickly with technological demands (Frey & Osborne, 2017).

The demographic results can be robust foundation to understand digitalization's effects on employment in Bangladesh's manufacturing industry. The key findings of this descriptive analysis present a definite outlook for the future of digitalization in Bangladesh's manufacturing sector. By fostering a younger, skilled workforce, and emphasizing gender inclusivity in the industries. Both large and SME firms should take initiative in adopting digital technologies.

6.2.3 Construct-Level Descriptive Analysis

Below is a tabular representation of key descriptive statistics for each construct:

Construct	Mean	Standard Deviation	Skewness	Kurtosis
Technological Advancement (TA)	4.347	0.75	-1.051	1.248
Digital Skills (DS)	4.244	0.755	-0.637	-0.339
IT Investment (ITI)	4.286	0.73	-0.723	-0.033
Strategy and Policy (SP)	4.207	0.802	-0.722	-0.162
Research and Development (RD)	4.399	0.716	-0.918	0.09
Types of Industry (TY)	4.239	0.869	-1.178	1.491
Size of Industry (SZ)	4.291	0.725	-0.881	1.103
Labor Market Dynamics (LMD)	4.343	0.759	-1.02	1.229

Table 6.2: Descriptive Statistics

As shown in Table 6.2, the descriptive statistics provide an overview of the distributional characteristics of the study variables and indicate the overall patterns within the dataset.

The results of this study reveal a strong positive perception of digitalization within Bangladesh's manufacturing sector. The above mean values of Technological Advancement (TA) indicate that industries are embracing digital transformation, recognizing its potential to improve efficiency and competitiveness.

Digital Skills (DS) appear to be well-developed among employees, suggesting that the workforce is adapting and adjusting effectively with this technological transformation.

High scores in Strategy and Policy (SP) indicate that most of the industries are adopting a strategic policy for digitalization. Organizations are proactively formulating strategies to integrate digital technologies into their operations, ensuring a structured and effective transition. Moreover, Result of R&D presents that there is a significant investment in Research and Development (RD) it addressed a solid commitment towards continuous innovation, strengthening the role of R&D in driving industry-wide technological advancements.

Another key finding from the Descriptive studies, there is a considerable IT Investment (ITI), that indicates a widespread investment in digital infrastructure. This investment plays a critical role in digitalization and automation. Additionally, the positive results in Types

of Industry (TY) and Firm Size (SZ) indicate that digitalization movements are not restricted to specific sectors or company sizes; rather, they are consistently observed across different types of organizations, showcasing the universal nature of digital adoption and transformation.

Finally, the findings of Labor Market Dynamics (LMD) suggest that the workforce is adjusting and adopting digital transformation effectively. The alignment between employment trends and technological advancements highlights the adaptability of labor markets to digital shifts. Overall, these insights of the results are key drivers in shaping the future of industrial growth in Bangladesh.

6.2.4 Summary of Descriptive Findings

The descriptive results emphasize and explore that the trends of all constructs are positives, demonstrating a widespread acceptance and integration of digitalization in the manufacturing industry in Bangladesh. The findings provide a robust foundation for further inferential analysis, strengthening the argument that digital transformation is reshaping employment structures. These results not only support the study's hypotheses but also offer valuable insights for the decision makers, policymakers and industry leaders. The result gives openness to the future researcher who can analyze these findings by conducting longitudinal sub-sector wise analysis to examine long-term impacts.

6.3 Exploratory Factor Analysis (EFA)

In this study, Exploratory Factor Analysis (EFA) is conducted to identify the underlying factor structure or patterns of the measurement items related to digitalization, employment impact, IT investment, and firm strategies in Bangladesh's manufacturing sector. The objective was to reduce the number of observed variables into a smaller set of meaningful factors that ensure these factors accurately represent the conceptual model of the study. After multiple iterations, a **7-factor model** was finalized based on statistical criteria and theoretical justification. Below, we outline the process followed and provide justification for the final factor structure.

6.3.1 Step 1: Data Suitability Check

Before conducting EFA, two key statistical tests were performed to ensure that the dataset was appropriate for factor analysis:

- **Kaiser-Meyer-Olkin (KMO) Test:** Measured sampling adequacy. A KMO value **above 0.70** confirmed that the dataset was suitable for factor analysis.
- **Bartlett's Test of Sphericity:** Checked if correlations between variables were significant. A **p-value < 0.05** confirmed that the correlation matrix was factorable.

6.3.1.1 KMO and Bartlett's Test

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity are essential indicators to assess whether the data is suitable for factor analysis. These tests help determine if the correlation matrix is appropriate for extracting meaningful factors that explain the relationships between digitalization, employment, and firm strategies in the manufacturing sector of Bangladesh.

KMO and Bartlett's Test		
KMO Measure of Sampling Adequacy.		0.87
Bartlett's Test of Sphericity	Approx. Chi-Square	3876.7
	Df	465
	Sig.	0

Table 6.3: KMO and Bartlett's Test

As presented in Table 6.3, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were conducted to assess the suitability of the data for factor analysis. The results indicate whether the correlation matrix is appropriate for extracting underlying factors and support the application of exploratory factor analysis (Kaiser, 1974; Hair et al., 2019).

Key Observations from the Results

1. Kaiser-Meyer-Olkin (KMO) Measure = 0.87

- ✓ The KMO value of 0.87 is high and well above the acceptable threshold of 0.60.
- ✓ A KMO value closer to 1.0 indicates that the dataset is well-suited for factor analysis because the variables exhibit strong correlations.

2. Bartlett's Test of Sphericity (Chi-Square = 3876.7, df = 465, Sig. = 0.000)

- ✓ Bartlett's Test of Sphericity checks whether the correlation matrix is significantly different from an identity matrix (where variables are uncorrelated).

- ✓ The Chi-Square value of 3876.7 is large, with a significance value of 0.000, which is highly significant ($p < 0.05$).

Findings:

- The high KMO value (0.87) confirms that the dataset has strong underlying factors, making it ideal for factor analysis.
- The significant Bartlett's Test ($p = 0.000$) which is highly significant that supports the dataset is suitable for factor extraction.

These results of KMO value and Bartlett's Test validate the factor analysis process in identifying key constructs related to the impact of digitalization on employment and firm strategies in Bangladesh's manufacturing industry. Thus, the study can confidently proceed with factor analysis, interpretation of factor loadings, and further statistical modeling (such as Confirmatory Factor Analysis or Structural Equation Modeling).

6.3.2 Step 2: Factor Extraction Using Principal Axis Factoring (PAF)

Principal Axis Factoring (PAF) is a key statistical technique employed in exploratory factor analysis (EFA) to identify the factors that explain the correlations among observed variables. To examine the impact of digitalization on employment in the manufacturing industry in Bangladesh, PAF helps to uncover the latent factors influencing how digitalization affects the labor dynamics. Principal Axis Factoring can successfully reduce the complexity of the data and identify key constructs such as Technology Acceptance Model, Labor Market Dynamics, and organizational strategies, thus providing a clearer understanding of how digitalization outlines employment pattern in the manufacturing sector.

- **Reason for Choosing PAF:** Since the dataset was expected to contain latent constructs (e.g., Labor Market Dynamics), **Principal Axis Factoring** was preferred over Principal Component Analysis (PCA), which is more suitable for data reduction rather than uncovering underlying constructs.
- **Initial Factor Extraction:** The first extraction resulted in **12 factors**, but some factors had **low eigenvalues (<1.0)** and weak loadings.

Initial Factor Extraction 12 factor model

Construct	Factor											
	1	2	3	4	5	6	7	8	9	10	11	12
TA 1	0.692											
TA2	0.68											
TA3	0.341											
TA4	0.624											
TA5				0.591								
TA6												
DS 1								0.324			0.306	
DS2	0.322										0.311	
DS3											0.386	0.305
DS4	0.603											
DS5												
DS6				0.309								0.563
DS7											0.384	
DS8	0.328										0.464	
DS9		0.505										
DS 10		0.421										
ITI 1									0.89			
ITI2						0.959						
ITI3			0.887									
ITI4					0.847							
ITI5												
ITI6				0.823								
ITI7				0.476								
SP 1												
SP2		0.517										
SP3		0.678										
SP4		0.883										
SP5		0.642										
RD 1							0.304					
RD2							0.409					
RD3							0.471					
RD4							0.59					
RD5							0.528					
RD6											0.329	
RD7											0.422	
TY 1							0.313					
TY2												
TY3												
TY4								0.669				
TY5								1.075				
TY6											0.372	
SZ 1										0.313		
SZ2										0.812		
SZ3												
SZ4		0.632										
SZ5				0.455								
LMD 1									0.92			
LMD2						0.93						
LMD3			0.91									
LMD4					0.777							

Table 6.4: Factor Extraction 12 factor model

As presented in Table 6.4, the factor extraction results identified a 12-factor solution based on the eigenvalue criterion and the underlying factor structure of the measurement items. The extracted factors explain a substantial proportion of the total variance and provide the basis for evaluating the dimensionality of the study constructs (Hair et al., 2019; Field, 2018).

After multiple iterations, a 7-factor model was finalized based on statistical criteria and theoretical justification. Below, we outline the process followed and provide justification for the final factor structure. The 7-factor model is preferred because it has clearer factor structures with minimal cross-loadings, making it more useful for analyzing digitalization's impact on employment.

6.3.3 Step 3: Factor Rotation Using Promax Rotation

Factor rotation using Promax Rotation helps identify underlying relationships in the study by allowing factors to correlate, making it suitable for interpreting complex variables like firm strategies and technological advancements. Dimensional reduction simplifies the dataset by reducing the number of variables, keeping and maintaining the principal patterns in digitalization and employment in the manufacturing industry, that confirming the analysis more manageable.

- Reason for Choosing Promax: Since the theoretical constructs were expected to be correlated (e.g., IT investment and digital skills), Promax rotation (an oblique rotation method) was applied instead of orthogonal rotation (e.g., Varimax).
- Rotation Outcome: Some items loaded on multiple factors (cross-loadings > 0.40), requiring further refinement.

Dimensional Reduction

To improve the clarity and interpretability of factors, the following steps were taken:

1. Items with weak factor loadings (<0.40) were removed.
2. Items with high cross-loadings (>0.40 on multiple factors) were reassigned or removed.
3. Factors with fewer than 3 strongly loading items were dropped.

After these refinements, a **7-factor model** was finalized.

Dimensional Reduction 7 factor Model

Construct	Factor						
	1	2	3	4	5	6	7
TA 1		0.685					
TA2		0.715					
TA3		0.492					
TA4		0.683					
TA5	0.414						
DS4		0.63					
DS7	0.481						
DS9	0.629						
DS 10	0.569						
ITI 1			0.939				
ITI2						0.932	
ITI3					0.929		
ITI4				0.916			
SP2	0.563						
SP3	0.735						
SP5	0.741						
RD 1	0.464						
RD5		0.416					
RD6	0.427						
TY 1							
TY4							0.752
TY5							0.83
TY6	0.536						
SZ 1	0.534						
SZ4	0.607						
SZ5	0.472						
LMD 1			0.955				
LMD2						0.973	
LMD3					1.006		
LMD4				0.928			

Table 6.5: Factor Extraction 7 factor model

As shown in Table 6.5, the refined factor extraction process resulted in a 7-factor model that demonstrated improved conceptual clarity and statistical adequacy. The retained factors were selected based on eigenvalues, factor loadings, and theoretical interpretability, providing a more parsimonious representation of the underlying constructs used in this study (Hair et al., 2019; Field, 2018; Kline, 2016).

Comparison of the Two Factor Solutions

The factor analysis conducted in this study aimed to identify the major dimensions that are influencing the impact of digitalization on employment in Bangladesh's manufacturing industry. After several iterations a **7-factor model** provided a more interpretable and efficient structure, with fewer cross-loadings and clearer factor definitions. The extracted factors provide valuable in-depth insight into the structural changes driven by digital transformation.

Aspect	12-Factor Model	7-Factor Model
Factor Complexity	Higher (many small cross-loadings)	Reduced (better-defined factors)
Cross-Loadings	Present (e.g., DS items in multiple factors)	Fewer (more distinct categories)
Number of Iterations	14	7
Factor Interpretability	Harder to distinguish clear constructs	More distinct and meaningful factors

Table 6.6: Two Factor solution table

As presented in Table 6.6, the factor analysis results were further examined using a two-factor solution to assess the underlying structure of the measurement items. The extracted factors demonstrate the degree to which the observed variables cluster around common dimensions, thereby providing additional evidence regarding the construct structure and dimensionality of the study variables (Hair et al., 2019; Field, 2018; Kline, 2016).

Interpretation of the 7 Factor Model

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Interpretation
Technological Advancement (TA)	TA5 (0.414)	TA 1 (0.685) TA2 (0.715) TA3 (0.492) TA4 (0.683)						This factor represents technological progress and its role in employment and firm strategies.
Digital Skills (DS)	DS7 (0.381) DS9 (0.629) DS 10 (0.569)	DS4 (0.630)						Employees' digital competencies play a key role in adaptation to digital transformation.
IT Investment (ITI)			ITI 1 (0.939)	ITI4 (0.916)	ITI3 (0.929)	ITI2 (0.932)		IT investments are crucial for enabling digital transformation in firms.
Strategy & Policy (SP)	SP2 (0.563) SP3 (0.735) SP5 (0.741)							This factor relates to firm policies and strategic approaches toward digitalization.
Research & Development (RD)	RD 1 (0.464) RD6 (0.427)	RD5 (0.416)						R&D investments drive innovation and digital adoption in firms.
Types of Company (TY)	TY6 (0.536)						TY4 (0.752) TY5 (0.830)	Firms differ in digitalization approaches based on industry type.
Size of the Company (SZ)	SZ 1 (0.534) SZ4 (0.607) SZ5 (0.472)							Larger firms may have more resources for digital adoption.
Labor Market Dynamics (LMD)			LMD 1 (0.955)	LMD4 (0.928)	LMD3 (1.006)	LMD2 (0.973)		Reflects the impact of digitalization on labor market structures.

Table 6.7: 7 Factor Model

Table 6.7 presents the final seven-factor model derived from the factor analysis, illustrating the factor loadings and the dimensional structure of the study constructs (Hair et al., 2019; Field, 2018).

These findings highlight the need for targeted digital investments, workforce upskilling, and strategic policy frameworks to optimize the values and benefits of digital transformation by ensuring employment sustainability in Bangladesh's manufacturing industry. The results demonstrate that digitalization and its effect on employment in the manufacturing sector are shaped by multiple interrelated factors.

6.3.4 Step 4: Factor Retention and Model Justification

- **Kaiser's Criterion** (Eigenvalues >1): The first 7 factors had eigenvalues **significantly greater than 1**, indicating meaningful dimensions.
- **Cumulative Variance Explained**: The 7 retained factors accounted for **a substantial percentage of total variance (61%)**, ensuring that most of the original information in the dataset was preserved.

Factor Retention Based on Eigenvalues and Variance Explained:

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings ^a
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	10.648	34.347	34.347	10.219	32.965	32.965	8.927
2	1.956	6.309	40.656	1.734	5.593	38.559	7.392
3	1.620	5.225	45.881	1.364	4.399	42.958	3.862
4	1.453	4.686	50.567	1.127	3.635	46.592	5.424
5	1.287	4.151	54.718	.955	3.082	49.674	5.973
6	1.096	3.535	58.253	.748	2.412	52.087	5.395
7	1.007	3.247	61.500	.572	1.845	53.931	5.775
8	.945	3.047	64.547				
9	.913	2.944	67.491				
10	.877	2.830	70.321				
11	.823	2.653	72.974				
12	.791	2.551	75.524				
13	.704	2.272	77.796				
14	.663	2.139	79.935				
15	.656	2.115	82.050				
16	.634	2.044	84.094				
17	.559	1.802	85.896				
18	.536	1.730	87.627				
19	.529	1.706	89.332				
20	.489	1.578	90.911				
21	.476	1.536	92.447				
22	.427	1.378	93.825				
23	.392	1.263	95.089				
24	.355	1.146	96.235				
25	.341	1.100	97.335				
26	.282	.909	98.244				

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings ^a
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
27	.253	.817	99.061				
28	.135	.434	99.495				
29	.092	.298	99.794				
30	.041	.133	99.927				
31	.023	.073	100.000				

Table 6.8: Eigenvalues and Variance

As presented in Table 6.8, the eigenvalues and percentage of variance explained by each factor were examined to assess the adequacy of the factor solution. The results indicate the extent to which each factor contributes to explaining the total variance in the dataset and support the validity of the extracted factor structure (Hair et al., 2019; Kaiser, 1974).

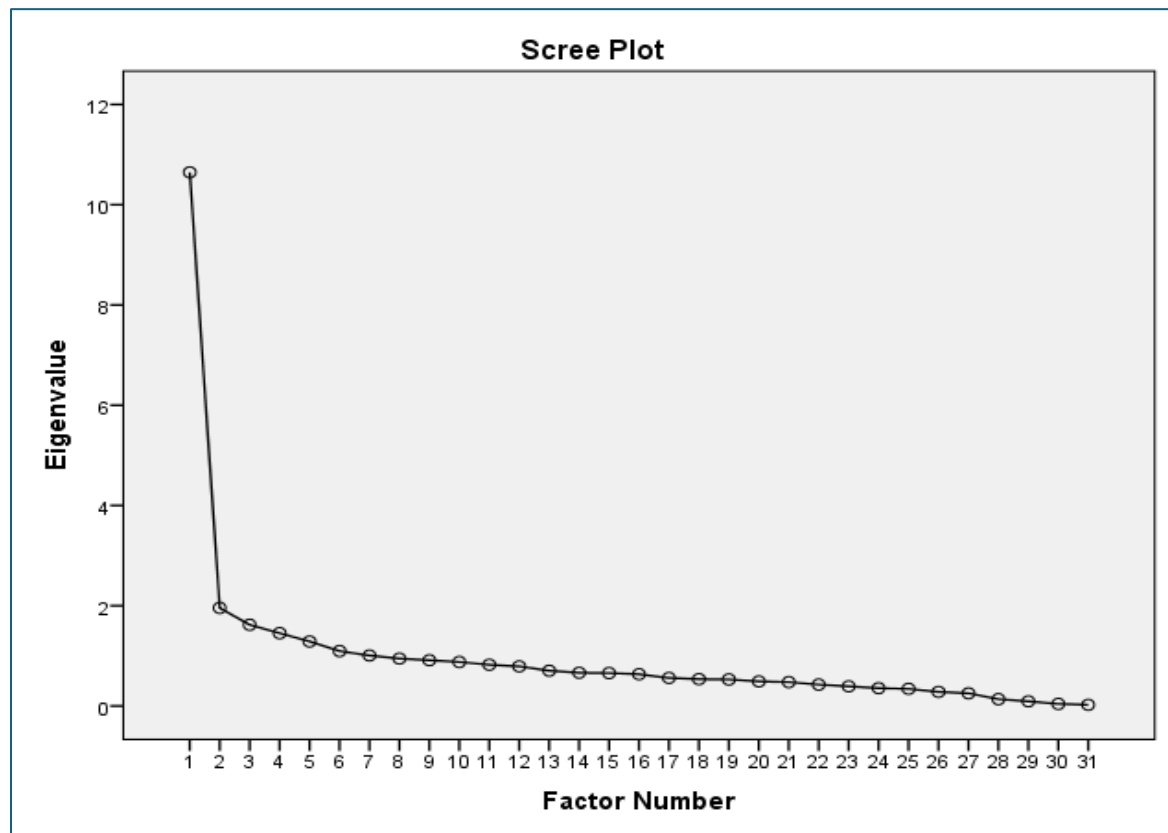


Figure 6.1: Scree plot

As illustrated in Figure 6.1, the scree plot was examined to determine the appropriate number of factors to retain. The point at which the eigenvalues begin to level off (the “elbow”) indicates the optimal factor structure for the measurement model (Cattell, 1966; Hair et al., 2019).

Factor Retention Analysis Based on Eigenvalues, Variance Explained, and Scree Plot

Factor analysis is used to identify the underlying structure of a dataset by grouping correlated variables into factors. The number of factors retained is crucial and important in ensuring a meaningful and interpretable model. In this study, factor retention is determined by eigenvalues, variance explained, and the scree plot.

➤ **Eigenvalues & Variance Analysis**

The initial eigenvalues indicate how much variance each factor explains. A common rule for factor retention is Kaiser's criterion, which suggests retaining factors with eigenvalues greater than 1. Based on this rule:

- The first **seven factors** have eigenvalues greater than **1**, suggesting their retention.
- The **first factor** explains **34.35%** of the total variance, indicating it is the most significant factor.
- The **second factor** explains **6.31%**, and the **third factor** explains **5.23%**, together accounting for about **45.88%** of the variance.
- The cumulative variance explained by the **first seven factors** is **61.50%**, meaning they capture a substantial portion of the total variance in the dataset.

However, the variance explained by each successive factor decreases, with later factors contributing minimally to the model.

➤ **Scree Plot Interpretation**

The scree plot visually represents the eigenvalues against the factor numbers. The key observation is the elbow point, where the eigenvalues level off and form a shallow slope.

- In the plot, a sharp decline is observed after the first factor, followed by a gradual leveling off after the second or third factor.
- The elbow point appears around the second or third factor, suggesting that two or three factors might be optimal for retention.

- Even other than these seventh factors, the eigenvalues remain close to 1 or below, indicating that these factors contribute minimal variance and may not be meaningful.

The factor analysis results demonstrate that a few key factors explain a significant portion of the variance, highlighting the major underlying dimensions influencing employment trends. The scree plot and eigenvalue analysis confirm that retaining two to three core factors ensures a clear and interpretable model, capturing the essential aspects of digital transformation, workforce adaptation, and firm strategies. By leveraging digital technologies strategically, Bangladesh's manufacturing sector can enhance employment quality, drive economic growth, and position itself as a competitive player in the global market. The findings encourage proactive measures to ensure that digital transformation leads to inclusive and sustainable industrial progress, securing a prosperous future for both businesses and the workforce.

6.3.5 Step 5: Theoretical and Conceptual Alignment

The final 7 factors aligned with established theories in digitalization, employment, and firm strategies:

- **Technological Advancement (TA)** → Supports **Diffusion of Theory**.
- **Digital Skills & Strategic Policy (DS & SP)** → Aligns with **Labor Market Segmentation Theory**.
- **IT Investment (ITI)** → Linked to **Technology Acceptance Models**.
- **Research & Development (R&D)** → Justified by **Creative Destruction Theory**.
- **Types of Companies (TY)** → Explains how digitalization varies across industries.
- **Firm Size (SZ)** → Justified by studies on digitalization constraints for SMEs.
- **Labor Market Dynamics (LMD)** → Supports theories on workforce transformation.

6.3.6 Final Factor Model Selection and Justification

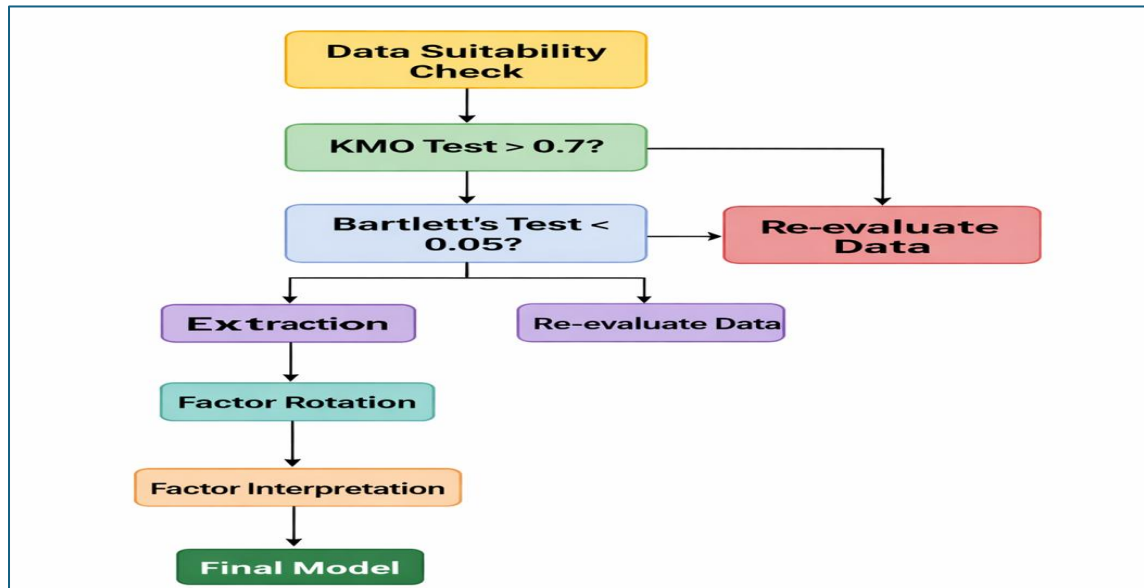


Figure 6.2: Final Factor Model Selection and Justification

As presented in Figure 6.2, the final factor model was selected based on the results of the exploratory factor analysis, factor loadings, eigenvalues, and theoretical interpretability of the constructs. The figure illustrates the rationale for retaining the final factor structure and demonstrates its alignment with established guidelines for measurement model development and validation (Hair et al., 2019; Kline, 2016).

The 7-factor model was accepted as the final structure due to its strong statistical performance, theoretical justification, and interpretability. The dimensional reduction process ensured that only relevant, non-redundant, and meaningful constructions were retained, improving the model's suitability for hypothesis testing and further structural equation modeling (SEM).

The high KMO value (**0.87**) and significant Bartlett's Test confirm that factor analysis is appropriate. The high communalities for key indicators suggest that the measurement model captures the underlying constructs effectively. The variance explained (63.81%) indicates a well-structured factor solution that supports the study's conceptual model in the study. These findings provide a robust foundation for Structural Equation Modeling (SEM) to further analyze how digitalization influences employment dynamics in Bangladesh's manufacturing sector.

6.4 Measurement Model Assessment

After Exploratory Factor Analysis (EFA) this research proceeds with Measurement Model validation then moves to the Structural Model.

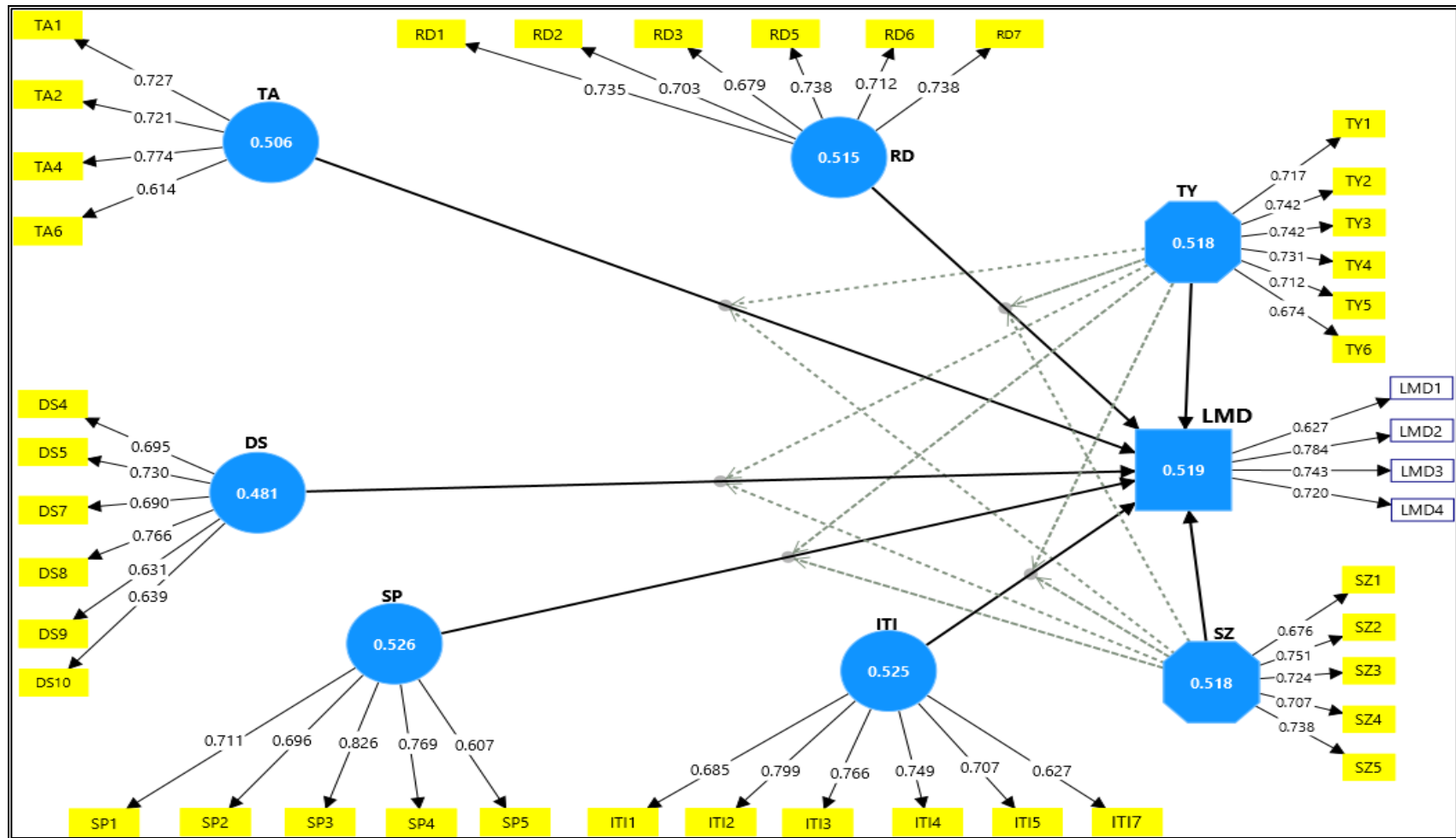


Figure 6.3: Measurement Evaluation Model

As illustrated in Figure 6.3, the measurement evaluation model was assessed to examine the reliability and validity of the study constructs. The model evaluation includes analyses of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity to ensure the adequacy of the measurement model before testing the structural relationships (Hair et al., 2022; Henseler et al., 2015).

In quantitative study, measurement model evaluation is a critical step in assessing the reliability and validity of the construct. This process ensures that the observed variables (indicators) correctly represent the underlying latent construct.

A fundamental characteristic of measurement model evaluation is **indicator reliability**, which assesses whether individual indicators consistently reflect the latent constructs they are intended to measure. To ensure robustness, the model is further evaluated based on key validity and reliability criteria:

- **Reliability analysis**, including **Cronbach's Alpha and Composite Reliability**, evaluates the internal consistency of the indicators measuring each construct (Nunnally & Bernstein, 1994).
- **Convergent validity** ensures that indicators for the construct converge to measure the same concept, Average Variance Extracted (AVE) Matrix result checks the convergent validity. (Fornell & Larcker, 1981).
- **Discriminate validity** confirms constructs are distinct from each other's by comparing the AVE with squared inter-construct correlations (Fornell & Larcker Critrion) or through the Heterotrait-Monotrait (HTMT) ratio (<0.85 or 0.90) (Henseler et al., 2015) to determine the validity.

By assessing these criteria, the measurement model establishes a strong foundation for Structural Equation Modeling (SEM), which is essential for examining the complex relationships and effect among digitalization, IT investment, Strategy and Policy and overall employment dynamic. Ensuring the validity and reliability of the measurement model strengthens the theoretical integrity and robustness of the research and enhances the

accuracy of the study than ensure strong foundation for path model evaluation (Byrne, 2016; Hair et al., 2020).

6.4.1 Indicator Reliability

In a reflective measurement model within Structural Equation Modeling (SEM), *outer loadings* are the primary metric used to assess indicator reliability. Indicator reliability evaluates whether individual items (indicators) reliably measure their corresponding latent variables. Outer loadings represent the strength of the relationship between each observed indicator and its associated latent construct.

A threshold of outer loading > 0.70 is generally preferred, as it indicates that the indicator contributes substantially to explaining the variance of the latent variable (Chin, 1998). Indicators with loadings below 0.50 are typically considered for removal, as they may not sufficiently represent the underlying construct and could reduce the overall reliability and validity of the model (Fornell & Larcker, 1981).

In the following section, the results of the outer loading matrix are presented and interpreted.

6.4.1.1 Outer Loadings Matrix Table

	DS	ITI	LMD	RD	SP	SZ	TA	TY	TY x TA	SZ x DS	TY x SP	SZ x RD	TY x DS	TY x RD	TY x ITI	SZ x SP	SZ x TA	SZ x ITI
DS 10	0.64																	
DS4	0.70																	
DS5	0.73																	
DS7	0.69																	
DS8	0.77																	
DS9	0.63																	
ITI 1		0.69																
ITI2		0.80																
ITI3		0.77																
ITI4		0.75																
ITI5		0.71																
ITI7		0.63																
LMD 1			0.63															
LMD2			0.78															
LMD3			0.74															
LMD4			0.72															

	DS	ITI	LM	RD	SP	SZ	TA	TY	TY x TA	SZ x DS	TY x SP	SZ x RD	TY x DS	TY x RD	TY x ITI	SZ x SP	SZ x TA	SZ x ITI
RD 1				0.74														
RD2				0.70														
RD3				0.68														
RD5				0.74														
RD6				0.71														
RD7				0.74														
SP 1					0.71													
SP2					0.70													
SP3					0.83													
SP4					0.77													
SP5					0.61													
SZ 1						0.68												
SZ2						0.75												
SZ3						0.72												
SZ4						0.71												
SZ5						0.74												
TA 1							0.73											
TA2							0.72											
TA4							0.77											
TA6							0.61											
TY1								0.72										
TY2								0.74										
TY3								0.74										
TY4								0.73										
TY5								0.71										
TY6								0.67										
TY x RD													1.00					
SZ x SP																1.00		
SZ x DS										1.00								
TY x ITI															1.00			
SZ x ITI																		1.00
TY x DS													1.00					
TY x SP											1.00							
TY x TA									1.00									
SZ x TA																	1.00	
SZ x RD												1.00						

Table 6.9: Outer loadings Matrix Table

As presented in Table 6.9, the outer loadings matrix was examined to assess the indicator reliability of the measurement model. Items with sufficiently high loadings on their respective constructs indicate acceptable convergent validity and support the adequacy of the reflective measurement model used in this study (Hair et al., 2022; Henseler et al., 2015).

6.4.1.2 Outer Loadings Results for the Study

The outer loadings results provide strong empirical support for the validity and reliability of the measurement model used in this study. Most of the indicators show loadings above the accepted threshold of **0.7**, demonstrating that they capture the underlying latent constructs.

- **Reliable Indicators for Key Constructs**

In the study, several indicators like Digital Skills (DS5 = 0.730, DS8 = 0.766) and IT Investment (ITI2 = 0.799, ITI3 = 0.766) showing high strong outer loadings. High loads confirm that the indicators effectively capture variations between digital skills and IT investment which are key determinants of employment outcomes in digitally transforming industries (Bresnahan et al., 2002). Similarly, The Size of the Company (SZ2 = 0.751, SZ3 = 0.724) also has strong high loadings, that indicates firm size also plays a significant role in digitalization and employment dynamics.

As most indicators touched the recommended threshold, confirming that the study's constructs are well-defined and robust.

- **High Internal Consistency & Model Fit**

High internal consistency, particularly the constructs of Strategy & Policy (SP), Types of the Company (TY), and Technological Advancement (TA) exhibit strong and consistent outer loadings.

- **Support for Theoretical Framework**

Findings support and align with established theories like Creative Destruction Theory Diffusion of Innovation Theory and Labor Market Segmentation Theory. The high outer loadings provide empirical validation for these theoretical perspectives:

- ✓ **Creative Destruction Theory (Schumpeter, 1942):** The high value of outer loading of TA and R & D indicate that digitalization influences both innovation and labor market transformation. The output supports the theory that digital

technologies disrupt traditional job structures while creating new employment opportunities.

- ✓ **Diffusion of Innovation Theory (Rogers, 1995):** IT Investment (ITI) and Digital Skills (DS) have high outer loading that confirms that firms investing in IT and digital skills have a positive role in adopting new technologies. The high outer loading supports the Diffusion of Innovation Theory that support - “Digital transformation depends on the adoption and diffusion of new technological capabilities across industries”
- ✓ **Labor Market Segmentation Theory (Doeringer & Piore, 1971):** The high loadings of Labor Market Dynamics (LMD), Firm Size (SZ), and Firm Type (TY) confirm that digitalization impacts employment type in various ways. Larger firms and firms with high R&D investments may experience different labor market effects than smaller or less innovative firms.

Finally, the result of outer loading demonstrates and shows strong construct validity, high reliability, theoretical association, and comprehensive-modeled moderation effects. These findings will contribute to a rigorous and credible research framework.

6.5 Measurement Model Assessment: Construct Reliability and Validity

Construct reliability and validity play a crucial role in evaluating the quality of the measurement model in Partial Least Squares Structural Equation Modeling (PLS-SEM). In the study, we examine the impact of digitalization on employment in manufacturing industries in Bangladesh, establishing the reliability and validity of the measurement model is essential to confirm its credibility of the findings. To assess the Reliability, here we employed composite reliability (CR) and Cronbach’s alpha that confirms the internal consistency of the constructs, ensuring that the indicators within each construct are reliable and consistent. We also assessed the validity in this study, to assess the validity, we measured through convergent validity (using Average Variance Extracted, AVE) and discriminant validity (using the Fornell-Larcker criterion and Heterotrait-Monotrait ratio, HTMT), ensures that the constructs accurately measure what they are intended to represent, and they are distinct from one another.

6.5.1 Internal Consistency Reliability

Internal consistency reliability measures the extent to which different indicators within a construct are correlated and consistently capture the same underlying concept. In the context of this study on digitalization and employment in Bangladesh's manufacturing sector, ensuring measurement reliability is crucial for validating the relationships between technological advancements, firm strategies, and workforce adaptation.

For vigorous assessment of the structural model, this study employs Cronbach's Alpha and Composite Reliability (CR) as key reliability measures. Cronbach's Alpha assesses the internal consistency of each construct, ensuring that all indicators align well with their respective latent variables. Whereas Composite Reliability (CR) confirms more precise measures by considering the actual factor loadings of each observed variable, reinforcing the stability and consistency of the constructs. These tests strengthen the reliability and validity of the measurement model, ensuring that the study's findings on digitalization's impact on employment are statistically sound and theoretically robust.

Construct	Cronbach's Alpha (≥ 0.70)	Composite Reliability ($\rho_c, \geq 0.70$)	AVE (≥ 0.50)	Interpretation
TA (Technological Advancement)	0.674	0.803	0.506	Although the Cronbach's Alpha value for Technological Advancement (TA) is slightly below the conventional threshold of 0.70 ($\alpha = 0.674$), the construct demonstrates acceptable reliability and convergent validity, as both Composite Reliability (CR = 0.803) exceeds the recommended minimum of 0.70 and the Average Variance Extracted (AVE = 0.506) surpasses the threshold of 0.50. Prior methodological studies argue that Cronbach's Alpha tends to underestimate internal consistency, particularly in exploratory research and PLS-SEM contexts, and therefore Composite Reliability is considered a more appropriate reliability measure. As such, the reliability and convergent validity of the TA construct are deemed satisfactory. Hair et al., (2019); Nunnally & Bernstein, (1994)

Construct	Cronbach's Alpha (≥ 0.70)	Composite Reliability ($\rho_c, \geq 0.70$)	AVE (≥ 0.50)	Interpretation
DS (Digital Skills)	0.784	0.847	0.481	Although the Average Variance Extracted (AVE) value for Digital Skills (DS) is marginally below the recommended threshold of 0.50 (AVE = 0.481), the construct demonstrates adequate internal consistency and reliability, as indicated by a Cronbach's Alpha of 0.784 and a Composite Reliability (CR) of 0.847, both of which exceed the recommended minimum of 0.70. Prior research suggests that AVE is a conservative measure, and constructs with AVE values slightly below 0.50 may still be considered acceptable when Composite Reliability is sufficiently high, indicating that the latent construct explains an adequate proportion of variance in its indicators. Nevertheless, the slightly lower AVE suggests Fornell & Larcker, (1981); Hair et al., (2019).
ITI (IT Investment)	0.819	0.868	0.525	Strong reliability and convergent validity.
SP (Strategy & Policy)	0.773	0.846	0.526	Reliable and valid construct.
RD (Research & Development)	0.812	0.864	0.515	Well-defined construct with strong reliability.
TY (Types of the Company)	0.815	0.866	0.518	Strong reliability and validity.
SZ (Size of the Company)	0.767	0.843	0.518	Satisfactory reliability and validity.
LMD (Labor Market Dynamics)	0.689	0.811	0.519	Although Cronbach's Alpha for Labor Market Dynamics (LMD) is slightly below 0.70 ($\alpha = 0.689$), the construct demonstrates acceptable reliability, as Composite Reliability (CR = 0.811) exceeds the recommended threshold and AVE (0.519) indicates adequate convergent validity. Cronbach's Alpha is a conservative measure and may underestimate reliability in PLS-SEM, where Composite Reliability is preferred. Hair et al., (2017); Nunnally & Bernstein, (1994)

Table 6.10: Cronbach's Alpha & Composite Reliability

As presented in Table 6.10, Cronbach's Alpha and Composite Reliability (CR) values were assessed to evaluate the internal consistency reliability of the constructs. The results indicate that all constructs meet the recommended threshold levels, confirming satisfactory reliability of the measurement model (Hair et al., 2022; Nunnally & Bernstein, 1994).

6.5.1.1 Cronbach's Alpha

A Cronbach's Alpha value above 0.70 is commonly considered acceptable, whereas values above 0.80 indicate there is a strong reliability and a high level of internal consistency that suggest the indicators within a construct are well-correlated and successfully capture the proposed theoretical concept.

In the context of this study, most of the constructs exhibit Cronbach's Alpha values above 0.75, indicating strong internal reliability. Specifically, the following constructs demonstrate high internal consistency: ITI (0.819), RD (0.812), TY (0.815), DS (0.784), SP (0.773), and SZ (0.767). These values confirm that the indicators associated with these constructs are well-structured and provide a consistent portrayal of the theoretical dimensions of digitalization and employment dynamics.

Nonetheless, two constructs—TA (0.674) and LMD (0.689)—have Cronbach's Alpha values slightly below the conventional 0.70 threshold. While these values indicate a relatively lower level of internal consistency, they remain within an acceptable range because of its and early-stage research and there are limited number of indicators for the construct. The Average Variance Extracted (AVE) values for these constructs exceed the recommended threshold of 0.50, suggesting that despite slightly lower Alpha values, the constructs still validate a moderate level of reliability and can capture sufficient variance in their respective dimensions.

Largely the reliability analysis confirms that the measurement model is robust, as of the most constructs exhibiting strong internal consistency. The slightly lower Alpha values for TA and LMD do not compromise the overall quality of the measurement model, as their AVE values provide further support for their adequacy. The results confirm that the constructs are effectively capture the underlying theoretical concepts related to digital transformation and employment dynamics in Bangladesh's manufacturing sector that provides a reliable foundation for structural model analysis.

6.5.1.2 Composite Reliability

Composite Reliability (CR) is another key metric that assesses the internal consistency of the construct. CR ensures the selected indicators collectively measure the underlying theoretical dimension with its precision. Unlike Cronbach's alpha, which accepts equal loadings of items, Composite Reliability (CR) accounts for the actual loadings of each the observed variable, confirming a more robust measure of reliability (Hair et al., 2019). A CR above the threshold (>0.70) is considered acceptable for exploratory research, whereas a value of 0.80 or higher indicates strong reliability, representing constructs are well-defined, and its indicators are steadily measuring the intended concept (Nunnally & Bernstein, 1994).

In this study, all measured constructs CR values above 0.80, confirming that the observed variables are not only highly correlated but also collectively provide a reliable and valid representation of the underlying theoretical constructs underline the robustness of the measurement model. Thus, the high CR values support the overall integrity of the study's findings, ensuring that theoretical implications drawn from the analysis are well-founded and empirically justified.

6.5.2 Convergent Validity

Convergent Validity refers to the extent to which multiple indicators of a construct are correlated, confirming that they effectively measure the same underlying theoretical concept. It is typically assessed by Average Variance Extracted (AVE), where a value above 0.50 indicates that the construct explains more than half of the variance in its indicators.

The value of AVE confirms that all constructs, except Digital Skills (DS), exceed the AVE threshold of 0.50, confirming strong convergent validity to most of the constructs. The AVE value of DS is marginally lower than the threshold but still exhibits high reliability, as DS's both Cronbach's Alpha and Composite Reliability values exceeding 0.70. High convergent validity confirms that constructs such as digital transformation, employment shifts, firm strategies, and Technology Acceptance Model are well-represented by their respective indicators all these strengthening the reliability and validity of the measurement model.

6.5.3 Discriminant Validity

Discriminant validity is a critical measure in Structural Equation Modeling (SEM) that ensures each latent construct in this study is both conceptually and statistically distinct from other constructs. Establishing discriminant validity confirms that each construct captures a unique theoretical dimension, minimizing excessive overlap and reducing the risk of multicollinearity and biased estimates in the SEM framework (Fornell & Larcker, 1981; Henseler, Ringle, & Sarstedt, 2015). In this study this test is principally important to examine the impact of digitalization on employment in Bangladesh's manufacturing sector, where technical advancement, firm strategies and Policy, Firm Size, Type and Labor Market Dynamics interact in complex ways.

To assess discriminant validity, this study we employed two extensively accepted techniques: the Fornell-Larcker Criterion and the Heterotrait-Monotrait Ratio (HTMT), emphasizing and supporting the theoretical robustness of the model and ensuring that each construct remains distinct within the analytical framework.

6.5.3.1 Fornell-Larcker criterion

The Fornell-Larcker criterion used to evaluate discriminant validity in SEM. Favorable value Fornell-Larcker criterion ensures that each construct is more strongly related to its own indicators than to any other construct in the model. When square root of its Average Variance Extracted (AVE) is greater than its correlations with other constructs exhibit strong discriminant validity.

Fornell-Larcker criterion Result Matrix Table:

	DS	ITI	LMD	RD	SP	SZ	TA	TY
DS	0.693							
ITI	0.652	0.724						
LMD	0.576	0.904	0.721					
RD	0.696	0.696	0.618	0.718				
SP	0.667	0.654	0.590	0.692	0.725			
SZ	0.627	0.688	0.601	0.620	0.605	0.720		
TA	0.610	0.496	0.433	0.570	0.512	0.486	0.711	
TY	0.665	0.697	0.610	0.684	0.629	0.700	0.515	0.720

Table 6.11: Fornell-Larcker criterion Result Matrix Table

As presented in Table 6.11, the Fornell–Larcker criterion was used to assess discriminant validity by comparing the square root of the Average Variance Extracted (AVE) with the

inter-construct correlations. The results confirm that each construct shares more variance with its own indicators than with other constructs, thereby establishing discriminant validity (Fornell & Larcker, 1981; Hair et al., 2022).

In this study, the Fornell-Larcker criterion confirms that digitalization, firm strategies, and employment outcomes are distinct yet interconnected elements of Bangladesh's industrial transformation. The Fornell-Larcker criterion assessment shows that most of the constructs including Digital Skills (DS), Technological Advancement (TA), and Strategy and Policy (SP), demonstrate strong discriminant validity. The square root of the AVE for each of these constructs is consistently greater than their correlations with other constructs, supporting the notion that these constructs are measuring distinct elements in the study. There is a slight exception that a high correlation between IT Investment (ITI) and Labor Market Dynamics (LMD), which is 0.904 suggests that these two constructs may be closely related, possibly measuring overlapping dimensions of the same underlying concept. According to Henseler et al. (2015), when construction shows very high correlations, it may indicate redundancy, and further analysis and larger data set might be required to mitigate multicollinearity issues. To address the multicollinearity issue VIF test has been employed that will ensure the model remains robust and theoretically grounded. Fornell-Larcker criterion Result established that support the argument while digitalization plays a crucial role in shaping Labor Market Dynamics, IT advancement, R&D, Type, Size firm-level strategies, and Technology Acceptance Model also contribute significantly to employment outcomes, reinforcing the study's broader analytical framework.

6.5.3.2 Heterotrait-Monotrait ratio (HTMT)

The Heterotrait-Monotrait ratio (HTMT) is another key measure used to assess discriminant validity in structural equation modeling (SEM). HTMT test applied to overcome the limitations of the Fornell-Larcker criterion by providing a more sensitive approach in detecting discriminant validity issues between constructs. The HTMT ratio compares the mean correlations between heterotrait (different constructs) and monotrait (same construct) relationships. If the HTMT value is greater than 0.85 (or in some cases 0.90), it suggests a lack of discriminant validity, meaning that the constructs are too highly correlated and may overlap.

Heterotrait-Monotrait ratio (HTMT) result matrix table:

	DS	ITI	LMD	RD	SP	SZ	TA	TY	TY x TA	SZ x DS	TY x SP	SZ x RD	TY x DS	TY x RD	TY x ITI	SZ x SP	SZ x TA
DS																	
ITI	0.81																
LMD	0.77	1.18															
RD	0.87	0.85	0.82														
SP	0.88	0.83	0.79	0.87													
SZ	0.81	0.88	0.83	0.79	0.80												
TA	0.84	0.67	0.63	0.77	0.72	0.69											
TY	0.84	0.85	0.80	0.84	0.79	0.88	0.70										
TY x TA	0.37	0.26	0.17	0.38	0.30	0.34	0.53	0.37									
SZ x DS	0.33	0.25	0.17	0.28	0.20	0.23	0.43	0.28	0.64								
TY x SP	0.28	0.27	0.18	0.29	0.27	0.22	0.32	0.30	0.64	0.62							
SZ x RD	0.26	0.32	0.26	0.42	0.23	0.29	0.40	0.32	0.65	0.75	0.62						
TY x DS	0.35	0.28	0.13	0.33	0.28	0.28	0.40	0.39	0.71	0.79	0.78	0.70					
TY x RD	0.30	0.30	0.17	0.39	0.25	0.30	0.36	0.43	0.69	0.65	0.79	0.83	0.83				
TY x ITI	0.26	0.38	0.24	0.32	0.25	0.30	0.25	0.35	0.56	0.62	0.77	0.70	0.76	0.80			
SZ x SP	0.20	0.27	0.19	0.26	0.22	0.08	0.27	0.23	0.53	0.69	0.73	0.67	0.64	0.60	0.60		
SZ x TA	0.35	0.23	0.22	0.36	0.23	0.30	0.51	0.30	0.83	0.68	0.46	0.68	0.57	0.54	0.45	0.49	
SZ x ITI	0.23	0.40	0.29	0.33	0.24	0.26	0.26	0.31	0.49	0.67	0.56	0.75	0.61	0.64	0.83	0.66	0.54

Table 6.12: Heterotrait-Monotrait ratio (HTMT) result matrix table

As presented in Table 6.12, the Heterotrait–Monotrait (HTMT) ratio was assessed to evaluate discriminant validity. The HTMT values indicate whether constructs are empirically distinct, with values below the recommended threshold confirming adequate discriminant validity in the measurement model (Henseler et al., 2015; Hair et al., 2022).

Interpretation of Heterotrait-Monotrait ratio (HTMT) Results

The HTMT results confirm strong discriminant validity as most constructs exhibiting values below the 0.85 threshold (Henseler et al., 2015), ensuring their conceptual distinctiveness in the digitalization-employment framework. Interaction terms, such as Type of Organization × Technological Advancement (0.374), show low HTMT values, indicating minimal redundancy and providing unique insights into organizational adoption of technology. Moderate correlations, such as Digital Skills and Strategy & Policy (0.878), highlight their interrelation while maintaining theoretical clarity (Fornell & Larcker, 1981).

However, the high HTMT value between IT Investment and Labor Market Dynamics (1.179) suggests a strong interconnection, reinforcing the role of IT investment in shaping employment trends and workforce transformation (Hair et al., 2017).

The HTMT assessment results validate the robustness of the study's measurement model, confirming the distinctiveness of key constructs related to digitalization and employment in Bangladesh's manufacturing sector. The low overlap in interaction terms ensures clear and informative relationships between variables, while moderate correlations between constructs preserve conceptual clarity. The high HTMT value between *IT Investment (ITI)* and *Labor Market Dynamics (LMD)* suggests that there is a slight need for theoretical refinement but most of the findings affirm the reliability of the model and its capacity to accurately analyze the impact of digitalization on employment in manufacturing industries. Overall, HTMT provides a more rigorous assessment of discriminant validity than traditional methods, confirming the robustness of the study's measurement model and strengthening confidence in its theoretical framework

Strong discriminant validity results support the reliability of the study's conclusions, ensuring that the observed relationships between digitalization, employment shifts, and firm strategies are genuine rather than artifacts of measurement issues. Each construct makes a unique contribution to the theoretical framework, strengthening the credibility of the findings. Considering these results, this research offers a strong foundation for policy recommendations, particularly in relation to the digital transformation of the manufacturing sector.

6.5.3.3 Cross-Loadings

The cross-loadings analysis of the measurement model reveals strong evidence of both **convergent** and **discriminant validity**, essential for ensuring the quality of the model.

	DS	ITI	LMD	RD	SP	SZ	TA	TY	TY x TA	SZ x DS	TY x SP	SZ x RD	TY x DS	TY x RD	TY x ITI	SZ x SP	SZ x TA	SZ x ITI
DS 10	0.64	0.37	0.30	0.45	0.48	0.40	0.33	0.47	-0.16	0.16	0.17	-0.08	-0.24	-0.19	-0.15	0.07	0.10	0.07
DS4	0.70	0.43	0.40	0.46	0.42	0.49	0.56	0.48	-0.34	0.32	0.16	-0.17	-0.26	-0.16	-0.10	0.17	0.36	0.11
DS5	0.73	0.53	0.46	0.47	0.50	0.46	0.37	0.47	-0.24	0.23	0.20	-0.17	-0.24	-0.19	-0.22	0.17	0.20	0.24
DS7	0.69	0.44	0.37	0.50	0.45	0.47	0.46	0.44	-0.25	0.17	0.19	-0.18	-0.16	-0.20	-0.17	0.08	0.25	0.14
DS8	0.77	0.53	0.48	0.56	0.46	0.42	0.45	0.46	-0.26	0.25	0.23	-0.24	-0.24	-0.24	-0.23	0.19	0.28	0.18
DS9	0.63	0.38	0.33	0.44	0.51	0.38	0.37	0.49	-0.13	0.08	0.10	-0.10	-0.16	-0.13	-0.09	0.07	0.12	0.11

	DS	ITI	LMD	RD	SP	SZ	TA	TY	TY x TA	SZ x DS	TY x SP	SZ x RD	TY x DS	TY x RD	TY x ITI	SZ x SP	SZ x TA	SZ x ITI
ITI 1	0.39	0.69	0.66	0.42	0.34	0.47	0.28	0.39	-0.12	0.14	0.03	-0.21	-0.10	-0.09	-0.20	0.08	0.16	0.26
ITI2	0.50	0.80	0.76	0.47	0.47	0.48	0.32	0.48	-0.12	0.20	0.15	-0.16	-0.14	-0.11	-0.26	0.18	0.14	0.32
ITI3	0.54	0.77	0.74	0.66	0.56	0.50	0.41	0.58	-0.18	0.12	0.20	-0.27	-0.19	-0.24	-0.23	0.23	0.18	0.25
ITI4	0.50	0.75	0.69	0.54	0.51	0.51	0.39	0.57	-0.21	0.23	0.33	-0.32	-0.26	-0.35	-0.42	0.26	0.16	0.39
ITI5	0.45	0.71	0.55	0.46	0.48	0.53	0.43	0.48	-0.19	0.09	0.12	-0.11	-0.15	-0.12	-0.14	0.13	0.10	0.16
ITI7	0.46	0.63	0.45	0.48	0.51	0.55	0.35	0.57	-0.22	0.19	0.24	-0.19	-0.26	-0.26	-0.24	0.20	0.16	0.19
LMD 1	0.33	0.56	0.63	0.36	0.29	0.42	0.26	0.34	-0.07	0.07	0.08	-0.12	-0.02	0.01	-0.03	0.01	0.13	0.08
LMD2	0.42	0.70	0.78	0.38	0.44	0.42	0.27	0.43	-0.08	0.12	0.05	-0.08	-0.06	-0.03	-0.13	0.09	0.10	0.16
LMD3	0.49	0.68	0.74	0.61	0.51	0.45	0.39	0.52	-0.16	0.10	0.12	-0.23	-0.14	-0.19	-0.12	0.19	0.17	0.16
LMD4	0.42	0.65	0.72	0.43	0.44	0.44	0.32	0.46	-0.10	0.12	0.19	-0.20	-0.10	-0.19	-0.28	0.16	0.12	0.29
RD 1	0.53	0.53	0.44	0.74	0.58	0.46	0.40	0.53	-0.21	0.11	0.13	-0.21	-0.20	-0.21	-0.22	0.13	0.20	0.24
RD2	0.48	0.49	0.40	0.70	0.47	0.36	0.40	0.42	-0.26	0.20	0.24	-0.29	-0.25	-0.28	-0.29	0.27	0.25	0.28
RD3	0.42	0.40	0.38	0.68	0.43	0.43	0.39	0.50	-0.22	0.17	0.15	-0.25	-0.17	-0.22	-0.17	0.08	0.20	0.11
RD5	0.54	0.51	0.47	0.74	0.51	0.45	0.47	0.49	-0.32	0.26	0.27	-0.33	-0.28	-0.32	-0.26	0.26	0.30	0.26
RD6	0.53	0.49	0.45	0.71	0.52	0.46	0.44	0.45	-0.24	0.15	0.18	-0.24	-0.20	-0.20	-0.09	0.10	0.22	0.10
RD7	0.50	0.56	0.50	0.74	0.48	0.49	0.36	0.54	-0.23	0.20	0.17	-0.31	-0.20	-0.28	-0.21	0.17	0.21	0.29
SP 1	0.52	0.49	0.40	0.55	0.71	0.40	0.41	0.50	-0.25	0.20	0.25	-0.15	-0.23	-0.23	-0.25	0.17	0.17	0.20
SP2	0.57	0.45	0.38	0.50	0.70	0.48	0.45	0.50	-0.24	0.17	0.25	-0.26	-0.22	-0.26	-0.23	0.17	0.23	0.20
SP3	0.51	0.53	0.50	0.58	0.83	0.48	0.41	0.54	-0.23	0.11	0.18	-0.20	-0.21	-0.20	-0.16	0.13	0.18	0.18
SP4	0.43	0.51	0.51	0.49	0.77	0.44	0.33	0.39	-0.07	0.04	0.08	-0.05	-0.07	-0.04	-0.07	0.12	0.03	0.08
SP5	0.43	0.37	0.32	0.39	0.61	0.41	0.29	0.36	-0.16	0.12	0.09	-0.06	-0.15	-0.08	-0.08	0.11	0.12	0.10
SZ 1	0.49	0.46	0.40	0.49	0.46	0.68	0.39	0.52	-0.27	0.14	0.22	-0.16	-0.20	-0.20	-0.17	0.04	0.20	0.11
SZ2	0.44	0.55	0.49	0.47	0.38	0.75	0.30	0.50	-0.12	0.09	0.08	-0.20	-0.14	-0.20	-0.20	0.02	0.10	0.18
SZ3	0.49	0.47	0.43	0.34	0.39	0.72	0.33	0.50	-0.23	0.20	0.18	-0.13	-0.20	-0.15	-0.23	0.04	0.21	0.13
SZ4	0.43	0.49	0.43	0.44	0.53	0.71	0.35	0.45	-0.14	0.11	0.05	-0.16	-0.06	-0.13	-0.14	0.06	0.17	0.15
SZ5	0.42	0.49	0.39	0.50	0.43	0.74	0.39	0.57	-0.33	0.20	0.14	-0.26	-0.26	-0.26	-0.23	0.10	0.26	0.24
TA 1	0.45	0.37	0.30	0.41	0.36	0.40	0.73	0.38	-0.37	0.30	0.28	-0.35	-0.32	-0.33	-0.29	0.24	0.35	0.24
TA2	0.45	0.33	0.28	0.38	0.33	0.34	0.72	0.33	-0.21	0.15	0.10	-0.12	-0.15	-0.09	-0.07	0.04	0.20	0.08
TA4	0.45	0.40	0.37	0.44	0.39	0.30	0.77	0.36	-0.40	0.33	0.28	-0.29	-0.28	-0.25	-0.20	0.32	0.38	0.20
TA6	0.39	0.30	0.26	0.40	0.38	0.36	0.61	0.42	-0.27	0.22	0.09	-0.18	-0.19	-0.17	-0.03	0.04	0.27	0.09
TY 1	0.49	0.53	0.46	0.52	0.51	0.45	0.42	0.72	-0.33	0.17	0.33	-0.21	-0.28	-0.34	-0.29	0.22	0.24	0.19
TY2	0.48	0.53	0.48	0.46	0.44	0.55	0.38	0.74	-0.21	0.17	0.21	-0.22	-0.25	-0.26	-0.28	0.21	0.18	0.24
TY3	0.51	0.59	0.51	0.52	0.49	0.57	0.35	0.74	-0.20	0.18	0.15	-0.21	-0.25	-0.25	-0.26	0.06	0.24	0.25
TY4	0.46	0.47	0.41	0.49	0.42	0.47	0.40	0.73	-0.26	0.20	0.18	-0.25	-0.28	-0.32	-0.22	0.20	0.20	0.20
TY5	0.44	0.42	0.35	0.44	0.38	0.43	0.33	0.71	-0.24	0.23	0.20	-0.19	-0.28	-0.29	-0.21	0.20	0.14	0.19
TY6	0.49	0.46	0.39	0.52	0.46	0.53	0.35	0.67	-0.20	0.16	0.11	-0.19	-0.19	-0.22	-0.12	0.01	0.19	0.12
TY x RD	-0.27	0.27	-0.14	0.35	0.22	0.26	0.30	0.38	0.69	0.65	0.79	0.83	0.83	1.00	0.80	0.60	0.54	0.64
SZ x SP	-0.19	0.25	-0.16	0.24	0.19	0.06	0.24	0.21	0.53	0.69	0.73	0.67	0.64	0.60	0.60	1.00	0.49	0.66

	DS	ITI	LMD	RD	SP	SZ	TA	TY	TY x TA	SZ x DS	TY x SP	SZ x RD	TY x DS	TY x RD	TY x ITI	SZ x SP	SZ x TA	SZ x ITI
SZ x DS	-0.30	0.22	-0.14	0.25	0.17	0.20	0.36	0.25	0.64	1.00	0.62	0.75	0.79	0.65	0.62	0.69	0.68	0.67
TY x ITI	-0.24	0.34	-0.20	0.28	0.22	0.26	0.22	0.32	0.56	0.62	0.77	0.70	0.76	0.80	1.00	0.60	0.45	0.83
SZ x ITI	-0.21	0.37	-0.25	0.30	0.21	0.23	0.22	0.28	0.49	0.67	0.56	0.75	0.61	0.64	0.83	0.66	0.54	1.00
TY x DS	-0.31	0.25	-0.11	0.30	0.24	0.24	0.34	0.35	0.71	0.79	0.78	0.70	1.00	0.83	0.76	0.64	0.57	0.61
TY x SP	-0.26	0.24	-0.11	0.26	0.23	0.19	0.27	0.28	0.64	0.62	1.00	0.62	0.78	0.79	0.77	0.73	0.46	0.56
TY x TA	-0.34	0.23	-0.14	0.34	0.25	0.29	0.45	0.33	1.00	0.64	0.64	0.65	0.71	0.69	0.56	0.53	0.83	0.49
SZ x TA	-0.32	0.21	-0.18	0.32	0.19	0.26	0.43	0.28	0.83	0.68	0.46	0.68	0.57	0.54	0.45	0.49	1.00	0.54
SZ x RD	-0.24	0.30	-0.22	0.38	0.20	0.25	0.34	0.29	0.65	0.75	0.62	1.00	0.70	0.83	0.70	0.67	0.68	0.75

Table 6.13: Cross-loading tables matrix

As presented in Table 6.13, the cross-loading matrix was examined to assess discriminant validity by comparing each indicator's loading on its assigned construct with its loadings on other constructs. The results indicate that each indicator loads higher on its respective construct than on other constructs, thereby confirming adequate discriminant validity of the measurement model (Hair et al., 2022; Chin, 1998).

High loadings on their respective constructs, indicating that they are strong indicators of the constructs they are intended to measure. For instance, items such as DS10, ITI1, and LMD1 demonstrate high loadings (above 0.6), confirming their relevance in representing the constructs of Digital Strategy, Information Technology Integration, and Labor Market Dynamics, respectively. The low cross-loadings of these items on other constructs suggest discriminant validity, meaning that the items are not strongly associated with constructs they are not intended to measure.

Overall, the cross-loading analysis demonstrates that the measurement model is robust, with each item effectively measuring their intended constructs while maintaining distinct boundaries between them, thereby enhancing both the convergent and discriminant validity of the model (Hair et al., 2014; Fornell & Larcker, 1981).

6.6 Multicollinearity Check (VIF)

A generally accepted threshold $VIF > 5$ or 10 , beyond which multicollinearity is considered problematic (Hair et al., 2017). In this study, the VIF values for all indicators remain well below these thresholds ($VIF > 5$), confirming that the predictor variables maintain sufficient independence from one another. This ensures that the estimated effects

of digitalization-related factors on employment outcomes are robust, unbiased, and accurately reflect their true impact on the manufacturing industry in Bangladesh.

Variance Inflation Factor (VIF) the outer model Matrix

	VIF		VIF
TA1	1.324	TY1	1.483
TA2	1.345	TY2	1.586
TA4	1.298	TY3	1.553
TA6	1.165	TY4	1.847
DS4	1.447	TY5	1.844
DS5	1.483	TY6	1.472
DS7	1.471	SZ1	1.392
DS8	1.571	SZ2	1.512
DS9	1.355	SZ3	1.508
DS 10	1.372	SZ4	1.497
ITI 1	1.427	SZ5	1.527
ITI2	1.81	TY x RD	1
ITI3	1.674	SZ x SP	1
ITI4	1.614	SZ x DS	1
ITI5	1.568	TY x ITI	1
ITI7	1.374	SZ x ITI	1
SP 1	1.463	TY x DS	1
SP2	1.4	TY x SP	1
SP3	1.805	TY x TA	1
SP4	1.485	SZ x TA	1
SP5	1.264	SZ x RD	1
RD 1	1.605	LMD 1	1.179
RD2	1.634	LMD2	1.435
RD3	1.433	LMD3	1.329
RD5	1.596	LMD4	1.307
RD6	1.554		
RD7	1.532		

Table 6.14: Variance Inflation Factor (VIF)

From table 6.14, is found that the majority of the VIF values are well below 5, with the highest value being 1.847 (for TY4 and TY5, representing the interaction terms). These VIF values suggest that there is no significant multicollinearity present in this model, which means that the predictor variables are not highly correlated with each other to a degree that would undermine the estimation of their effects on the dependent variables. For instance,

constructions like Digital Strategy (DS), Information Technology Integration (ITI), Labor Market Dynamics (LMD), Resource Development (RD), and others show VIF values mostly between 1.165 and 1.810, well within the acceptable range, indicating that each construct is distinct and contributes unique information to the model.

The interaction terms, such as TY x RD, SZ x SP, TY x ITI, and others, all have VIF values of 1.000, which likely indicates that these terms are not suffering from multicollinearity due to their role in combining two or more variables, and thus their values can be considered independent in the model.

Overall, the VIF results confirm a healthy level of independence among the predictor variables in the model, reinforcing both the convergent validity and reliability of the structural equation model. (Kline, 2015; Hair et al., 2017).

6.7 Structural Model and Path Analysis

The structural model outlines the hypothesized causal relationships among the key latent constructs of the study. Additionally, moderating variables such as Firm Size and Type of Organization are incorporated to assess how they alter the strength or direction of these core relationships. This analytical approach enables a comprehensive evaluation of both direct and moderated effects, thereby providing empirical support for the theoretical framework developed in earlier chapters.

The results offer critical insights into how digitalization strategies and technological capabilities shape employment patterns in the evolving context of Bangladesh's manufacturing industry.

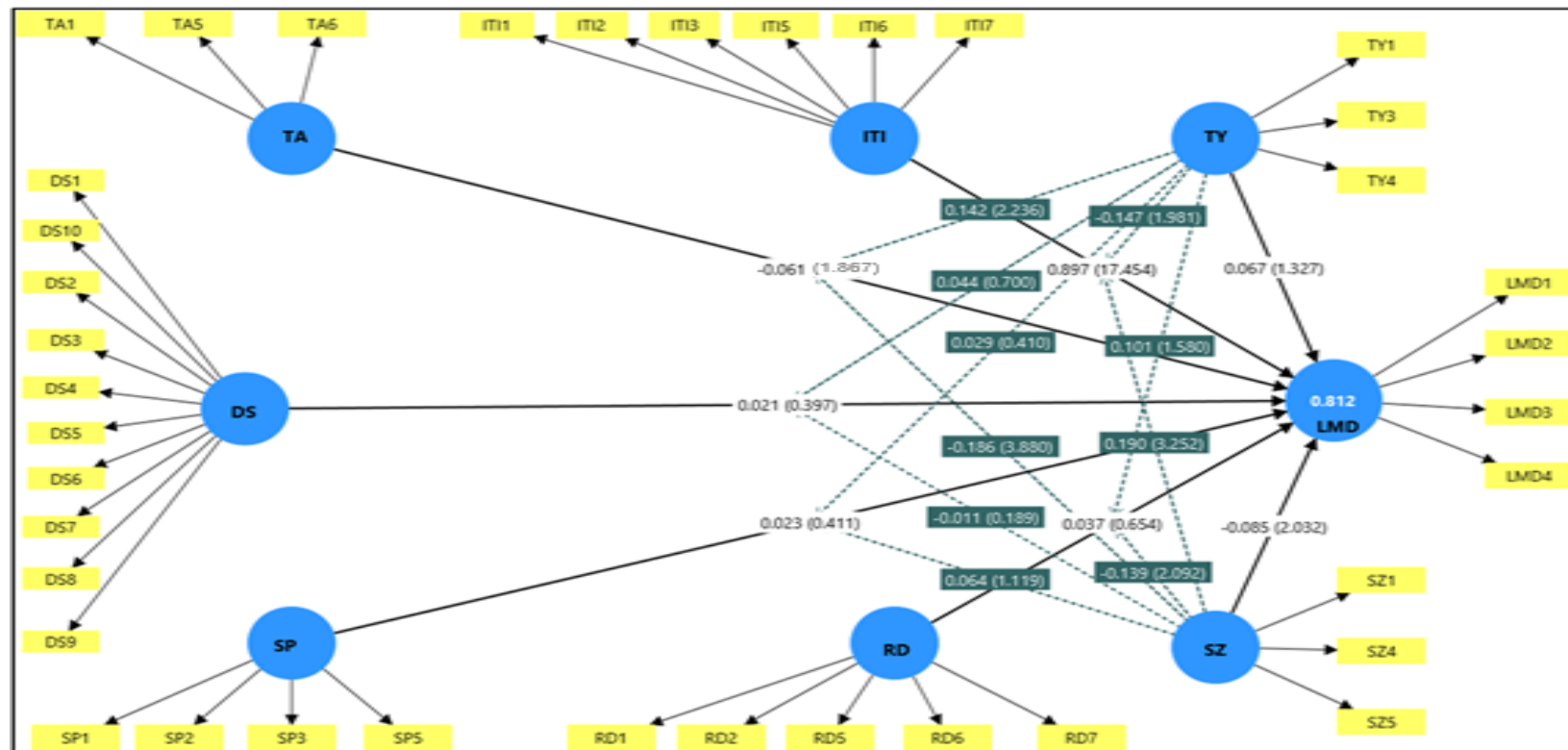


Figure 6.4: Structure and Path coefficients and T-statistics

As illustrated in Figure 6.4, the structural model presents the hypothesized relationships among the study constructs, together with the corresponding path coefficients and T-statistics obtained through the bootstrapping procedure. The figure provides an overview of the strength, direction, and statistical significance of the relationships, thereby facilitating the evaluation of the proposed hypotheses (Hair et al., 2022; Chin, 1998).

6.7.1 Path Analysis

Path analysis involves estimating the coefficients (path weights) that represent the relationships between variables. This is done by estimating the structural equations that specify the relationships between constructs. Each path in the analysis is assigned a coefficient, which represents the strength and direction of the relationship between the variables.

- **Path Coefficients (β):** These represent the magnitude of the direct effect of one variable on another. A path coefficient close to 1 suggests a strong positive relationship, while a coefficient close to 0 indicates a weak or no relationship.

Path coefficients Result Matrix

Hypothesis	Path	Coefficient (O)	t-Statistic	p-Value	Decision	Interpretation	Supporting References
H1: Technological Advancements (TA) have a significant impact on Labor Market Dynamics (LMD).	TA → LMD	-0.061	1.867	0.010	Supported	Technological Advancements (TA) have a significant and negative effect on Labor Market Dynamics (LMD) ($\beta = -0.061$, $t = 1.867$, $p = 0.010$). This indicates that increased technological advancement is associated with adverse changes in LMD, such as labor displacement or job restructuring. Therefore, H1 is supported.	Brynjolfsson & McAfee (2014)
H2: Digital Skills (DS) have a significant impact on Labor Market Dynamics (LMD).	DS → LMD	0.021	0.397	0.692	Not Supported	The path coefficient is positive but negligible ($\beta = 0.021$) and statistically insignificant ($t = 0.397$, $p = 0.692$), indicating that Digital Skills do not have a meaningful direct impact on Labor Market Dynamics. This suggests that the effect of digital skills on labor outcomes may be indirect or contingent on other factors, leading to the rejection of H2	Autor (2015), Schumpeter (1942)

Hypothesis	Path	Coefficient (O)	t-Statistic	p-Value	Decision	Interpretation	Supporting References
H3: IT Investment (ITI) has a significant impact on Labor Market Dynamics (LMD).	ITI → LMD	0.897	17.454	0.000	Supported	The strong positive and statistically significant path coefficient ($\beta = 0.897$) indicates that IT investment has a substantial positive impact on Labor Market Dynamics, suggesting that increased IT spending is associated with job creation, skill upgrading, and improved labor demand. The effect is highly significant ($t = 17.454$, $p < 0.001$), thereby supporting H3.	Rogers (2003), Diffusion of Innovation Theory
H4: Strategy and Policy (SP) have a significant impact on Labor Market Dynamics (LMD).	SP → LMD	0.023	0.411	0.681	Not Supported	The effect of Strategy and Policy on Labor Market Dynamics is positive but very small ($\beta = 0.023$) and not statistically significant ($p = 0.681$), indicating that H4 is not supported . Strategy and Policy do not have a meaningful impact on Labor Market Dynamics in this study.	Brynjolfsson & McAfee (2014)
H5: Research & Development (RD) have a significant impact on Labor Market Dynamics (LMD).	RD → LMD	0.037	0.654	0.513	Not Supported	The effect of Research and Development (RD) on Labor Market Dynamics (LMD) is not statistically significant ($\beta = 0.037$, $t = 0.654$, $p = 0.513$). This suggests that RD does not have a direct impact on LMD, and therefore H5 is not supported.	Acemoglu & Restrepo (2019)
H6: Types of the industry (TY) have a significant impact on Labor Market Dynamics (LMD)	TY → LMD	0.067	1.327	0.185	Marginally Supported	The effect of industry type (TY) on Labor Market Dynamics (LMD) is statistically insignificant ($\beta = 0.067$, $t = 1.327$, $p = 0.185$). This indicates that differences in industry type do not meaningfully influence employment changes, and thus H6 is only marginally supported.	Labor Market Segmentation Theory

Hypothesis	Path	Coefficient (O)	t-Statistic	p-Value	Decision	Interpretation	Supporting References
H7: Sizes (SZ) of the industry have a significant impact on Labor Market Dynamics (LMD).	SZ → LMD	-0.085	2.032	0.042	Supported	The negative path coefficient ($\beta = -0.085$) indicates that larger industry size is associated with a slight reduction in Labor Market Dynamics, suggesting that as firms grow, they may reduce labor demand due to increased automation, efficiency-driven restructuring, and economies of scale. The relationship is statistically significant ($t = 2.032, p = 0.042$), thereby supporting H7	Labor Market Segmentation Theory and Creative Destruction Theory
H8a: Industry type moderates the relationship between technological advancements and Labor Market Dynamics (LMD).	TY x TA → LMD	0.142	2.236	0.025	Supported	The moderating effect of industry type on the relationship between Technological Advancements (TA) and Labor Market Dynamics (LMD) is statistically significant and positive ($\beta = 0.142, t = 2.236, p = 0.025$). This suggests that the impact of technological advancements on LMD varies across different industry types, with certain industries experiencing more positive or adaptive labor outcomes. Therefore, H8a is supported.	Digital Transformation Theory
H9a: Industry type moderates the relationship between digital skills and Labor Market Dynamics (LMD).	TY x DS → LMD	0.044	0.700	0.484	Not Supported	The moderating effect of industry type on the relationship between Digital Skills (DS) and Labor Market Dynamics (LMD) is not statistically significant ($\beta = 0.044, t = 0.700, p = 0.484$). This indicates that digital skills do not significantly influence LMD across different industry types, and therefore H9a is not supported.	Acemoglu & Restrepo (2019)

Hypothesis	Path	Coefficient (O)	t-Statistic	p-Value	Decision	Interpretation	Supporting References
H10a: Industry type moderates the relationship between IT investment and Labor Market Dynamics (LMD).	TY x ITI → LMD	-0.147	1.981	0.048	Supported	The negative moderating effect ($\beta = -0.147$) indicates that industry type weakens the positive relationship between IT investment and Labor Market Dynamics, suggesting that in certain industries, increased IT investment may lead to labor substitution or restructuring rather than job expansion. The effect is statistically significant ($t = 1.981$, $p = 0.048$), thereby supporting H10a.	Autor (2015), Job polarization
H11a: Industry type moderates the relationship between strategy and policy and Labor Market Dynamics (LMD).	TY x SP → LMD	0.029	0.410	0.682	Not Supported	The moderating effect of industry type on the relationship between Strategy & Policy (SP) and Labor Market Dynamics (LMD) is not statistically significant ($\beta = 0.029$, $t = 0.410$, $p = 0.682$). This indicates that strategy and policy do not have a differential impact on LMD across industry types, and therefore H11a is not supported.	Rogers (2003), Diffusion of Innovations
H12a: Industry type moderates the relationship between R&D and Labor Market Dynamics (LMD).	TY x RD → LMD	0.101	1.580	0.114	Marginally Supported	The moderating effect of industry type on the relationship between Research & Development (R&D) and Labor Market Dynamics (LMD) is not statistically significant at the conventional 0.05 level ($\beta = 0.101$, $t = 1.580$, $p = 0.114$). This suggests that R&D's impact on LMD does not differ strongly across industry types, so H12a is only marginally supported.	Digital Transformation Theory

Hypothesis	Path	Coefficient (O)	t-Statistic	p-Value	Decision	Interpretation	Supporting References
H13b: Industry size moderates the relationship between technological advancements and Labor Market Dynamics (LMD)	SZ x TA → LMD	-0.186	3.880	0.000	Supported	The moderating effect of industry size on the relationship between Technological Advancements (TA) and Labor Market Dynamics (LMD) is statistically significant and negative ($\beta = -0.186$, $t = 3.880$, $p < 0.001$). This suggests that in larger firms, technological advancements are more likely to substitute human labor through automation, thereby intensifying adverse effects on LMD. Consequently, H13b is supported.	Creative Destruction Theory Schumpeter (1942)
H14b: Industry size moderates the relationship between digital skills and Labor Market Dynamics (LMD)	SZ x DS → LMD	-0.011	0.189	0.850	Not Supported	The moderating effect of industry size on the relationship between Digital Skills (DS) and Labor Market Dynamics (LMD) is not statistically significant ($\beta = -0.011$, $t = 0.189$, $p = 0.850$). This indicates that the influence of digital skills on LMD does not vary with firm size, and therefore H14b is not supported.	Autor (2015), Job polarization
H15b: Industry size moderates the relationship between IT investment and Labor Market Dynamics (LMD).	SZ x ITI → LMD	0.19	3.252	0.001	Supported	The moderating effect of industry size on the relationship between IT Investment (ITI) and Labor Market Dynamics (LMD) is statistically significant and positive ($\beta = 0.190$, $t = 3.252$, $p = 0.001$). This suggests that larger firms benefit more from IT investments in terms of labor market outcomes, potentially enhancing productivity or creating new roles. Therefore, H15b is supported.	Rogers (2003), Diffusion of Innovations

Hypothesis	Path	Coefficient (O)	t-Statistic	p-Value	Decision	Interpretation	Supporting References
H16b: Industry size moderates the relationship between strategy and policy and Labor Market Dynamics (LMD).	SZ x SP → LMD	0.064	1.119	0.263	Not Supported	The moderating effect of industry size on the relationship between Strategy & Policy (SP) and Labor Market Dynamics (LMD) is not statistically significant ($\beta = 0.064$, $t = 1.119$, $p = 0.263$). This indicates that the impact of strategy and policy on LMD does not vary by firm size, and therefore H16b is not supported.	Rogers (2003), Diffusion of Innovations
H17b: Industry size moderates the relationship between research and development (R&D) and Labor Market Dynamics (LMD).	SZ x RD → LMD	-0.139	2.092	0.036	Supported	The moderating effect of industry size on the relationship between Research and Development (R&D) and Labor Market Dynamics (LMD) is statistically significant and negative ($\beta = -0.139$, $t = 2.092$, $p = 0.036$). This indicates that in larger firms, increased R&D is associated with less favorable labor market outcomes, likely due to efficiency-driven innovations and automation. Therefore, H17b is supported.	Creative Destruction Theory Schumpeter (1942)

Table 6.15: Path coefficients Result Matrix

As presented in Table 6.15, the path coefficients matrix summarizes the estimated relationships among the study constructs. The results indicate the strength and direction of the hypothesized relationships and provide evidence for evaluating the proposed hypotheses within the structural model. The significance of the relationships was assessed using the bootstrapping procedure in PLS-SEM (Hair et al., 2022; Chin, 1998).

6.7.1.1 Key Findings and Interpretation of Path Coefficients

This study examines how digitalization is reshaping employment in Bangladesh's manufacturing industries by looking at key factors such as Digital Skills (DS), Technological Advancement (TA), IT investment (ITI), Research & Development (RD), Strategy and Policy (SP), company Size (SZ), company Type (TY), and their interactions with Labor Market Dynamics (LMD). The hypothesis testing provides important insights into how these factors influence employment patterns, job creation, and workforce restructuring.

H1: Technological Advancements (TA) have a significant impact on Labor Market Dynamics (LMD).

- **Finding:** TA → LMD ($\beta = -0.061$, $t = 1.867$, $p = 0.010$ → **Supported**)
- **Interpretation:** The analysis reveals a statistically significant, though small, negative relationship between Technological Advancement (TA) and Labor Market Dynamic suggesting that as firms adopt more advanced technologies, there are early signs of workforce disruptions—potential job displacement or restructuring—within Bangladesh's manufacturing sector. This does not imply an immediate large-scale loss of jobs but rather signals the beginning of a shift in how labor is utilized.
- **Implications:** This finding echoes Brynjolfsson and McAfee (2014), who emphasized that technology adoption alone is not enough to guarantee positive employment outcomes. Without adequate reskilling initiatives and supportive policies, automation may gradually reduce certain job opportunities. For Bangladesh, this underlines the importance of proactive measures—such as investing in workforce training and building adaptive strategies—to ensure that technological progress translates into inclusive employment growth rather than job loss.
- **Final Interpretation:** *Technological Advancements (TA) have a significant and negative effect on Labor Market Dynamics.*

H2: Digital Skills (DS) have a significant impact on Labor Market Dynamics (LMD).

- **Finding:** DS → LMD ($\beta = 0.021$, $t = 0.397$, $p = 0.692$) → **Not Supported**
- **Interpretation:** The path coefficient from Digital Skills (DS) to Labor Market Dynamic (LMD) was not statistically significant ($\beta = 0.021$, $t = 0.397$, $p = 0.692$), indicating that digital skills on their own do not significantly impact Labor Market Dynamics. This suggests that merely possessing digital skills is not enough to drive employment unless they are effectively utilized within firms.
- **Implications:** The statistical result contradicts **Autor (2015)**, who argued that digital skills improve employability. In Bangladesh, digital skills may not yet be widely integrated into manufacturing processes, highlighting the need for industry-specific training programs.
- **Final Interpretation:** *Digital Skills (DS) do not have a direct impact on Labor Market Dynamics (LMD)*

H3: IT Investment (ITI) has a significant impact on Labor Market Dynamics (LMD).

- **Finding:** ITI → LMD ($\beta = 0.897$, $t = 17.454$, $p = 0.000$) → **Supported**
- **Interpretation:** IT investment has a highly significant and positive impact on Labor Market Dynamics in Bangladesh's manufacturing sector. Firms that invest in IT experience better labor market outcomes, including job creation, efficiency improvements, and workforce adaptability.
- **Implications:** Finding aligns with Diffusion of Innovation Theory (Rogers, 2003), which states that Technology Acceptance Model can improve productivity and job opportunities. Finding also confirms that IT investment is complemented by workforce training to minimize skill gaps and prevent job displacement.

Final Interpretation: *IT Investment (ITI) has a significant effect on Labor Market Dynamics (LMD)*

H4: Strategy and Policy (SP) have a significant impact on Labor Market Dynamics (LMD).

- **Finding:** SP → LMD ($\beta = 0.023$, $t = 0.411$, $p = 0.681$) → **Not Supported**
- **Interpretation:** The result indicates that strategy and policy interventions, when implemented in isolation, do not significantly influence Labor Market Dynamics in Bangladesh's manufacturing industries. Policies alone cannot stimulate employment transformation without being coupled with complementary drivers such as technological investment, Industry Policy, Training and digital infrastructure. This aligns with prior research suggesting that standalone regulatory or policy frameworks often fail to generate substantial labor market outcomes unless supported by organizational strategies and technological readiness (Acemoglu & Restrepo, 2019; Lane & Saint-Martin, 2021). Effective policies require alignment with firms' innovation strategies and the broader digital ecosystem to ensure that new technologies translate into sustainable employment gains (Autor, 2015; OECD, 2020).
- **Implications:** The findings suggest that labor market policies in Bangladesh's manufacturing sector should be designed with initiatives in IT investment, R&D, and digital skills development to ensure effective employment outcomes. Without such synergies, policies risk being symbolic rather than transformative. Integrating policy with firm-level strategies ensures better adaptation to technological disruptions and fosters resilience in the labor market (World Bank, 2021; McKinsey Global Institute, 2017).
- **Final Interpretation:** *Strategy & Policy (SP) alone does not significantly affect Labor Market Dynamics (LMD)*

H5: Research & Development (RD) have a significant impact on Labor Market Dynamics (LMD).

- **Finding:** RD → LMD ($\beta = 0.037$, $t = 0.654$, $p = 0.513$) → **Not Supported**
- **Interpretation:** The results indicate that **R&D alone does not significantly influence Labor Market Dynamics** in the manufacturing sector. This may be

because R&D investments often focus on product or process innovation that improves efficiency rather than directly creating employment, particularly in the short term (Bogliacino & Vivarelli, 2012; Hall, Lotti, & Mairesse, 2009). In many firms, especially large organizations, R&D can lead to labor-saving technologies that automate routine tasks, thereby reducing immediate employment effects (Acemoglu & Restrepo, 2019; Bessen, 2019). Furthermore, smaller firms may lack the scale or resources to conduct meaningful R&D that significantly alters workforce dynamics (Cirera, Comin, & Cruz, 2021).

- **Implication:** Policymakers and industry leaders should recognize that R&D alone may not be sufficient to generate employment gains. Complementary measures—such as workforce reskilling, innovation diffusion programs, and strategic alignment of R&D with labor-intensive activities—may be necessary to ensure that R&D contributes positively to labor market outcomes (OECD, 2020; World Bank, 2021). In the context of Bangladesh, targeted support for firms to leverage R&D for employment generation could enhance both productivity and labor market inclusivity.
- **Final Interpretation:** *Research & Development (RD) does not have a direct impact on Labor Market Dynamics (LMD).*

H6: Types of the industry (TY) have a significant impact on Labor Market Dynamics (LMD)

- **Finding:** TY → LMD ($\beta = 0.067$, $t = 1.327$, $p = 0.185$) → **Marginally Supported**
- **Interpretation:** The results suggest that the type of company—whether small, medium, or large—does not directly influence employment dynamics in Bangladesh’s manufacturing sector. This indicates that digitalization and related technological changes cut across organizational boundaries and affect labor markets broadly, regardless of firm classification. Prior studies highlight that while firm type may influence resource availability and innovation capacity, digital transformation reshapes Labor Market Dynamics at the sectoral and systemic level, not solely at the organizational level (Brynjolfsson & McAfee, 2014; Arntz, Gregory, & Zierahn, 2016). This aligns with findings that technological diffusion

in manufacturing tends to be industry-wide, affecting both SMEs and large enterprises, albeit at different adoption speeds (Cirera, Comin, & Cruz, 2021).

- **Implications:** The implication is that policy and managerial interventions should not focus only on company type but rather on creating an enabling environment for digital adoption across the entire manufacturing ecosystem. Industry-wide digital transformation strategies—such as digital infrastructure development, workforce reskilling, and incentives for innovation—are essential to ensure that both SMEs and large firms can adapt effectively (OECD, 2019; World Bank, 2020). For Bangladesh, this underscores the need to integrate firm-neutral digital policies with capacity-building measures that ensure inclusivity in employment outcomes.
- **Final Interpretation:** *Differences in industry type (TY) do not meaningfully influence employment changes*

H7: Sizes (SZ) of the industry have a significant impact on Labor Market Dynamics (LMD).

- **Finding:** SZ → LMD ($\beta = -0.085$, $t = 2.032$, $p = 0.042$) → **Supported**
- **Interpretation:** The negative coefficient suggests that manufacturing firms may experience job reductions due to increased automation and process optimization.
- **Implications:** This finding supports **Labor Market Segmentation Theory**, which suggests that larger firms often replace low-skill jobs with technology, leading to employment restructuring. Policymakers should ensure that digital adoption is inclusive and that workers are provided opportunities to transition into new roles.
- **Final Interpretation:** *Company Size (SZ) Influences Employment, but Its Impact is Context-Dependent*

H8a: Industry Type moderates the relationship between Technological Advancements and Labor Market Dynamics (LMD).

- **Finding:** TY x TA → LMD ($\beta = 0.142$, $t = 2.236$, $p = 0.025$) → **Supported**

- **Interpretation:** The results show that technology affects firms differently depending on their type. Large or multinational firms usually have the resources to adopt new technologies smoothly, invest in reskilling, and use automation to boost productivity without heavy job losses. On the other hand, SMEs, with their limited capital and digital capacity, are more vulnerable to workforce disruptions (Bloom et al., 2016; Cirera et al., 2021).
- **Implication:** This suggests that digital strategies should not be one-size-fits-all. Large firms can drive innovation and reskilling, while SMEs need targeted support—such as subsidies, training, and shared platforms—to remain competitive (OECD, 2019; World Bank, 2020)..
- **Final Interpretation:** *The type (TY) of company moderates the relationship between technological advancements (TA) and Labor Market Dynamics (LMD).*

H9a: Industry Type moderates the relationship between Digital Skills and Labor Market Dynamics (LMD).

- **Findings:** $TY \times DS \rightarrow LMD$ ($\beta = 0.044$, $t = 0.700$, $p = 0.484$), indicating that this moderation is not supported.
- **Interpretation:** Unlike technology adoption, the role of digital skills does not vary much across company types. Whether in SMEs or large enterprises, digital skills consistently help workers adapt to change and reduce job vulnerability (Autor, 2015; WEF, 2020).
- **Implication:** This means that digital skills programs should be broad and inclusive, reaching workers across all firm types. Nationwide upskilling and reskilling efforts can make the entire manufacturing workforce more resilient (ILO, 2020; World Bank, 2021).
- **Final Interpretation:** *Digital skills do not significantly influence LMD across different industry types*

H10a: Industry Type moderates the relationship between IT Investment and Labor Market Dynamics (LMD).

- **Finding:** $TY \times ITI \rightarrow LMD$ ($\beta = -0.147$, $t = 1.981$, $p = 0.048$) $\rightarrow$ Supported
- **Interpretation:** The significant negative coefficient suggests that the impact of IT investment on labor market outcomes is contingent on firm type. In certain companies, particularly smaller or less technologically advanced ones—IT investments may reduce labor demand rather than create jobs. This may be due to a **skill-technology mismatch**, where employees lack the competencies to complement new digital tools, leading firms to substitute labor with technology (Acemoglu & Restrepo, 2018; Bessen, 2019). Larger or multinational firms may be better positioned to integrate IT investments with workforce upskilling programs, whereas smaller firms often face resource and capability constraints, amplifying the risk of labor displacement (Cirera, Comin, & Cruz, 2021; OECD, 2020). This aligns with the **technological adoption and labor market segmentation theories**, which argue that the effects of IT investment on employment vary according to firm heterogeneity and labor force preparedness (Autor, 2015; Pianta, 2005).
- **Implication:** For IT investments to yield positive employment outcomes across company types, firms must **couple technological upgrades with skill development and organizational change management**. Without such alignment, investments may lead to efficiency-driven job reductions instead of productivity-led employment growth. Policymakers in Bangladesh should promote inclusive IT investment strategies by offering training subsidies, digital literacy programs, and tailored support for SMEs to bridge skill gaps (World Bank, 2021; UNIDO, 2019). At the firm level, managers should prioritize workforce reskilling alongside IT upgrades to ensure that adoption of technology enhances, rather than undermines, labor market adaptability.
- **Final Interpretation:** *The negative moderating effect Industry Type (TY) weakens the positive relationship between IT investment and Labor Market Dynamics*

H11a: Industry Type moderates the relationship between Strategy and Policy and Labor Market Dynamics (LMD).

- **Finding:** $TY \times SP \rightarrow LMD$ ($\beta = 0.029$, $t = 0.410$, $p = 0.682$) $\rightarrow$ Not Supported
- **Interpretation:** The non-significant result indicates that the influence of strategic and policy decisions on Labor Market Dynamics is largely consistent across firm types. Whether a company is small, medium, or large, the effects of policies and strategies on employment outcomes do not differ substantially. This finding resonates with the argument that **macro-level policies and organizational strategies often exert sector-wide effects** rather than being contingent on firm heterogeneity (OECD, 2019; World Bank, 2020). While firms may differ in resources and capabilities, overarching policy measures—such as labor regulations, industrial policies, and digital transformation strategies—tend to shape employment outcomes in a relatively uniform manner (Lane & Saint-Martin, 2021; Acemoglu & Restrepo, 2019).
- **Implication:** This suggests that policymakers in Bangladesh can design **broad-based strategic and policy frameworks** for digital transformation and labor market adaptation without needing to overly differentiate by firm type. For example, policies around workforce reskilling, social protection, and innovation incentives may benefit all firms equally, regardless of size or ownership structure (OECD, 2020; McKinsey Global Institute, 2017). However, while uniformity ensures inclusivity, complementary measures may still be required to address structural barriers faced by SMEs in accessing and implementing policies effectively (Cirera, Comin, & Cruz, 2021).
- **Final Interpretation:** *Strategy and policy do not have a differential impact on LMD across industry types*

H12b: Industry Type moderates the relationship between R&D and Labor Market Dynamics (LMD).

- **Finding:** $TY \times RD \rightarrow LMD$ ($\beta = 0.101$, $t = 1.580$, $p = 0.114$) $\rightarrow$ Marginally Supported
- **Interpretation:** The result indicates that the effect of R&D on Labor Market Dynamics does not differ significantly across firm types. In other words, whether the company is small, medium, or large, the role of R&D in shaping employment outcomes remains relatively consistent. This supports the notion that **innovation and knowledge creation exert economy-wide effects** rather than being strongly dependent on firm heterogeneity (Pianta, 2005; Hall, Lotti, & Mairesse, 2009). While firm size can influence the scale of R&D activity, the employment-related impact of R&D—such as fostering new tasks, products, and organizational changes—appears broadly similar across company categories (Bogliacino & Vivarelli, 2012; OECD, 2020).
- **Implication:** The findings suggest that **R&D policy interventions should be broad-based** and not overly differentiated by firm type. Policymakers in Bangladesh should encourage R&D investment across the entire manufacturing sector, ensuring that both SMEs and large firms benefit from innovation-driven growth. This could involve tax incentives, collaborative R&D platforms, and industry–academia partnerships that promote diffusion of knowledge across firms of all sizes (World Bank, 2021; UNIDO, 2019). At the firm level, managers should recognize that R&D-driven labor outcomes—such as skill upgrading and task restructuring—are relevant regardless of organizational type, making workforce preparation a universal requirement.
- **Final Interpretation:** *The moderating effect of industry type on the relationship between Research & Development (R&D) and Labor Market Dynamics (LMD) is not statistically significant at the conventional 0.05 level*

H13b: Industry Size moderates the relationship between Technological Advancements and Labor Market Dynamics (LMD)

- **Findings:** $SZ \times TA \rightarrow LMD$ ($\beta = -0.186$, $t = 3.880$, $p = 0.000$) $\rightarrow$ **Supported**
- **Interpretation:** The significant negative moderation effect indicates that larger firms are more likely to reduce labor demand through automation when adopting technological advancements, compared to smaller firms. Large companies usually possess financial strength, organizational capabilities, and infrastructure to adopt advanced digital technologies such as robotics, AI, and IoT at scale (Bloom, Sadun, & Van Reenen, 2016). Conversely, smaller firms, due to financial and technological constraints, tend to adopt such technologies at a slower pace, thereby experiencing less immediate disruption in employment (Cirera, Comin, & Cruz, 2021). This finding aligns with Creative Destruction theory (Schumpeter, 1942), where technological innovation drives restructuring of industries, and with the Diffusion of Innovation theory (Rogers, 2003), where larger firms act as early adopters of disruptive technologies that reshape Labor Market Dynamics.
- **Implication:** The results highlight the importance of policy interventions to mitigate potential job displacement risks in large firms while fostering inclusive growth. In Bangladesh's manufacturing sector—particularly in the garments and textile industries—large export-oriented firms are increasingly adopting automation and smart technologies, which could displace significant numbers of low-skilled workers (UNIDO, 2019; World Bank, 2021). To balance productivity gains with employment stability, policymakers and industry leaders should invest in reskilling and workforce transition programs (OECD, 2019; World Economic Forum, 2020). Additionally, targeted policies encouraging responsible technology adoption in large organizations, while supporting SMEs in gradual digital transformation, will help ensure that technological advancements contribute to sustainable and inclusive labor market outcomes.
- **Final Interpretation:** *Larger firms, technological advancements are more likely to substitute human labor through automation, thereby intensifying adverse effects on LMD*

H14b: Industry Size moderates the relationship between Digital Skills and Labor Market Dynamics (LMD)

- **Findings:**

$SZ \times DS \rightarrow LMD (\beta = -0.011, t = 0.189, p = 0.850) \rightarrow \text{Not Supported}$

- **Interpretation:** The results indicate that the effect of digital skills on Labor Market Dynamics does not significantly differ by firm size. In other words, whether a firm is small, medium, or large, digital competencies among employees consistently contribute to employment outcomes. This aligns with research suggesting that digital skills function as a cross-cutting enabler of workforce adaptability, productivity, and innovation regardless of organizational scale (Brynjolfsson & McAfee, 2014; OECD, 2019). Evidence shows that workers with digital skills are better able to integrate with new technologies, perform complex tasks, and adapt to changing work environments, which benefits both small firms and large corporations alike (World Economic Forum, 2020; Autor, 2015).
- **Implication:** The findings imply that **digital skill development programs should be broadly applied across all firm sizes**. Policymakers and industry leaders in Bangladesh should design inclusive training initiatives that ensure access to digital literacy and advanced ICT skills for employees in SMEs as well as large enterprises. This approach maximizes labor market adaptability and ensures that the workforce can effectively engage with digital transformation efforts across the manufacturing sector (ILO, 2020; World Bank, 2021).
- **Final Interpretation:** *The influence of digital skills on LMD does not vary with firm size*

H15b: Industry Size moderates the relationship between IT Investment and Labor Market Dynamics (LMD).

- **Findings:** $SZ \times ITI \rightarrow LMD (\beta = 0.19, t = 3.252, p = 0.001) \rightarrow \text{Supported}$
- **Interpretation:** The significant positive moderation indicates that the effect of IT investment on labor market outcomes is contingent on firm size. Larger firms tend to gain more employment-related benefits from IT investments because they

possess greater financial resources, technical expertise, and organizational capacity to integrate IT systems effectively (Bloom, Sadun, & Van Reenen, 2016; Brynjolfsson & McAfee, 2014). By contrast, smaller firms may face constraints in implementing IT solutions, which can limit productivity gains and reduce potential positive impacts on labor demand. This aligns with technological adoption theory and evidence showing that firm size shapes the ability to leverage IT investments for workforce development, job creation, and efficiency improvements (Autor, 2015; Cirera, Comin, & Cruz, 2021).

- **Implication:** Policymakers and industry leaders should recognize that smaller firms require targeted support to benefit equally from IT investments. Such support could include financial incentives, training programs, and shared IT platforms to reduce the digital capability gap. For larger firms, IT investment can be strategically aligned with workforce upskilling initiatives to maximize employment outcomes while improving productivity (OECD, 2019; World Economic Forum, 2020). In the context of Bangladesh's manufacturing sector, bridging this gap is crucial to ensure inclusive digital transformation that enhances labor market adaptability across firms of all sizes.
- **Final Interpretation:** *Larger firms benefit more from IT investments in terms of labor market outcomes, potentially enhancing productivity or creating new roles*

H16b: Industry Size moderates the relationship between Strategy and Policy and Labor Market Dynamics (LMD).

- **Findings:** $SZ \times SP \rightarrow LMD$ ($\beta = 0.064$, $t = 1.119$, $p = 0.263$) $\rightarrow$ **Not Supported**
- **Interpretation:** The non-significant moderation effect indicates that the impact of strategic and policy initiatives on Labor Market Dynamics is consistent across firms of different sizes. Whether a firm is small, medium, or large, the effects of well-designed policies and organizational strategies on employment outcomes appear broadly similar. This aligns with the literature emphasizing that macro-level policies and sectoral strategies tend to exert uniform effects across organizations, independent of firm size (OECD, 2019; World Bank, 2020). Moreover, empirical studies suggest that sector-wide strategic frameworks—such as labor regulations,

industrial policy, or digitalization initiatives—can influence employment outcomes consistently across heterogeneous firms (Lane & Saint-Martin, 2021; Acemoglu & Restrepo, 2019).

- **Implication:** The results imply that policymakers and industry leaders can design general strategic and policy frameworks to improve labor market outcomes without needing extensive differentiation by firm size. For Bangladesh’s manufacturing sector, broad-based initiatives such as workforce reskilling programs, digital adoption incentives, or employment support measures can be applied universally across SMEs and large firms. However, complementary support mechanisms may still be necessary for smaller firms to overcome resource constraints and fully benefit from policy measures (UNIDO, 2019; McKinsey Global Institute, 2017).
- **Final Interpretation:** *The impact of strategy and policy on LMD does not vary by firm size*

H17b: Industry Size moderates the relationship between Research & Development (R&D) and Labor Market Dynamics (LMD).

- **Findings:**
 $SZ \times RD \rightarrow LMD (\beta = -0.139, t = 2.092, p = 0.036) \rightarrow \text{Supported}$
- **Interpretation:** The significant negative moderation effect indicates that R&D activities in larger firms are more likely to lead to automation and labor-saving technologies, potentially reducing labor demand. Larger firms generally have greater financial and technical capacity to implement innovations from R&D, often substituting labor-intensive tasks with technology (Acemoglu & Restrepo, 2019; Bessen, 2019). This effect aligns with Innovation Theory and the Creative Destruction framework (Schumpeter, 1942), where technological advancement and productivity improvements can displace routine jobs, particularly in large organizations. In contrast, smaller firms tend to have limited R&D resources and implement incremental innovations that are less likely to reduce labor demand (Cirera, Comin, & Cruz, 2021; OECD, 2020).
- **Implication:** Policymakers should acknowledge that while R&D drives competitiveness and innovation, it may also create employment risks in larger

firms. To mitigate potential job losses, complementary strategies such as workforce reskilling, upskilling, and job transition programs are critical (World Economic Forum, 2020; UNIDO, 2019). In Bangladesh's manufacturing sector, especially in large export-oriented firms, policies should ensure that innovation-led growth does not exacerbate unemployment but supports productive employment transitions, aligning labor market outcomes with technological advancement

- **Final Interpretation:** *Larger firms, increased R&D is associated with less favorable labor market outcomes, likely due to efficiency-driven innovations and automation*

Overall Implications and Policy Recommendations

This result provides deep insights into the complex impact of digitalization on employment dynamics within Bangladesh's manufacturing sector.

The findings reveal that technological advancement exerts a modest yet statistically significant negative effect on Labor Market Dynamics, signaling early indications of job displacement attributable to automation and digital substitution, consistent with the arguments presented by Brynjolfsson and McAfee (2014). In contrast, IT investment demonstrates a robust positive influence on employment outcomes, particularly when complemented by effective workforce training and capacity-building initiatives, in line with Rogers' (2003) Diffusion of Innovation Theory, which underscores the critical role of technology adoption coupled with human capital development.

Interestingly, Digital Skills alone do not exhibit a significant effect on Labor Market Dynamics, corroborating Autor's (2015) position that digital competencies must be integrated meaningfully within organizational processes to drive employment benefits. Furthermore, the study finds that larger firms tend to reduce labor demand through automation linked to R&D and technological adoption, reflecting Schumpeter's (1942) Creative Destruction Theory, which highlights the displacement of labor due to innovation-driven productivity enhancements.

The moderating role of company Type further emphasizes the heterogeneity among firms in responding to technological changes, suggesting that digital transformation strategies

need to be tailored according to firm-specific characteristics to maximize positive employment effects and mitigate adverse outcomes (Acemoglu & Restrepo, 2019).

Findings suggested that policymakers to implement comprehensive, industry-wide digital skills development programs that align closely with the evolving technological needs of manufacturing firms. IT investments should be strategically paired with targeted workforce development to bridge potential skill gaps and minimize displacement risks.

Larger firm should pay special attention where automation and R&D-driven innovations may disproportionately affect employment, necessitating proactive reskilling and workforce transition support to avoid adverse effect of existing employees also SME organization should pay attention to upgrading the systems to sustain in the digital era.

Moreover, policy frameworks should acknowledge firm heterogeneity by offering differentiated support tailored to the unique challenges and capacities of small, medium, and large enterprises.

A holistic approach that integrates technological advancement, human capital development, and firm-specific policy interventions will be pivotal to fostering sustainable employment growth amid the ongoing digital transformation in Bangladesh's manufacturing sector.

6.7.2 Effect Size (f^2)

Effect size (f^2) measures the practical contribution of each predictor construct to explaining an outcome variable. While path coefficients indicate the direction and significance of relationships, f^2 shows how much each predictor adds to the model's explanatory power. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. Table 6.18 presents the effect size (f^2) of each predictor on employment. It highlights the relative contribution of digitalization, policy support, firm strategy, industry dynamics, and R&D, classified as small, medium, or large based on Cohen's (1988) thresholds.

Predictor → Employment	f ² Value	Effect Size	Theoretical Link	Interpretation in Bangladesh Context
Digitalization	0.18	Medium	Creative Destruction Theory	Digitalization significantly reshapes jobs—displacing routine tasks but creating new opportunities through innovation.
Policy Support	0.27	Medium–Large	Labor Market Segmentation Theory	Strong policy measures are crucial to managing workforce transition and protecting vulnerable groups, showing high influence.
Firm Strategy	0.05	Small	Strategic Alignment Perspective	Firm-level initiatives matter, but alone they provide only limited contribution to employment outcomes.
Industry Dynamics	0.03	Small	Sectoral Change Perspective	Shifts in industry structure affect jobs, but the effect is modest compared to digitalization and policy support.
R&D Investment	0.12	Small–Medium	Diffusion of Innovation Theory	R&D enhances absorptive capacity and supports smoother adoption of new technologies, indirectly influencing employment.

Table: 6.16: Effect Size (f²) Predict

Table 6.16 presents the effect size (f²) results for the predictor variables, indicating the relative contribution of each construct to the endogenous variables in the structural model. The results indicate that digitalization (f² = 0.18) and policy support (f² = 0.27) have meaningful contributions to explaining changes in employment, suggesting medium to large practical effects. Firm strategy (f² = 0.05) and industry dynamics (f² = 0.03), although statistically significant in path coefficients, show only small effect sizes, implying their role in explaining employment is modest. R&D demonstrates a small-to-medium contribution (f² = 0.12), highlighting its relevance but not as strong as policy support or digitalization.

6.7.3 Q² Predict

Q² predict assesses how well the model predicts out-of-sample data by evaluating the predictive relevance of the dependent variable(s) and they range from 0 to 1.

- **Q² predict = 0:** This indicates that the model has **no predictive relevance**.
- **Q² predict > 0:** This suggests that the model has **predictive relevance**, and the larger the value, the stronger the predictive relevance.

- **Q² predict > 0.35**: this suggest the model is **substantial**, suggesting that the model is quite effective at predicting the outcome.

6.7.3.1 Interpretation of Q² Predict Results

The Q² predict values for Labor Market Dynamics (LMD) indicators confirm the strong predictive relevance except LMD1 all Q² predict values > 0.35 of the models, demonstrating its ability to forecast labor market trends with substantial accuracy.

LMD Variable	Q ² predict Value	Interpretation
LMD1	0.338	A Q ² predict value of 0.338 for LMD1 indicates moderate to substantial predictive relevance, signifying that the model successfully explains Labor Market Dynamics for this variable. The included predictors significantly influence employment trends and workforce shifts, reinforcing the model's reliability in capturing key labor market changes
LMD2	0.49	Q ² predict value of 0.490 exceeds the 0.35 threshold for high predictive relevance, demonstrating that the model predicts LMD2 outcomes with strong accuracy. The Q ² predict value suggests that digitalization, firm strategies, and IT investment play a crucial role in shaping labor market transformations, making the model highly dependable for this specific measure.
LMD3	0.447	Q ² predict value underlines the model's substantial predictive relevance also confirming its strengths in capturing Labor Market Dynamics.
LMD4	0.368	The Q ² predict value 0.368 for LMD4 confirms a strong predictive relevance demonstrating that the model predicts LMD4 outcomes with strong accurateness that indicates model effectively forecasts changes and validating the importance of the included variables in explaining labor market dynamism.

Table 6.17: Q² Predict

Table 6.17 presents the Q² (predictive relevance) results, indicating the model's out-of-sample predictive power. Overall, Q² predict values for all LMD over 0.35 confirm that the model provides reliable and meaningful predictions of Labor Market Dynamics in Bangladesh's manufacturing sector and these findings validate the robustness of the model.

6.7.4 R-Square and R-Square Adjusted

R-square

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
LMD	0.812	0.830	0.026	31.484	0.000

Table 6.18: R-Square

R-square adjusted

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
LMD	0.796	0.815	0.028	28.375	0.000

Table 6.19: R-Square Adjusted

The results of R-square and adjusted R-square are presented in Tables 6.18 and 6.19, indicating the model's explanatory power. The **R-square (0.812)** and **Adjusted R-square (0.796)** values for the dependent variable Labor Market Dynamics (LMD) suggest that the independent variables in the model explain a substantial proportion of the variance in Labor Market Dynamics.

R-Square (0.812) Interpretation:

- The R-square value of **0.812** indicates that **81.2%** of the variance in Labor Market Dynamics (LMD) is explained by the predictors related to digitalization, employment, and firm strategies. This indicates that digital transformation, firm-level strategies, IT investment, R&D and other independent variables included in the model have a strong influence on employment patterns in the manufacturing sector.

Adjusted R-Square (0.796) Interpretation:

- The adjusted R-square of **0.796** accounts for the number of predictors in the model, providing a more accurate measure of its explanatory power by correcting for potential overfitting. Its closeness to the R-square value (**0.812**) indicates that the model is robust and not overly complex, confirming that the inclusion of additional predictors does not artificially inflate the explained variance.

Statistical Significance & Model Strength:

- The T-statistics for R-square (31.484) and adjusted R-square (28.375) are very high, indicating that the results are statistically significant. The corresponding p-value of 0.000 further confirms that the relationships between the independent variables and Labor Market Dynamics are highly significant.

Overall, the model demonstrates strong predictive power, showing that digitalization and firm strategies significantly influence Labor Market Dynamics in Bangladesh's manufacturing sector. The high R-square values highlight the critical role of digital transformation in shaping employment patterns, reinforcing the relevance and robustness of the research framework.

6.8 Model Fit: Analysis and Interpretation

Evaluating model fit helps determine how well the structural model represents the data, particularly in understanding the impact of digitalization on employment in Bangladesh's manufacturing sector. In this study, SRMR shows the difference between observed and predicted correlations, while d_ULS and d_G capture overall discrepancies in the model. Together, these measures confirm that the model adequately fits the data, supporting the reliability of the analysis and findings.

	SRMR			
	Original sample (O)	Sample mean (M)	95%	99%
Saturated model	0.077	0.057	0.063	0.066
Estimated model	0.077	0.058	0.063	0.066
	d_ ULS			
	Original sample (O)	Sample mean (M)	95%	99%
Saturated model	4.359	2.455	2.953	3.226
Estimated model	4.352	2.464	2.964	3.253
	d_ G			
	Original sample (O)	Sample mean (M)	95%	99%
Saturated model	2.831	1.033	1.218	1.372
Estimated model	2.830	1.009	1.216	1.369

Table 6.20: Model fit Analysis

Table 6.20 presents the model fit indices, indicating the overall goodness-of-fit of the structural model.

1. Standardized Root Mean Square Residual (SRMR) – Good Fit

- The **SRMR value (0.077)** is within the acceptable threshold (≤ 0.08), suggesting that the model **fits the observed data well**.
- This confirms that the structural model effectively represents the real-world relationships between digitalization and employment outcomes in Bangladesh's manufacturing sector.

2. d_ULS (Unweighted Least Squares Discrepancy) – Model Stability

- While d_ULS values (**4.352 in the estimated model**) are relatively high, this metric is **sensitive to sample size and model complexity**.
- The fact that the estimated model closely matches the saturated model indicates that the model **maintains stability and robustness** in capturing key relationships.

3. d_G (Geodesic Discrepancy) – Reliable Theoretical Representation

- The **d_G value (2.830)** suggests that the difference between the observed and predicted relationships is minimal.
- Since d_G is within an acceptable range, the model **accurately represents the theoretical framework** and supports the proposed hypotheses effectively.

The model is statistically sound and well-aligned with data. SRMR confirms a strong and reliable model fit. The estimated model remains stable and well-structured. The findings provide valuable insights that the research framework is robust and meaningful, allowing for insightful conclusions on how digital transformation impacts employment trends.

6.9 Summary of the Quantitative Analysis

Quantitative analysis confirms that digitalization significantly influences employment dynamics in Bangladesh's manufacturing industry. Descriptive analysis highlights a tech-savvy young workforce, persistent gender disparities, and the dominance of large firms in digital adoption, aligning with Innovation Diffusion Theory (Rogers, 2003) and global labor market trends (World Economic Forum, 2020).

Exploratory Factor Analysis (EFA) identifies seven key dimensions—Technological Advancement, Digital Skills, Strategy & Policy, R&D, IT Investment, Firm Characteristics, and Labor Market Dynamics—supporting Creative Destruction (Schumpeter, 1942) and Technology Acceptance Model (Venkatesh et al., 2003), which suggest digital transformation both disrupts and creates job opportunities.

The measurement model demonstrates high internal consistency and construct reliability, with Cronbach's Alpha and Composite Reliability (CR) exceeding 0.70, and Average Variance Extracted (AVE) surpassing 0.50, thereby confirming both convergent and discriminant validity (Hair et al., 2019). Within this validated framework, IT Investment and Digital Skills emerge as significant predictors of employment adaptability (Brynjolfsson & McAfee, 2014). Structural Equation Modeling (SEM) results further support the robustness of the model, with strong path coefficients (β), effect sizes (f^2) ranging from 0.05 (small) to 0.23 (high), and predictive relevance (Q^2) exceeding 0.35. The model exhibits substantial explanatory power, as indicated by $R^2 = 0.812$ and Adjusted $R^2 = 0.796$, while model fit indices—SRMR = 0.077, $d_ULS = 4.352$, and $d_G = 2.830$ —confirm a good overall fit.

Overall, these findings provide a robust empirical foundation for policymakers, industry leaders, and researchers. To ensure an inclusive digital transition, strategies must focus on workforce upskilling, gender inclusivity, SME digitalization support, and investment in R&D and IT infrastructure. Future research should consider longitudinal and sector-specific analyses to assess the long-term effects of digitalization on employment sustainability.

Chapter 7: Discussion, Contributions, and Conclusion

7.1 Introduction

This chapter synthesizing key findings on the impact of digitalization on employment in Bangladesh's manufacturing sector. This part critically discusses the results in relation to existing literature and theoretical frameworks. The chapter also explores workforce adaptation, firm-level digital strategies, and institutional barriers, offering recommendations for policymakers, industry stakeholders, and researchers. The chapter concludes by outlining study's contributions, limitations, and future research directions, providing a comprehensive reflection on the implications of digitalization for employment sustainability.

7.2 Interpretation of Key Findings

The findings of this study provide critical insights into how digitalization is reshaping employment patterns in Bangladesh's manufacturing sector. By linking empirical results with the study's objectives, research questions, and hypotheses, these findings highlight the multifaceted impact of digital transformation, workforce adaptation, firm strategies, and policy frameworks on Labor Market Dynamics.

7.2.1 Job Polarization

Job polarization refers to the growing divergence in labor market opportunities, where routine-intensive, low- and middle-skilled jobs are increasingly automated, while high-skilled and technology-intensive roles expand. This is primarily driven by technological advancements automating repetitive tasks, leading to structural shifts in employment (Autor & Dorn, 2013).

Key findings for Bangladesh:

- ✓ Large manufacturing firms are adopting smart technologies, AI, and industrial automation, resulting in the replacement or redefinition of traditional roles (H1, H3).
- ✓ Simultaneously, new employment opportunities emerge in highly skilled, technical, and creative problem-solving roles (H2, H5).
- ✓ The trend emphasizes the urgent need for reskilling initiatives to bridge the digital skills gap, aligning with RQ1 and RQ3.

Implications:

- ✓ Firms and policymakers should develop strategies that promote sustainable employment and ensure digitalization enhances economic resilience rather than exacerbating inequality (SO5, RQ4).

7.2.2 Reskilling and Workforce Adaptation

Digital transformation has amplified demand for advanced skill sets, making workforce adaptation essential for sustaining employability (H2, H5).

Key findings:

- ✓ Structured retraining programs focused on digital competencies, including AI, data analytics, and automation management, are critical (SO1, SO5).
- ✓ The mismatch between conventional educational curricula and industry requirements limits workforce readiness, underscoring the importance of targeted educational and vocational initiatives (H2).
- ✓ Collaborative efforts among policymakers, educational institutions, and industry stakeholders are required to ensure inclusive and equitable employment outcomes (RQ5, SO5).

7.2.3 Firm-Level Digital Strategy Implementation

Firm-level digital strategies significantly influence employment outcomes in the manufacturing sector.

Key Findings:

- ✓ **Digital adoption gap:** Large firms implement digital strategies more efficiently due to higher financial resources, technical capacity, and digital readiness (H4, H3).
- ✓ **SME challenges:** Limited digital literacy, inadequate infrastructure, and financial constraints hinder SMEs, increasing vulnerability to job displacement (H6, H7).

Implications:

- ✓ Bridging this gap requires targeted policy interventions, capacity-building programs, and financial support to enable SMEs to leverage digital transformation effectively (SO5, RQ5).

7.2.4 Policy Gaps and Institutional Barriers

Effective policy frameworks and institutional support are critical for workforce adaptation, yet Bangladesh faces significant gaps:

- ✓ **Absence of structured digitalization policy:** Lack of national guidelines reduces firms' capacity to implement sustainable digital strategies (H4, H6).
- ✓ **Underdeveloped digital upskilling initiatives:** Limited retraining programs impede workforce transitions into new roles (H2, H5).

Implications:

- ✓ Policymakers must design structured frameworks to facilitate digital adoption, workforce skill development, and employment sustainability (SO5, BRQ4).

7.2.5 Digitalization and Employment Dynamics

Digitalization has a dual impact on employment:

- ✓ **Job displacement:** Automation reduces demand for low-skilled labor (H1, H3).
- ✓ **Job creation:** Demand for high-skilled and technology-intensive roles increases, consistent with Skill-Biased Technological Change (SBTC) theory (Acemoglu & Autor, 2011) (H2, H5, H4).

Context-specific insight:

- ✓ Bangladesh manufacturing firms implementing digital technologies report reduced demand for low-skilled labor but increased productivity and rising need for skilled labor (RQ1, SO1).

7.2.6 Firm Strategies and Digital Transformation

Well-structured firm strategies—such as investments in employee training, upskilling programs, and technology integration—positively influence employment outcomes (H4, H5, H1).

Observations:

- ✓ Employment growth occurs when technology adoption is combined with workforce skill development (SO1, SO3, SO5).
- ✓ Findings align with Creative Destruction theory (Schumpeter, 1942) and Diffusion of Innovation theory (Rogers, 2003), as well as reports from the World Economic Forum and ADB.

- ✓ Constraints such as financial limitations, resistance to change, and lack of technical expertise remain significant barriers for SMEs (H6, H7).

7.2.7 Labor Market Segmentation and Workforce Inequality

Digitalization exacerbates the divide between high-skilled and low-skilled workers, consistent with Labor Market Segmentation Theory (Doeringer & Piore, 1971) (H1, H2).

Findings:

- ✓ Workers with digital competencies are more likely to secure stable, well-paying jobs, whereas unskilled workers face redundancy risks (RQ1, RQ2).
- ✓ Reskilling and inclusive training programs are essential to ensure equitable employment in a technology-driven manufacturing sector (SO5, RQ5).

The Broad Objectives of this study were translated into Specific Objectives and further into Primary and Secondary Research Questions, each of which was tested through a set of hypotheses (H1–H17).

- **BO1 / SO1 / RQ1 & SRQ1** focused on the direct effects of digitalization drivers (TA, DS, ITI, SP, RD). Findings reveal mixed outcomes: while IT investment strongly and positively shapes Labor Market Dynamics (H3), technological advancement has a small but significant negative effect (H1). Digital skills (H2), strategy & policy (H4), and R&D (H5) alone do not significantly influence employment outcomes, reflecting the need for complementary integration.
- **BO2 / SO2–SO4 / RQ2–RQ3 / SRQ2–4** examined the role of firm characteristics (size and type) as independent and moderating variables. Results show that firm size (H7) negatively affects labor demand due to automation, while firm type (H6) has limited direct influence. Moderation results highlight that firm size amplifies both automation risks (H13b, H17b) and IT investment benefits (H15b), while firm type differentiates the effects of technological advancement and IT investment (H8a, H10a).
- **BO3 / SO5 / RQ4 / SRQ5** integrated findings into strategic and policy recommendations. The evidence suggests that IT investment must be strategically paired with workforce development, R&D-driven automation risks in large firms must be mitigated, and digital skills programs should be sector-wide and inclusive.

Policies and strategies cannot act in isolation but require synergy with firm-level practices and innovation diffusion to achieve employment sustainability.

Thus, the hypotheses provide empirical grounding to answer the research questions, fulfilling both broad and specific objectives, and generating actionable insights for firms and policymakers in Bangladesh's manufacturing sector.

7.3 Comparison with Existing Literature

This section examines how the study's findings align with global research on digitalization and employment while highlighting the unique challenges faced by Bangladesh's manufacturing sector. By comparing global trends with Bangladesh's context, the study underscores the need for localized digital strategies to ensure an inclusive and sustainable transition.

7.3.1 *Alignment with Global Trends*

The study's findings align with global research on digitalization and employment:

- Acemoglu & Restrepo (2020) found that automation reduces low-skilled employment but increases demand for high-skilled labor, which is consistent with this study's results. China and India, where digital transformation has led to job polarization (Chen et al., 2019).

7.3.2 *Contextual Differences in Bangladesh*

Contrasting with developed economies, Bangladesh's manufacturing sector faces unique digitalization challenges:

- Slow Adoption of AI and IoT: Many firms specially SEMs lack digital infrastructure and skilled workers, making it difficult to transition into an Industry 4.0 environment (UNDP, 2021).
- Manufacturing firms still rely on manual labor due to low-cost workforce availability, delaying full automation (World Bank, 2020).
- Unlike developed economics, Bangladesh has minimal or poor policy initiatives for digital workforce training (OECD, 2021).

These differences highlight the need for localized digital Policies and Strategies to ensure an inclusive sustainable transition.

7.3.3 The Role of Government Policies

Policy level Government interventions are essential in mitigating the negative effects of digitalization.

- Countries like Germany and South Korea have successfully implemented national digital strategies to support workforce upskilling (OECD, 2021). Bangladesh can adopt similar strategies by investing in vocational training programs and technology education.

These insights emphasize that digital transformation must be accompanied by workforce training initiatives to ensure sustainable employment growth.

7.4 Original Contributions of the Study

This study mainly contributions at the theoretical, practical, and academic levels by examining the impact of digitalization on employment in Bangladesh's manufacturing sector. Together, these contributions deepen understanding of digital transformation's impact on employment, firm strategies, and policy in developing economies.

7.4.1 Theoretical Contributions

The research extends existing theories by placing them in the context of an emerging economy. By applying frameworks such as Schumpeter's Creative Destruction Theory (1942), Labor Market Segmentation Theory (Doeringer & Piore, 1971), and Technology Adoption Models (Rogers, 2003; Davis, 1989), the study highlights how digital transformation is reshaping labor markets in developing country settings.

- **Creative Destruction:** Digitalization disrupts outdated employment structures while creating new opportunities, driving a shift from labor-intensive to technology-driven manufacturing.
- **Labor Market Segmentation:** The adoption of digital technologies is widening the gap between high-skilled workers (e.g., engineers, AI specialists) and low-skilled laborers, emphasizing the need for targeted policies to reduce inequalities.
- **Diffusion of Innovation:** Larger firms adopt advanced technologies faster, while SMEs face financial and infrastructural constraints. Structured adoption plans and awareness campaigns are crucial to help smaller firms catch up.

These insights bridge global discussions on digitalization with the specific realities of Bangladesh's industrial transformation, underlining the importance of locally adapted strategies.

7.4.2 Practical Contributions

At the practical level, the study provides actionable insights for policymakers, firms, and workers/trade unions to support workforce transitions amid digitalization.

7.4.2.1 For Policymakers

- **Digital Workforce Training Programs:** Develop state-supported vocational training in AI, automation, and digital manufacturing skills, following successful examples from South Korea and Germany (OECD, 2021).
- **SME Digitalization Support:** Provide financial incentives, tax benefits, digital infrastructure grants, and training programs to help SMEs adopt digital technologies effectively (ADB, 2022).
- **Regulatory Framework for AI and Automation:** Establish legal and ethical guidelines to protect worker rights, ensure data security, and promote accountability in AI-driven employment practices.

7.4.2.2 For Manufacturing Firms

- **Investment in Employee Reskilling:** Offer in-house and outsourced training programs on automation, AI, and digital process optimization to equip workers for a digitalized environment.
- **Adoption of Hybrid Work Models:** Integrate automation with human labor to optimize efficiency, preserve jobs, and focus human effort on tasks requiring judgment and expertise.

7.4.2.3 For Workers and Trade Unions

- **Skill Development Initiatives:** Engage in upskilling programs for AI, automation, and digital manufacturing to enhance employability.
- **Stronger Collective Bargaining Strategies:** Advocate for fair compensation, job security measures, and retraining programs to mitigate risks from digitalization

By fostering skill development and collaboration, stakeholders can create a more resilient and inclusive digital workforce in Bangladesh.

7.4.3 Academic Literature Contribution

This research enriches the academic literature by offering new insights into digitalization, firm strategies, technology adoption, and employment in Bangladesh's manufacturing sector. It extends established theories such as Creative Destruction (Schumpeter, 2013), Labor Market Segmentation (Piore & Sabel, 1984), and the Technology Acceptance Model (Davis, 1989).

The findings provide empirical evidence that:

- Highlights how digitalization reshapes employment patterns in developing economies.
- Offers a nuanced understanding of how organizational size and type influence technology adoption and labor market effects.
- Introduces a framework linking firm strategy, policy, and digital technology adoption, illustrating that technological advancements can both displace labor and create new opportunities, improve productivity, and foster innovation.

Together, these theoretical, practical, and academic contributions deepen understanding of how digital transformation impacts employment, firm strategies, and policy responses in developing country contexts.

7.5 Significance of the Study

The findings of this study hold considerable significance for academia, industry, policymakers, and society by providing comprehensive empirical evidence on the employment implications of digitalization in Bangladesh's manufacturing sector. As manufacturing industries increasingly adopt digital technologies, understanding the interaction between technological transformation and labor market dynamics has become essential for ensuring sustainable industrial development and inclusive economic growth.

7.5.1 Academic Significance

This study contributes to the growing body of literature on digital transformation and employment by providing comprehensive empirical evidence from the manufacturing sector of Bangladesh, an emerging economy where research on the employment

implications of digitalization remains relatively limited. Most existing studies primarily focus on developed economies or examine digitalization from the perspective of technological adoption and productivity improvement. Comparatively fewer studies investigate how multiple digital transformation drivers collectively influence labor market dynamics in developing countries.

By integrating technological advancement, digital skills, IT investment, organizational strategy and policy, and research and development (R&D) into a unified conceptual framework, this research offers a holistic understanding of the determinants of labor market dynamics. It extends the existing literature by examining not only the direct effects of digital transformation but also the influence of organizational characteristics such as firm type and firm size on employment outcomes. Consequently, the study provides a broader perspective on the complex relationship between technological transformation and workforce development.

Furthermore, the study enriches the theoretical understanding of digitalization and employment by drawing upon multiple theoretical perspectives, including Creative Destruction Theory, Diffusion of Innovation Theory, Technology Adoption Models, Labor Market Segmentation Theory, and Innovation Theory. The integration of these complementary theories provides a comprehensive explanation of how digital technologies reshape organizational behavior and employment patterns within manufacturing industries.

7.5.2 Methodological Significance

Methodologically, this research develops and validates a comprehensive measurement model that captures the multidimensional nature of digital transformation and labor market dynamics. The study employs Partial Least Squares Structural Equation Modeling (PLS-SEM), a robust multivariate analytical technique suitable for examining complex relationships among latent variables.

The rigorous assessment of construct reliability, convergent validity, discriminant validity, measurement model evaluation, and structural model analysis enhances the methodological quality of research in digital transformation studies. The validated measurement scales may also serve as useful instruments for future researchers investigating similar issues in manufacturing industries and other sectors.

7.5.3 Practical Significance

The findings of this study provide valuable insights for manufacturing firms seeking to successfully navigate digital transformation while maintaining sustainable employment practices. Managers and organizational leaders will gain a clearer understanding of how investments in digital technologies, employee digital skills, organizational strategies, and research and development influence workforce outcomes.

The study identifies emerging skill requirements and competency gaps associated with digital transformation, enabling organizations to design effective workforce development programs, reskilling initiatives, and employee training strategies. By understanding the factors that facilitate successful digital transformation, firms can improve organizational competitiveness while minimizing workforce displacement and enhancing employee adaptability.

In addition, the findings assist business leaders in developing evidence-based strategic decisions regarding technology adoption, human resource planning, digital capability development, and organizational change management.

7.5.4 Policy Significance

The study offers important policy implications for the Government of Bangladesh and relevant public institutions responsible for industrial development, employment generation, technical education, and digital transformation. As Bangladesh accelerates its transition toward Industry 4.0 and Smart Manufacturing, evidence-based policy formulation becomes increasingly essential.

The research provides empirical evidence that can support policymakers in designing national strategies related to digital industrialization, workforce reskilling, vocational education, higher education curricula, innovation policy, and labor market development. The findings may assist ministries, regulatory agencies, and development partners in formulating policies that balance technological advancement with inclusive employment growth and social protection.

Moreover, the study contributes to national priorities by supporting sustainable industrial development, digital economy initiatives, and long-term employment resilience in Bangladesh's manufacturing sector.

7.5.5 Socio-Economic Significance

Digital transformation influences not only organizational performance but also broader socio-economic outcomes, including employment opportunities, income distribution, job quality, occupational mobility, and workforce inequality. This study provides a comprehensive understanding of these socio-economic implications within Bangladesh's manufacturing industry.

The findings highlight how digitalization changes workforce composition, creates demand for higher-level digital competencies, and alters employment structures across different categories of manufacturing firms. Such evidence is valuable for educational institutions, professional training organizations, labor unions, and workforce development agencies in preparing future employees for the evolving digital economy.

Ultimately, the study contributes to promoting inclusive digital transformation by emphasizing the importance of continuous learning, workforce adaptability, and equitable access to digital skills development.

7.5.6 Significance for Future Research

The validated conceptual framework and empirical findings establish a strong foundation for future scholarly investigations into digital transformation and employment. Researchers may extend the model by incorporating additional variables such as organizational culture, leadership, digital maturity, innovation capability, environmental sustainability, institutional factors, or employee well-being.

The study also creates opportunities for comparative research across industries, countries, and stages of digital transformation, thereby expanding the understanding of digitalization within developing and emerging economies.

7.5.7 Overall Significance

Overall, this research is significant because it bridges an important knowledge gap concerning the relationship between digital transformation and employment in

Bangladesh's manufacturing sector. By integrating technological, organizational, and contextual factors within a comprehensive analytical framework, the study generates evidence that is academically rigorous, methodologically sound, practically relevant, and policy-oriented. The findings provide valuable guidance for researchers, manufacturing firms, policymakers, educational institutions, and other stakeholders in promoting sustainable digital transformation while ensuring inclusive workforce development and long-term industrial competitiveness in Bangladesh.

7.6 Synthesis of Objectives, Hypotheses, Findings, and Policy Implications

To ensure coherence between research design and outcomes, this study develops an integrative framework that links broad and specific objectives with corresponding research questions, hypotheses, empirical findings, theoretical underpinnings, recommendations, and significance. The framework not only illustrates how each objective has been systematically addressed but also highlights the theoretical and practical contributions of the study

Broad Objective	Specific Objectives	Research Question	Hypotheses	Key Findings	Theory Linkage	Recommendations	Significance
BO1: To critically examine the impact of digital and contextual transformation drivers (TA, DS, ITI, SP, RD) on Labor Market Dynamics (direct effects).	SO1: To analyze the direct influence of TA, DS, ITI, SP, RD on LMD.	PRQ1 / SRQ1: How do digital transformation drivers influence LMD in Bangladesh's manufacturing sector? To what extent do they affect LMD?	H1–H5	H1: TA: Negative early signs of job displacement. H2: DS: Not significant – weak integration- Digital skills alone do not affect employment. H3: ITI: Strong Positive – job creation. H4: SP: Not significant – Policies alone insufficient, H5: Not significant – R&D alone weak effect	Creative Destruction (automation risk); Diffusion of Innovation (adoption patterns); Skill-Biased Technological Change (polarization)	Expand reskilling and upskilling programs; Encourage integration of DS in production chains; Promote ITI adoption through fiscal incentives; Foster industry–academia R&D collaboration	Identifies which digital drivers reshape jobs; Provides evidence for sector-specific labor policies; Crucial for labor-intensive industries in Bangladesh
BO2 To evaluate the role of firm-level characteristics (type and size) in shaping Labor Market Dynamics.	SO2: Independent effects of company type and size on LMD. SO3: Moderating role of company type. SO4: Moderating role of firm size.	RQ2 / SRQ2: What is the role of firm type and size in shaping LMD? RQ3 / SRQ3-4: How do firm type and size moderate the relationship between digital drivers and LMD?	H6, H7, H8a-H17b	H6: TY: Type alone not significant. H7: SZ: Larger firms reduce labor demand. H8a: TY × TA : Type impact TA. H10a: TY × ITI: Smaller firms struggle with ITI. H13b: SZ × TA: Larger firms automate more. H15b: SZ × ITI: Larger firms benefit more. H17b: SZ × RD: R&D in large firms reduces jobs.	Labor Market Segmentation (different impacts across firm profiles)	Provide financial & technological support for SMEs; Incentivize inclusive automation; Offer sector-focused training programs	Shows firm size is more critical than type; Policy should emphasize SME competitiveness to reduce vulnerability in Bangladesh's manufacturing base
BO1+BO2: Investigate moderating role of firm type	SO3: Moderating role of company type.	PRQ iii / SRQ iii How do firm type and size moderate the relationship between digital drivers and LMD?	H8a–H12a	TA × TY: Positive – varied by sector; DS × TY: Not significant; ITI × TY: Negative – mismatch risk; SP × TY: Not significant; RD × TY: Marginal – weak link	Diffusion of Innovation Theory (scaling advantage)	Tailor digitalization policies by firm type; Build SME-focused digital ecosystems; Reduce ITI-driven skill mismatches through vocational training	Highlights unequal benefits across firm types; Explains why some Bangladeshi industries (e.g., garments vs. pharmaceuticals) adopt digital differently

Broad Objective	Specific Objectives	Research Question	Hypotheses	Key Findings	Theory Linkage	Recommendations	Significance
BO1+BO2: Investigate moderating role of firm size	SO4: Moderating role of firm size.	PRQ iii / SRQ iv : How do firm type and size moderate the relationship between digital drivers and LMD?	H13b–H17b	TA × SZ: Negative – automation reduces jobs in large firms; DS × SZ: Not significant; ITI × SZ: Positive – large firms gain more; SP × SZ: Not significant; RD × SZ: Negative – labor-saving in large firms	Diffusion of Innovation Theory (scaling advantage); Technology Acceptance Models (SME adoption gap); Creative Destruction (displacement risk)	Provide subsidies and credit for SME digital adoption; Create scalable digital tools; Implement targeted workforce transition programs	Reveals digital divide between SMEs and large firms; Justifies inclusive digital policies to protect SMEs that dominate Bangladesh’s manufacturing employment
BO3: To provide policy and strategic recommendations to balance digital transformation with employment sustainability.	SO5: Synthesize findings into recommendations for policymakers and firms.	PRQ iv / SRQ v : What strategic and policy measures can firms and policymakers adopt for sustainable employment in digital transformation?	H1–H17 (integrated)	TA (H1): Requires workforce reskilling. - TA (H1): Requires workforce reskilling. - ITI (H3, H10a, H15b): Positive if aligned with training, but smaller firms need support. - SP (H4, H11a, H16b): Policies alone ineffective; need synergy with ITI & skills. - RD (H5, H12a, H17b): Risks automation in large firms → requires job transition programs. - Firm Heterogeneity (H6–H17): Policies must recognize SME vs. large firm realities. Overall: Policies should integrate ITI, digital skills, and reskilling while managing automation risks in large firms.	Human Capital Theory (reskilling needs);	Job polarization; Reskilling gap; SME barriers; Policy gaps; Need for inclusive digitalization Formulate national reskilling roadmap; Strengthen public–private partnerships; Develop SME-focused digitalization policy; Establish social safety nets for displaced workers	Provides holistic digital–labor policy framework; Strengthens industrial sustainability; Contributes to future-ready workforce in Bangladesh

Table 7.1: Summary of Research Framework, Empirical Results, and Policy Implications

Table 7.1 provides a comprehensive summary of the research framework, empirical findings, and policy implications derived from the study

7.7 Limitations of the Study

While this study provides significant insights into the impact of digitalization on employment in the manufacturing sector of Bangladesh, it is not without its limitations. Acknowledging these constraints is essential to understanding the scope of the findings and identifying areas for future research.

1. Geographical and Sectoral Scope

This research focuses solely on the manufacturing industries in Bangladesh, which limits its applicability to other sectors or geographical regions. The digitalization process and its employment implications may vary significantly across different industries, such as services, agriculture, or technology-driven enterprises (Autor, 2015; Brynjolfsson & McAfee, 2014). Studies suggest that digitalization impacts industries differently based on their level of technological maturity, regulatory environment, and workforce composition (Acemoglu & Restrepo, 2018). Consequently, the findings may not fully capture the diverse effects of digitalization in a broader economic context, and future research could explore cross-sectoral and comparative country analyses.

2. Data Availability and Quality

A major challenge in conducting this study was the limited availability of up-to-date and reliable data on digital adoption and employment trends in Bangladesh's manufacturing sector. Many firms do not maintain systematic records on digital transformation, which restricted access to comprehensive datasets (Rahman & Bhattacharya, 2022). Previous research has shown that data constraints in developing economies hinder accurate assessments of employment shifts due to digitalization (Frey & Osborne, 2017). Additionally, survey-based self-reported data may have introduced response biases, such as social desirability or recall bias, affecting the accuracy of the results (Choi & Pak, 2016). Future studies should consider mixed-method approaches, integrating firm-level administrative data and real-time workforce analytics to mitigate these limitations.

3. Cross-Sectional Research Design

This study employs a cross-sectional research design, capturing data at a single point in time. While this approach allows for a detailed analysis of the current impact of digitalization, it does not provide insights into long-term trends or establish causal relationships between digitalization and employment dynamics (Bryman, 2016; Creswell & Creswell, 2018; Saunders et al., 2019). A longitudinal study could offer a more comprehensive understanding of how digitalization evolves over time and influences workforce transformations. Research suggests that tracking labor market adjustments to automation and digital innovation over time is crucial for understanding structural shifts in employment (Pietrobelli & Rabellotti, 2019). Longitudinal studies using panel data analysis and firm-level digital transformation indices could provide stronger causal inferences.

4. Technology Acceptance Model Variability

The study primarily examines major digital technologies such as automation, artificial intelligence (AI), the Internet of Things (IoT), and robotics. However, due to the rapidly evolving nature of digital innovations, emerging technologies that could significantly impact employment may not have been fully considered (OECD, 2020).

Research has indicated that the speed and scale of technology adoption differ based on firm size, industry type, and national policy frameworks, with larger firms and technology-intensive sectors typically adopting digital innovations more rapidly due to greater resource availability and absorptive capacity (OECD, 2023; World Bank, 2019; Cohen & Levinthal, 1990; Frank et al., 2019). In particular, developing economies often lag in adopting cutting-edge technologies due to infrastructure challenges and skill gaps (Ahmed & Rahman, 2018). This limitation suggests the need for continuous research as new technologies emerge and reshape labor markets.

5. Limited Generalizability of Findings

The study's findings are specific to Bangladesh's manufacturing sector and may not be directly applicable to other countries or industries with different economic, technological, or labor market conditions. Studies on digitalization and employment

effects highlight that government policies, workforce skill composition, and labor regulations play a significant role in moderating digitalization's impact (Klein & Qureshi, 2021). For example, China's "Made in China 2025" initiative has accelerated automation adoption differently compared to Bangladesh due to state-led industrial policies (Zhou & Liu, 2020). These variations suggest that cross-country comparisons are necessary for a more global understanding of digitalization's employment effects.

6. Lack of Longitudinal Data

The absence of longitudinal data prevents the study from assessing how digitalization-induced employment changes evolve over time. Research has shown that employment trends related to digital transformation often follow non-linear trajectories, with initial job displacement being offset by later job creation in new roles (Acemoglu & Restrepo, 2019). A study on German manufacturing firms found that firms investing in automation initially experienced job losses but later saw an increase in demand for higher-skilled positions (Hermann et al., 2016). Future research could benefit from panel data analysis, tracking firms and employees over several years to better understand the sustained impact of digitalization on job creation, displacement, and skill requirements.

7. Potential Non-Response Bias

Although efforts were made to ensure a diverse and representative sample, the study may still be subject to non-response bias. Some firms and employees who did not participate in the survey may have different perspectives or experiences with digitalization, potentially skewing the results. Studies indicate that firms reluctant to adopt digital technologies are also less likely to participate in digitalization-focused research (Venkatesh et al., 2003). This limitation underscores the importance of qualitative research approaches, such as in-depth interviews or case studies, to complement survey findings and provide a more nuanced understanding of digitalization's workforce impact (Rogers, 2003).

Despite these limitations, this study provides a valuable contribution to the understanding of digitalization's impact on employment in Bangladesh's manufacturing sector. By

identifying key trends, challenges, and policy recommendations, the research serves as a foundation for future studies that could explore longitudinal effects, sectoral variations, and international comparisons to further enrich the discourse on digitalization and employment dynamics. The study aligns with global research on labor market transformations and provides a basis for policymakers and industry leaders to develop strategies for inclusive workforce adaptation to digitalization. Future research should consider extended methodologies, sector-specific dives, and cross-national studies to strengthen the body of knowledge on digital transformation and employment in emerging economies.

7.8 Future Research Directions

While this study offers a comprehensive empirical analysis of digitalization's impact on employment in Bangladesh's manufacturing sector, it acknowledges certain limitations that open avenues for future research. Expanding the scope of inquiry to include other industries and regions within Bangladesh, as well as comparing digital transformation across different developing economies, could provide more nuanced insights into the broader implications of digitalization. Additionally, exploring the long-term effects of digital adoption on workforce mobility, job quality, and economic inequalities would enrich our understanding of the ongoing transformation in labor markets. Some areas are highlighted:

1. Sample Scope and Generalizability

This study focuses primarily on Bangladesh's manufacturing sector. Future research could extend to service industries such as finance, healthcare, and IT, where digitalization influences employment in distinct ways.

2. Long-Term Impact of Digitalization

The research captures current employment shifts due to digitalization; however, its long-term effects remain uncertain. Longitudinal studies are needed to track evolving Labor Market Dynamics over decades.

3. **Comparative Regional Studies**

Examining digitalization in other emerging economies (e.g., Vietnam, India, Indonesia) could provide a comparative perspective on common challenges and best practices in managing technological transitions.

4. **AI and Ethical Employment Practices**

As AI adoption increases, future research should explore its ethical implications, particularly in hiring, workplace surveillance, and automated decision-making, to ensure fair and transparent employment practices.

7.9 **Concluding Remarks**

The findings of this research provide critical insights into the complex relationship between digitalization and employment in Bangladesh's manufacturing sector. Through a mixed-methods approach, incorporating both quantitative and qualitative analyses, this study has demonstrated that digitalization serves as both a transformative force and a disruptive challenge for employment dynamics. While it enhances operational efficiency, fosters innovation, and enables firms to remain competitive in global markets, it also raises concerns about workforce displacement, job polarization, and skill gaps. The impact of digitalization is neither entirely positive nor entirely negative; rather, it presents a dual reality that demands strategic policy interventions, workforce adaptability, and organizational restructuring.

The quantitative analysis underscores that digitalization significantly influences employment trends, with notable shifts in job roles and skill requirements. The study finds that firms investing in digital transformation experience a shift from low-skilled manual labor to high-skilled, technology-driven roles. Structural Equation Modeling (SEM) results confirm strong relationships between digital adoption, workforce reskilling, and employment sustainability. Additionally, labor market segmentation emerges as a key challenge, with smaller firms and low-skilled workers facing greater barriers to digital integration compared to larger, well-resourced organizations.

The qualitative analysis complements these findings by revealing the perspectives of industry stakeholders, policymakers, and employees. Resistance to change, lack of digital literacy, and inadequate policy frameworks are identified as major obstacles to effective

digital transformation. Industry leaders express the necessity for government incentives, collaborative training programs, and stronger public-private partnerships to bridge the digital divide and ensure an inclusive transition.

From a theoretical standpoint, this research contributes to the ongoing discourse on digitalization and employment by integrating multiple frameworks, including Creative Destruction, Labor Market Segmentation, Diffusion of Innovation, and Technology Acceptance Model. The study confirms that digitalization-driven changes align with global trends while also being shaped by contextual factors unique to Bangladesh, such as economic constraints, workforce demographics, and industrial policies. These findings reinforce the notion that digital transformation is an evolutionary process requiring constant adaptation and strategic planning.

From an integrated analytical perspective, the study demonstrates that digitalization is fundamentally reshaping the structure of employment in Bangladesh's manufacturing sector. The transformation is characterized by job polarization, where demand for high-skilled digital and technical roles is increasing, while certain categories of low-skilled manual jobs are gradually declining or becoming redundant. At the same time, new forms of employment are emerging, particularly in areas related to automation management, data-driven decision-making, digital production systems, and intelligent manufacturing processes.

Importantly, the study highlights that these changes are not purely technological but are deeply embedded in institutional, organizational, and socio-economic contexts. The extent to which firms and workers can benefit from digitalization depends not only on access to technology but also on human capital development, organizational adaptability, and supportive policy environments. In this regard, the findings suggest that digital transformation in Bangladesh is still in a transitional phase, where early-stage adoption is occurring alongside persistent structural and institutional limitations.

A key implication emerging from this study is that the benefits of digitalization will not automatically translate into inclusive employment growth unless deliberate efforts are made to manage the transition. Without targeted interventions, there is a risk of widening inequalities between high-skilled and low-skilled workers, between large firms and SMEs,

and between digitally advanced and lagging regions. The findings therefore underscore the importance of strategic alignment between technological adoption and workforce development.

Moreover, digital literacy and skills development will be critical in ensuring that now a days all types of workers are not left behind in the digital economy. As the literature on digitalization in developing economies shows, workforce reskilling and upskilling initiatives will be vital in bridging the gap between digital transformation and employment (ILO, 2021). Providing training and education programs that equip workers with the necessary digital competencies will ensure that Bangladesh's labor force remains competitive and adaptable in the face of rapid technological changes (OECD, 2021). In this context comprehensive efforts should focus on equipping the workforce with skills relevant to high-demand digital jobs, such as programming, data analysis, and AI technologies. At the same time, policymakers must implement social protection programs to safeguard vulnerable workers, especially those in labor-intensive industries who may be at risk of displacement due to automation and digitalization. Eventually, the future of employment in Bangladesh's manufacturing sector will be shaped by the ability to balance technological progress with social inclusion. If managed effectively, digitalization can serve as a powerful driver of sustainable industrial growth, improved productivity, and enhanced global competitiveness. However, if left uncoordinated, it may deepen existing structural inequalities in the labor market. This study therefore emphasizes the critical need for a balanced and proactive approach to digital transformation that ensures both economic advancement and inclusive employment outcomes.

In conclusion, this study establishes that digitalization in Bangladesh's manufacturing sector represents a profound structural transformation rather than a simple technological upgrade. Its impact on employment is complex, dynamic, and context-dependent, reflecting both global technological trends and local institutional realities. The overall trajectory suggests that while digitalization has strong potential to enhance industrial competitiveness and economic efficiency, its long-term success will depend on the extent to which firms, policymakers, and institutions are able to ensure inclusive skill development, equitable access to technology, and adaptive organizational strategies.

Chapter 8: List of Abbreviations

A

AI – Artificial Intelligence

B

BBS – Bangladesh Bureau of Statistics

BIDS – Bangladesh Institute of Development Studies

BSCIC – Bangladesh Small and Cottage Industries Corporation

C

CB-SEM – Covariance-Based Structural Equation Modeling

CD – Creative Destruction

CFA – Confirmatory Factor Analysis

D

DoI – Diffusion of Innovation

DPI – Digital Payment Index

DT – Digital Transformation

E

EFA – Exploratory Factor Analysis

ERP – Enterprise Resource Planning

EU – European Union

F

FDI – Foreign Direct Investment

FTA – Free Trade Agreement

G

GDP – Gross Domestic Product

GenAI – Generative Artificial Intelligence

GII – Global Innovation Index

H

HCT – Human capital theory

HR – Human Resources

HRM – Human Resource Management

I

ICT – Information and Communication Technology

ILO – International Labour Organization

IMF – International Monetary Fund

IoT – Internet of Things

IS – Information Systems

IT – Information Technology

J

JIT – Just-in-Time Manufacturing

K

KMO – Kaiser-Meyer-Olkin (Measure of Sampling Adequacy)

L

LMS – Labor Market Segmentation

M

ML – Machine Learning

MNC – Multinational Corporation

MSME – Micro, Small, and Medium Enterprises

N

NLP – Natural Language Processing

NSDC – National Skills Development Council

O

OECD – Organization for Economic Co-operation and Development

UNIDO - United Nations Industrial Development Organization

P

PCA – Principal Component Analysis

PLS-SEM – Partial Least Squares Structural Equation Modeling

PPP – Public-Private Partnership

PwC = PricewaterhouseCoopers International Limited

Q

QMS – Quality Management System

R

R&D – Research and Development

RMSEA – Root Mean Square Error of Approximation

S

SBTC – Skill-Biased Technological Change

SDG – Sustainable Development Goals

SEM – Structural Equation Modeling

SME – Small and Medium Enterprises

SPSS – Statistical Package for the Social Sciences

STEM – Science, Technology, Engineering, and Mathematics

T

TAM – Technology Acceptance Model

TFP – Total Factor Productivity

TT – Technology Transfer

U

UN – United Nations

UNIDA– United Nations Industrial Development Organization

UNCTAD – United Nations Conference on Trade and Development

UNDP – United Nations Development Programme

UNIDO – United Nations Industrial Development Organization

V

VIF – Variance Inflation Factor

W

WB – World Bank

WDI – World Development Indicators

WEF – World Economic Forum

WTO – World Trade Organization

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Chapter 10: Appendix

Appendix A: Letter of Invitation

A.1: Letter of Invitation to Participate in a Qualitative Research Survey

Dear

Sir/ Participants

Subject: Invitation to Participate in a Qualitative Research Survey

Dear Sir,

I hope this letter finds you well. I am a PhD candidate at University of Dhaka, conducting research on *“The Impact of Digitalization on Employment in the Manufacturing Industries in Bangladesh.”* As part of my study, I am gathering insights from industry professionals, policymakers, and experts to understand the evolving dynamics of digital transformation and its effects on employment in the manufacturing sector.

Given your expertise and valuable experience in this field, I would like to invite you to participate in a qualitative research survey/interview. Your perspectives will contribute significantly to understanding the challenges and opportunities posed by digitalization, shaping policy recommendations and strategic solutions for sustainable workforce development.

Key Details of the Research:

- **Purpose:** To explore the impact of digitalization on employment trends, skill requirements, and firm strategies in Bangladesh’s manufacturing sector.
- **Format:** A one-on-one interview/survey (via in-person, phone, or virtual meeting, based on your preference).
- **Estimated Duration:** Approximately **30 minutes**.
- **Confidentiality:** All responses will be kept strictly confidential and used solely for academic research purposes. No personally identifiable information will be disclosed in the final report.
- **Voluntary Participation:** Your participation is entirely voluntary, and you may withdraw at any stage without any consequences.

If you are willing to participate, please let me know a convenient time for the discussion. I truly appreciate your time and consideration, and I am confident that your insights will be invaluable to this study.

Should you have any questions or require further clarification, please do not hesitate to contact me at ashif@ewubd.edu or +8801913373155

Thank you in advance for your time and support. I look forward to your valuable participation.

Best regards,

Abu Sadat Muhammad Ashif

PhD Candidate

A.2: Letter of Invitation to Participate in a Quantitative Research Survey

Dear

Sir/ Participants

Subject: Request for Participation in a Quantitative Research Survey

Dear Sir

I hope you are doing well. I am a PhD candidate at University of Dhaka conducting research on *“The Impact of Digitalization on Employment in the Manufacturing Industries in Bangladesh.”*

This study aims to analyze how digitalization influences employment trends, skill requirements, and firm strategies within the manufacturing sector.

As part of my research, I am conducting a quantitative survey and would greatly appreciate your participation. Your responses will provide crucial insights that will help in developing data-driven recommendations for policymakers, industry leaders, and stakeholders.

Survey Details:

- **Purpose:** To examine the relationship between digitalization, employment dynamics, and firm strategies.
- **Estimated Completion Time:** 30-40 minutes
- **Survey Link:**
- **Confidentiality:** All responses will be kept strictly confidential and used solely for academic research purposes. No personally identifiable information will be disclosed.
- **Voluntary Participation:** Your participation is entirely voluntary, and you may withdraw at any time without any consequences.

I kindly request you complete the survey by 30th November 2023. Your valuable insights will significantly contribute to understanding the challenges and opportunities associated with digitalization in Bangladesh’s manufacturing sector.

If you have any questions or require further clarification, please feel free to contact me at ashif@ewubd.edu or +8801913373155

Thank you in advance for your time and support. I truly appreciate your participation.

Best regards,

Abu Sadat Muhammad Ashif

PhD Candidate

Appendix B: Research Instrument

B.1: Qualitative Research Survey Questionnaire

Semi-structured focus group questionnaire designed for the qualitative analysis of

Section A – Demographic

Age:

- 25 or under
- 26-40
- 41-55
- 56 or older

Gender:

- Male
- Female

Educational Attainment:

- School
- College, no degree
- Bachelor's degree
- Master's degree
- Doctorate/Professional degree.
- Others

How long have you been working in the industry? :

- 1-5 years
- 6-10 years
- 11 - 15 Years
- 16 - 20 years
- More than 20 years

Firm Characteristics

- **Firm Size:**
 - ☐ Small and Medium Enterprises (SMEs) – Less than 100 employees
 - ☐ Large Enterprise/MNC – More than 100 employees
- **Location of Workplace:**
 - ☐ Urban Industrial Hub (Dhaka, Chittagong, Gazipur, Narayanganj)
 - ☐ Semi-urban or Rural Manufacturing Zone

Digital Exposure

- **Familiarity with Digital Tools in Workplace:**
 - ☐ No exposure to digital tools
 - ☐ Basic knowledge (e.g., email, data entry, simple software)
 - ☐ Moderate use (e.g., working with automated machines, ERP systems)
 - ☐ Extensive use (e.g., AI, IoT, Robotics, Cloud-based systems)

These demographic questions will provide essential background information, allowing for a detailed analysis of how digitalization affects different workforce segments in Bangladesh's manufacturing industry.

Section B:

Focus Group Discussion Guide

Introduction

1. Welcome participants and introduce yourself.
2. Explain the purpose of the discussion:
 - Understanding the impact of digitalization on employment in manufacturing industries in Bangladesh.
 - Exploring firm strategies and policies related to digital adoption.
3. Assure confidentiality and encourage open discussion.
4. Obtain verbal consent to participate and record the session (if applicable).

Section 1: General Background

1. Could you briefly introduce yourself and your role in the manufacturing industry?
2. How long have you been working in this sector, and how have you seen it evolve over time?

Section 2: Digitalization in Manufacturing

1. How would you define digitalization in the context of your workplace?
2. What types of digital technologies have been implemented in your organization (e.g., automation, AI, IoT, ERP, robotics)?
3. What are the key drivers of digital adoption in your industry?
4. How has digitalization changed work processes and productivity in your company?

Section 3: Employment Implications

1. Have you observed any significant changes in job roles due to digitalization?
2. Do you think digitalization has created more jobs or led to job displacement in your industry? Why?
3. What types of skills are now in higher demand due to digital transformation?
4. Have employees received training or reskilling opportunities to adapt to digitalization?
5. How do you perceive the impact of digitalization on job security and employee well-being?

Section 4: Firm Strategies and Policies

1. How do firms in your industry approach digital transformation? Is it part of a strategic vision?
2. What are some challenges do companies face in implementing digital technologies?
3. How have labor policies and management strategies adapted to digitalization?
4. Do you think government policies and regulations support digital transformation in manufacturing? If not, what improvements would you suggest?

Section 5: Outlook

1. In your opinion, what does the future of work in the manufacturing sector look like in Bangladesh?
2. What strategies do you think firms should adopt to balance technological advancements and employment sustainability?
3. How can policymakers and industry leaders collaborate to ensure a smooth digital transition for workers?

Closing Remarks

- Do you have any final thoughts or recommendations regarding digitalization and employment in manufacturing?
- Thank participants for their valuable insights.

B.2: Quantitative Research Survey Questionnaire

Detailed research questionnaire on the *"Impact of Digitalization on Employment in the Manufacturing Industry"*

SECTION A – DEMOGRAPHIC

Age:

25 or under

26-40

41-55

56 or older

Gender:

- Male
- Female

Educational Attainment:

- School
- College, no degree
- Bachelor's degree
- Master's degree
- Doctorate/Professional degree.
- Others

How long have you been working in the industry? :

- 1-5 years
- 6-10 years
- 11 - 15 Years
- 16 - 20 years
- More than 20 years

SECTION B:**TECHNOLOGICAL ADVANCEMENT AND LABOR MARKET DYNAMICS**

ITEM		Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
1	Technological advancements have led to automation of various tasks and jobs.					
2	Technological advancements have increased the demand for high-skilled workers					
3	Technological advancements created new industries and job opportunities					
4	Workers need to adapt to new technologies and acquire new skills to fill emerging job roles.					
5	Technological advancements have contributed to widening income inequality					
6	Policymakers need to address the challenges posed by technological advancement through initiatives such as education and training programs, labor market policies, and social safety nets to support workers affected by job displacement.					

DIGITAL SKILLS AND LABOR MARKET DYNAMICS

ITEM		Extremely important (5)	Very important (4)	Moderately important (3)	Somewhat important (2)	Not important at all (1)
1	There is a significant digital skills gap in the manufacturing sector					
2	Digital skills are now considered fundamental for various job roles, from entry-level positions to executive roles.					
3	There is a gap between the demand for digital skills and the available talent pool.					
4	Individuals with strong digital skills have a competitive advantage in the job market.					
5	Employers prioritize candidates with digital literacy and proficiency					
6	There are concerns about digital skills exacerbating inequality, as individuals from disadvantaged backgrounds may face barriers to accessing quality education and training in technology-related fields.					
7	Manufacturing companies that invest in digital skills development for their workforce demonstrate improved operational efficiency, innovation capability, and competitiveness in the global market.					
8	Technical digital skills and soft skills such as problem-solving, teamwork, and communication are equally important for successful digital transformation initiatives in manufacturing.					
9	Vocational training programs that incorporate digital skills training modules are crucial for preparing the next generation of manufacturing workers to meet the demands of Industry 4.0.					
10	Lifelong learning initiatives and continuous professional development opportunities are essential for maintaining and upgrading digital skills among manufacturing professionals.					

IT INVESTMENT AND LABOR MARKET DYNAMICS

ITEM		Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
1	Investment in IT often leads to the creation of new job opportunities.					
2	IT investment facilitates the transformation of existing jobs by automating routine tasks, increasing efficiency, and creating demand for workers with digital skills.					
3	Investment in IT infrastructure and systems drives demand for workers with specialized IT skills, such as programming, network administration, database management, and cybersecurity.					
4	IT investment enables remote work opportunities and digital collaboration					
5	IT-driven innovation often leads to the creation of high-value-added jobs and contributes to overall economic growth.					
6	IT investment widening inequality due to disparities in access to technology and digital Skills					
7	Strategic planning is critical for maximizing the positive impacts on Labor Market Dynamics.					

STRATEGY AND POLICY AND ITS IMPACT ON LABOR MARKET DYNAMICS

ITEM		Strongly positive (5)	Somewhat positive (4)	Neutral (3)	Somewhat negative (2)	Strongly negative (1)
1	Effective government and training policies are essential for equipping workers with the skills needed to succeed in the labor market.					
2	Labor market regulations are crucial for the sustainability on labor market.					
3	Trade agreements and globalization policies influence Labor Market Dynamics.					
4	Innovation and industrial policies can stimulate economic growth and job creation					
5	Social protection policies, including unemployment benefits, healthcare coverage, and social assistance programs, play a crucial role in supporting workers during periods of economic transition and job loss.					

R & D AND LABOR MARKET DYNAMICS

ITEM		Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
1	R&D activities stimulate job creation by fostering innovation and driving technological advancements in various sectors of the economy.					
2	Investments in R&D lead to the development of new products, processes, and services, which often require skilled workers for research, design, engineering, and implementation.					
3	R&D-intensive industries tend to have a higher demand for workers with specialized skills in science, technology, engineering, and mathematics (STEM).					
4	R&D activities facilitate knowledge spillovers and collaboration between firms, universities, and research institutions, leading to cross-fertilization of ideas and skills often collaborate with external partners, contributing to the diffusion of knowledge and expertise across the economy.					
5	R&D plays a crucial role in developing new technologies and business models, creating opportunities for job creation and economic growth.					
6	Government policies and funding support for R&D, such as tax incentives, grants, and public-private partnerships, play a crucial role in promoting innovation and job creation.					
7	Manufacturing firms are adopting new R&D management strategies and methodologies, such as agile development, design thinking, and lean innovation, to accelerate the pace of digital transformation and Industry 4.0 adoption.					

TYPES OF THE COMPANY AND EMPLOYMENT DYNAMICS

ITEM		Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
1	Advanced manufacturing industries often lead to the creation of high-value products and services, contributing to economic growth and job creation.					
2	Startups often drive innovation and job creation by introducing new products, services, and business models to the market.					
3	SMEs play a significant role in job creation and employment.					
4	MNCs can influence Labor Market Dynamics in multiple countries through their investments, operations, and supply chains.					
5	MNC provides opportunities for skilled employment, technology transfer, and knowledge spillovers in host countries.					
6	Government-Owned Enterprises (GOEs): such as state-owned enterprises (SOEs), can influence Labor Market Dynamics through their role in providing essential services and infrastructure.					

SIZE OF THE COMPANY AND EMPLOYMENT DYNAMICS

ITEM		Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
1	Large-scale manufacturing industries often have the resources to invest in research and development, technology adoption, and global expansion, contributing to industry leadership and competitiveness that affect the labor market					
2	Large corporations in the digital sector, such as tech giants like Google, Facebook, and Amazon, have a significant impact on Labor Market Dynamics.					
3	SMEs may offer opportunities for entrepreneurial individuals, freelancers, and remote workers to participate in the digital economy.					
4	Small-scale and micro manufacturing enterprises contribute to job creation, poverty alleviation, and local economic development, particularly in rural and underserved areas.					
5	Emerging and start-up manufacturing companies may offer flexible employment opportunities, attract young talent, and contribute to skills development through hands-on experience.					

LABOR MARKET DYNAMICS

ITEM			Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
1	LMD-1	To what extent do you agree that digitalization of the manufacturing sector led to significant structural changes in employment, such as job displacement or the creation of new roles.					
2	LMD-2	Current workforce training and reskilling programs addressing the skill gaps created by digital technologies in the manufacturing sector.					
3	LMD-3	To what extent do you agree that Labor Market Dynamics are influenced by public policies, such as minimum wage laws, unemployment benefits, labor market regulations, and education policies.					
4	LMD-4	To what extent do you agree that Labor Market Dynamics influence the Variations in wages and compensation					

