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Exploring the Benefits of Artificial Intelligence Adoption in Ready-Made Garment Industry of Bangladesh

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Abstract: *This study investigates the transformative potential of Artificial Intelligence (AI) technologies—including Machine Learning (ML), Expert Systems (ES), Decision Support Systems (DSS), Optimization Systems (OS), Image Recognition and Vision (IRV), Deep Learning (DL), and Neural Networks (NN)—in Bangladesh's ready-made garment (RMG) industry. Employing a quantitative methodology, data were collected via questionnaire surveys from 300 RMG factories using convenience sampling and analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. The results demonstrate statistically significant correlations ($p < 0.05$) among five AI technologies—ES, DSS, IRV, DL, and NN—indicating their synergistic role in enhancing operational efficiency, product quality, and sustainability within the sector. In contrast, ML and OS exhibited a negative association with industry outcomes, suggesting contextual limitations in their current implementation. These findings provide empirical evidence for RMG stakeholders to prioritize AI tools with proven efficacy, while reevaluating the adoption strategies for ML and OS to address potential implementation barriers. The study contributes to the emerging discourse on AI-driven industrial transformation in developing economies, offering actionable insights for policymakers and industry leaders in Bangladesh's RMG sector.*

Keywords: *Artificial Intelligence (AI) tools, Benefits, Opportunities, Apparel Industry, Bangladesh.*

1. Introduction

The readymade garments (RMG) sector serves as the backbone of Bangladesh's economy, accounting for 84.21% of total exports ($35.81 billion) and employing over 4 million workers (BGMEA, 2022). While the "Made in Bangladesh" label has cemented the country's position as a global apparel leader, the industry faces significant challenges in managing variable costs - particularly labor, material

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handling, and supply chain overheads - making AI adoption critical for maintaining competitiveness. Leading manufacturers are already implementing Industry 4.0 solutions: Mohammadi Group's automated knitting machines, DBL Group's intelligent dyeing systems, Envoy Textiles' robotic autoconers, and Beximco's AI-powered ThreadSol fabric optimization software (Fiber Fashion, 2020). These technologies demonstrate AI's potential to reduce production costs by 18-22% while improving quality control (Edlich, 2019).

For Bangladesh’s RMG stakeholders to remain globally competitive, strategic AI adoption is imperative given rising variable costs—particularly in labor (38% of production costs), material handling (22%), and supply chain overheads (BGMEA, 2023). While AI optimizes these expenditures through predictive analytics and automation (18-22% savings potential), implementation challenges include high upfront investments ($250K-$500K per factory) and workforce reskilling requirements (World Bank, 2022). A balanced evaluation of these trade-offs is critical for sustainable technological integration in Bangladesh’s cost-sensitive apparel ecosystem. Thus, embracing AI could be crucial for the future of Bangladesh's RMG sector, helping it navigate a complex market and ensuring resilience in the global apparel landscape.

2. Literature review and hypothesis development:

The ready-made garment (RMG) sector in Bangladesh is undergoing a significant technological revolution, with artificial intelligence (AI) emerging as a central driver of innovation across the entire apparel value chain. As global competition intensifies, industry leaders increasingly recognize AI's potential to enhance operational efficiency, reduce production costs, and improve product quality. A survey of 288 South Korean executives revealed that 80% consider AI a disruptive force with transformative potential for manufacturing sectors (Hong, 2022). This technological shift aligns with the broader Industry 4.0 framework, characterized by the integration of cyber-physical systems, IoT, and big data analytics in manufacturing processes (Nguyen et al., 2019).

AI technologies are revolutionizing quality assurance in textile manufacturing through advanced computer vision systems. Artificial neural networks (ANN) combined with nonlinear regression models have demonstrated remarkable accuracy in detecting fabric defects, achieving classification rates that significantly outperform traditional manual inspection methods (Sikka et al., 2024). These automated systems not only improve detection accuracy but also reduce inspection costs while maintaining non-invasive quality control protocols (Das et al., 2021).

The implementation of AI extends beyond quality control to optimize various production processes. Machine learning algorithms analyze historical and real-time operational data to enhance labor efficiency and workflow optimization (Kotsiantis, 2017). AI's transformative impact is particularly evident in supply chain management and product design. Predictive analytics and decision support systems enable manufacturers to optimize inventory management, reduce

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material waste, and improve order fulfillment rates (Giri et al., 2019; Noor et al., 2022). Design automation tools powered by AI streamline pattern creation and color selection processes, significantly reducing development timelines while maintaining product quality (Hassani et al., 2020). The creative potential of AI is transforming fashion design through generative algorithms that produce market-responsive patterns and enable mass customization (Ahmed et al., 2023).

AI contributes significantly to sustainability initiatives in the RMG sector. Through optimized material utilization and intelligent resource allocation, AI systems help reduce waste and improve energy efficiency (Le et al., 2019). Advanced analytics enable manufacturers to assess the environmental impact of production processes and make informed decisions about sustainable material sourcing (Khan et al., 2023).

As Bangladesh's RMG sector continues to evolve, AI adoption will play an increasingly critical role in maintaining global competitiveness. From automated production systems to data-driven design innovations, AI offers comprehensive solutions to the complex challenges facing the industry. By leveraging these technologies, Bangladeshi manufacturers can enhance their operational efficiency, product quality, and environmental sustainability while adapting to rapidly changing market demands .

2.1 Hypothesis Development

2.1.1 Machine Learning & Apparel Industry

Machine learning (ML), a critical branch of artificial intelligence, enables systems to autonomously learn from data and refine performance over time (Sikka et al., 2024). Within the apparel industry, ML significantly contributes to enhancing operational efficiency, product quality, and market responsiveness. Supervised learning models evaluate predicted outcomes against actual results, facilitating error detection and model refinement (Lloyd et al., 2013).

A key application of ML lies in sales forecasting, where algorithms assist brands in aligning inventory with consumer demand, thus reducing overproduction and stockouts (Kumar & Poonkuzhali, 2018). Additionally, ML supports trend analysis and colour prediction, allowing designers to tailor products to evolving preferences (Hsiao et al., 2017). In manufacturing, ML-based defect detection systems identify fabric flaws more accurately than manual inspection, enhancing quality control and reducing dependency on skilled labour (Ghosh et al., 2011). Moreover, ML helps predict fabric behaviour using mechanical properties, improving material selection and process efficiency (Pavlinic & Gersak, 2004). Together, these applications affirm the hypothesis that ML plays a pivotal role in advancing design, production, and sustainability in the apparel sector.

H_1: H1: Machine learning tools positively influence operational efficiency, product quality, and demand forecasting in the apparel industry.

2.1.2 Expert Systems and Apparel Industry

Expert systems, a foundational component of artificial intelligence (AI), are computer-based programs that emulate the decision-making capabilities of

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human experts by applying logical inference rules to a knowledge base (Fu et al., 2018). These systems operate on "if-then" logic structures and were first developed in the 1970s, gaining significant traction in the 1980s as a means to replicate domain-specific expertise in decision-intensive tasks (Leondes, 2001). In the apparel industry, expert systems have demonstrated substantial utility in addressing both operational and strategic challenges.

One notable application is in environmentally responsible manufacturing, where expert systems assist in selecting appropriate processes and machinery that reduce pollutant emissions and resource consumption (Metaxiotis, 2004). By simulating expert reasoning, these systems support the selection of dyeing techniques, chemical usage, and waste minimisation strategies—crucial in aligning with global sustainability standards. In fashion retail, expert systems are also used to enhance customer satisfaction through recommendation engines. By analysing customer preferences, purchase histories, and style trends, these systems can suggest personalised product options, thereby improving customer experience and retention (Wong et al., 2009). These examples collectively support the hypothesis that expert systems offer positive implications for the apparel industry by improving production decision-making, supporting sustainability, and enhancing consumer engagement.

H_2: Expert systems contribute to enhanced decision-making and process automation, thereby improving sustainability and customer satisfaction in the apparel industry.

2.1.3 Decision Support System (DSS) and Apparel Industry

Decision Support Systems (DSS), a key component of artificial intelligence, integrate mathematical models with conventional data retrieval methods to support semi-structured and complex decision-making processes (Sprague, 1980). In the context of the apparel industry, DSS plays a critical role in enhancing operational efficiency across supply chain functions. These systems facilitate real-time analysis and scenario planning, allowing stakeholders to make informed decisions regarding resource allocation, production scheduling, and inventory management (Tu & Yeung, 1997). By leveraging DSS, apparel manufacturers can evaluate alternative strategies under varying constraints, leading to cost reduction and improved supply chain performance. Furthermore, DSS tools aid in identifying process bottlenecks and optimising workflow, which contributes to overall agility in responding to fluctuating market demands (Wong & Leung, 2008). Therefore, the evidence substantiates the hypothesis that DSS tools have positive implications for the apparel industry by supporting strategic planning and operational adaptability.

H_3: Decision Support Systems (DSS) facilitate strategic planning and resource optimization, leading to improved supply chain performance in the apparel industry.

2.1.4 Optimization Systems and Apparel Industry

Artificial intelligence demonstrates considerable capability in addressing complex, multifaceted problems by employing intelligent search mechanisms that can identify multiple viable solutions (Luger, 1998). Among the most prominent techniques within AI's evolutionary algorithms are Genetic Algorithms (GA), gene expression programming, and genetic programming, which mimic natural evolutionary processes to optimize problem-solving (Holland, 1992). In the apparel sector, GA has found extensive application, particularly in resolving intricate scheduling and design layout challenges inherent in textile production (Guruprashad & Behera, 2009). Its adaptive nature allows for rapid responses to the fast-paced developments characteristic of the fashion industry, facilitating improved operational agility. Additionally, GA has been successfully applied to enhance garment fitting services, offering personalized solutions that improve customer satisfaction and reduce return rates (Hui et al., 2007). Collectively, these applications illustrate the capacity of GA and related optimization algorithms to streamline production processes and support innovation in the apparel industry.

H_4: Optimization algorithms enable effective production scheduling and inventory management, resulting in cost reduction and operational agility in the apparel industry.

2.1.5 Image Recognition and Vision and Apparel Industry

In the textile and apparel industry, image recognition and computer vision technologies play a crucial role in automating quality control and defect detection processes. These AI-enabled systems facilitate rapid and accurate inspection of fabrics, significantly reducing manual errors and enhancing manufacturing precision (Cushen & Nixon, 2011).

H_5: Image recognition and computer vision technologies improve quality control and defect detection, enhancing manufacturing precision in the apparel industry.

2.1.6 Deep Learning and Apparel Industry

Deep learning is an AI approach that simulates the data processing and decision-making capabilities of the human brain (Sikka et al., 2024). Initial models were created to recognize objects within small images (Samek et al., 2017). For the detection of yarn defects, deep learning systems need to understand a wide range of defect combinations (Nateri et al., 2014; Sharma & Sindhe, 2016; Gultekin et al., 2019; Czimmermann et al., 2020). These techniques are crucial for deriving meaningful design insights from fashion images (Hossain et al., 2022). In 2021, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was introduced to forecast yarn tenacity and unevenness using six input parameters related to cotton fibers. This model integrates neural networks with fuzzy logic, enabling the prediction of various yarn quality metrics based on fiber properties (Das & Chakraborty, 2021).

H_6: Deep learning tools have positive implications for quality control and product development in the apparel industry.

2.1.7 Neural Networks and Apparel Industry

Neural networks are advanced computational systems that simulate the processing abilities of human brain neurons, enabling complex tasks like pattern

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recognition and predictive modeling. In the textile industry, they offer significant benefits across various functions. For example, Almodarresi et al. (2019) created a neural network-based scanner for precise color matching of reactive dyed cotton, enhancing efficiency in garment production. Moreover, neural networks forecast apparel sales, aiding brands in inventory management and production alignment with market demand (Caglayan et al., 2020). Additionally, they excel in pattern recognition, identifying trends and designs that appeal to consumers (Iqbal Hussain et al., 2020).

H_7: Neural network models positively impact pattern recognition, predictive analytics, and automated quality assessments in apparel production.

3. Objectives of the Study

The objectives of this research are:

1. To examine the current applications and usage of AI technologies in the RMG industry of Bangladesh.
2. To identify the opportunities for enhancing AI adoption in the RMG sector, considering industry-specific challenges and market dynamics.
3. To evaluate the potential practical implications of AI implementation for key stakeholders, aimed at optimizing the benefits of AI across the RMG value chain.

4. Conceptual Framework

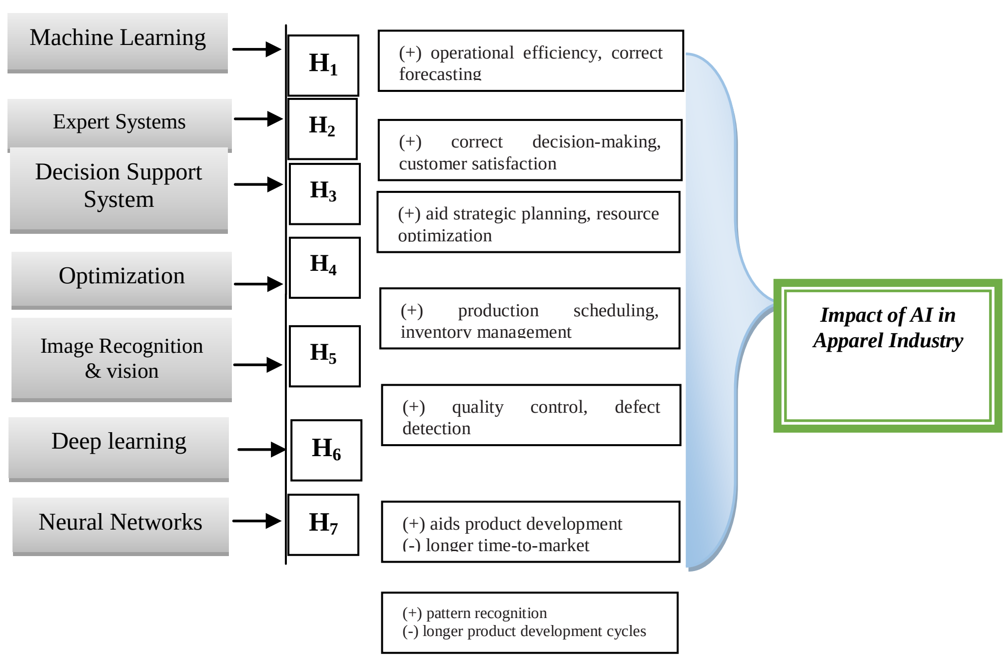

Figure 1: Proposed model for benefits of AI adoption in Apparel Industry (developed by Author)

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5. Research Methodology

5.1 Research Design, Sampling and Sample Size:

This research aims to identify the benefits of AI adoption in the apparel industry's performance using a quantitative research design. The sample size was calculated using Cochran's statistical formula (Nunnally, 1978) to ensure accurate evaluation of AI adoption and its quantifiable effects.

Where, $n = \frac{n0}{1+(n0-1)/N}$

Where, $n0 = \frac{z^2 p(1-p)}{d^2} \times (deft)$

In this formula, value of z was 1.96 which corresponds to 95% confidence level and d was set at 5% (as usual practice) and the design effect was set at 1 and p was reasonably assumed to be 0.5 as the safest procedure. Thus n0= 384.

Population N = 4498 (BGMEA, 2022)

So, the sample size = $n = \frac{n0}{1+(n0-1)/N}$ = $\frac{384}{1+(384-1)/4498}$ = = 354 RMG factories,

The study employed simple random sampling (SRS) to select 354 RMG factories from a population of 4,498, as this method ensures each unit had an equal and independent chance of selection, thereby minimizing selection bias and enhancing representativeness (Cochran, 1977). The final sample of 300 factories was achieved after accounting for non-responses and incomplete surveys, maintaining statistical power for robust analysis.

5.2 Data Analysis Technique & Measurement of Reliability and Validity

This study employs PLS-SEM to explore AI adoption benefits in Bangladesh's RMG industry, as it aligns with our predictive, exploratory goals (Henseler et al., 2016). PLS-SEM accommodates the study’s small-to-moderate sample size and potential non-normal data while evaluating formative AI-adoption constructs (Hair et al., 2019). Unlike CB-SEM’s strict fit requirements (Kline, 2015), PLS-SEM’s variance-based approach prioritizes practical insights (R^2), crucial for this emerging research context. An initial survey was performed to assess the validity of the questionnaire, and Cronbach's alpha was employed to measure the internal consistency of the data. Items with a Cronbach's alpha value above 0.70 are considered to demonstrate good internal consistency (Guilford, 1950; Nunnally, 1978).

5.3 Questionnaire design

The study utilized a 1 to 5 rating scale for a survey assessing experiences with Artificial Intelligence (AI) in the ready-made garments (RMG) industry, where 1 means "Strongly Disagree" and 5 "Strongly Agree." It included 33 questions

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covering eight factors, such as Machine Learning, Expert Systems, Decision Support Systems, Optimization, Image Recognition and Vision, Deep Learning, Neural Networks, and the overall impact of AI. The questionnaire classified respondents by age (21 and older) and job role, facilitating accurate demographic analysis. Informed consent was obtained to ensure privacy and confidentiality, with ethical protocols in place to protect personal data and minimize harm to participants.

5.4 Items and Measurements

Table 2: Items and Measurements of the study

Serial	IVs	Serial	Items	Source
1	**Machine Learning**	i.	Sales forecasting	Kumar and Poonkuzhali, 2018
		ii.	Trend analysis,	Hsiao et al., 2017
		iii.	Color prediction	Hsiao et al., 2017
		iv.	Demand forecasting	Thomassey and Zeng, 2018
		v.	Fabric defect detection	Ghosh et al., 2011
2	**Expert Systems**	i.	Pick appropriate techniques	Metaxiotis, 2004
		ii.	Pick appropriate equipment	
		iii.	Produce less environmental contamination	
		iv.	Create a suggestion engine	Wong et al., 2009
		v	Boost client happiness	
3	**Decision Support System (DSS)**	i.	Industrialize innumerable tasks	Tu and Yeung, 1997
		ii.	Help to choose appropriate process	Wong and Leung, 2008
		iii.	Help to choose resources	
		iv.	Decrease the overall cost	
		v.	Enhance the performance	
4	**Optimization**	i.	Solve scheduling challenges	Guruprashad and Behera, 2009
		ii.	Solve design layout challenges	
		iii.	Enhance fitting services	Hui, et al, 2007
5	**Image Recognition and Vision**	i.	Inspection control	Steger, et al, 2018
		ii.	Process control	
		iii.	Content-based image retrieval systems	

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Serial	IVs	Serial	Items	Source
		iv.	Virtual try-on	Cushen and Nixon, 2011
		v.	Augmented reality	
6	**Deep Learning**	i.	Extract valuable design information from photos	Das and Chakraborty, 2021
		ii.	forecast various yarn quality metrics	
		iii.	Provides allowable values	
7	**Neural networks**	i.	Evaluate dimensional changes in the fabrics	Kalkanci et al., 2017, Caglayan et al., 2020, Iqbal Hussain et al., 2020
		ii.	Apparel sales forecasting	
		iii.	pattern recognition	

6. Data Analysis, Interpretation & Findings

Results of data analysis presented in tables and figures. Confirmatory factor analysis (CFA) assessed construct validity and reliability. Additional metrics, including average variance extracted (AVE) and composite reliability (CR), were analyzed to validate the measurement model. These analyses ensured robust psychometric properties for the study's constructs.

6.1 Output of the Measurement Model

To determine the impact of AI tools in Apparel Industry, the study conducted analysis on Smart PLS-4 because this path analysis will help to find out the relationship between them and to make the model fit. Smart PLS helps to make the model fit and find the reliability and validity of the model.

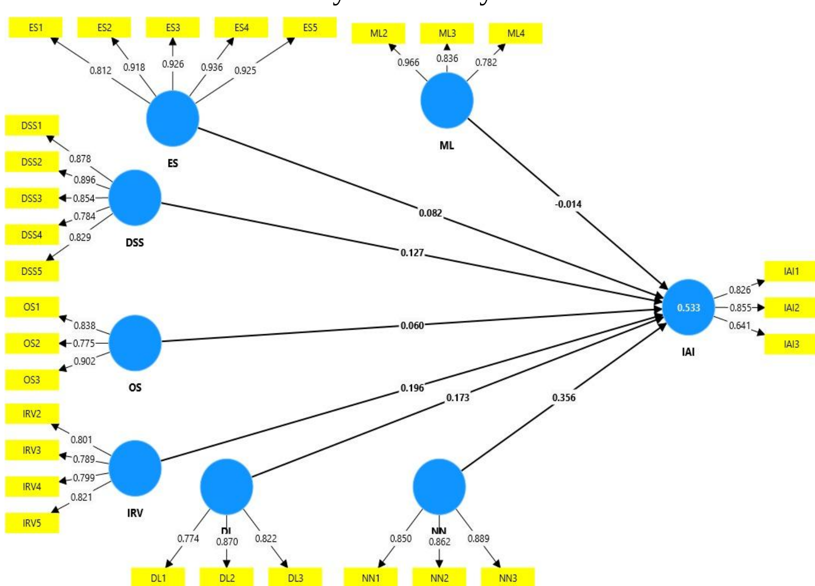

Figure 1: Graphical presentation of the PLS structural equation modeling.

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According to Chin (2010), the loading indicators of the research construct surpass a threshold of 0.60. Four indicators, namely ML1 (-0.287), ML5 (-0.399), IRV1 (0.330), and IAI4 (0.286), were excluded because their values were below the acceptable threshold of less than 0.60.From the figure, the study can say that all the AI tools have impacts on apparel industry in RMG industry of Bangladesh. All the variables have positive impact except machine learning (-0.014). The inner model suggests that Neural Networks (0.356) has the strongest impact on apparel industry of Bangladesh.

6.1.1 Reliability Test

Table 5 revealed that the value of Cronbach's Alpha (CA), rho_A value and Composite Reliability (CR) FOR ALL constructs were higher than the recommended value of 0.70 (Chin, 2010, Dijkstra and Henseler, 2015). Therefore, the result confirm that the reliability of the constructs has been well established through these perameters. The table further indicates that the average variance extracted (AVE) exceeded the recommended threshold of 0.50 (Hair, et al, 2014) and loading factors were greater than 0.60. Thus, it is quite obvious from these results that all these measures confirmed the convergent validity of the constructs.

Table 5: Reliability & Convergent validity Analysis Outputs

Constructs	Items	Loading score	Cronbach's Alpha	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Machine Learning	ML2	0.966			
	ML3	0.836			
	ML4	0.782	0.858	0.899	0.749
Expert Systems	ES1	0.812			
	ES2	0.918			
	ES3	0.926			
	ES4	0.936			
	ES5	0.925	0.944	0.957	0.818
Decision Support System	DSS1	0.878			
	DSS2	0.896			
	DSS3	0.854			
	DSS4	0.784			
	DSS5	0.829	0.903	0.928	0.721
Image Recognition and Vision	IRV2	0.801			
	IRV3	0.789			
	IRV4	0.799			
	IRV5	0.821	0.815	0.878	0.644

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Constructs	Items	Loading score	Cronbach's Alpha	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Deep Learning	DL1	0.774			
	DL2	0.870			
	DL3	0.822	0.762	0.863	0.678
Neural networks	NN1	0.850			
	NN2	0.862			
	NN3	0.889	0.835	0.901	0.752
Optimization Systems	OS1	0.838			
	OS2	0.775			
	OS3	0.902	0.795	0.877	0.705
Impact of AI in Apparel Industry	IAI1	0.826			
	IAI2	0.855			
	IAI3	0.641	0.700	0.821	0.608

Confirmatory factor analysis is employed to evaluate reliability and validity. The results of the convergent validity assessment are presented in Table 5. "The validation of measurement models through Average Variance Extracted (AVE) and Composite Reliability (CR) is fundamental to assessing AI adoption in Bangladesh's RMG industry. Following Fornell and Larcker's (1981) criterion, AVE values exceeding 0.50 establish convergent validity, confirming that latent constructs (e.g., perceived AI benefits, organizational readiness) are sufficiently represented by their indicators. Similarly, CR scores above 0.70 (Hair et al., 2019) ensure internal consistency, demonstrating that survey items cohesively measure their intended theoretical constructs. These psychometric standards are particularly crucial in technology adoption research.

6.1.2 Discriminant Validity test:

Construct validity represents a fundamental psychometric property that evaluates whether an instrument adequately measures the theoretical construct it purports to assess (Hair et al., 2019). Within this framework, discriminant validity was empirically examined using the Fornell-Larcker criterion (Fornell & Larcker, 1981), as presented in Table 6. This methodological approach requires that the square root of the average variance extracted (√AVE) for each latent variable must be greater than its highest correlation with any other construct in the measurement model (Henseler et al., 2015).

Each √AVE value (diagonal elements) exceeded all corresponding inter-construct correlations (off-diagonal elements). However, IAI-NN Correlation (0.647) approaches IAI's √AVE (0.780), suggesting marginal discriminant validity and DL-NN (0.654) and DL-IRV (0.637) correlations are moderately high but still below DL's √AVE (0.823). This indicates, IAI and NN may require further

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refinement (e.g., removing overlapping indicators) due to their high correlation (0.647). ML's negative correlations suggest it measures a distinct dimension compared to other AI tools.

Table 6: Fornell -Larcker Criterion Analysis Outputs for discriminant validity test

	DL	DSS	ES	IAI	IRV	ML	NN	OS
DL	**0.823**							
DSS	0.439	**0.849**						
ES	0.112	0.048	**0.905**					
IAI	0.607	0.462	0.144	**0.780**				
IRV	0.637	0.448	0.043	0.587	**0.802**			
ML	-0.084	-0.041	0.166	-0.051	-0.05	**0.865**		
NN	0.654	0.435	0.037	0.647	0.585	-0.093	**0.867**	
OS	0.183	0.206	0.294	0.199	0.189	0.191	0.064	**0.840**

Table 7: Heterotrait- Monotrait Ratio (HTMT) Matrix Analysis Outputs

	DL	DSS	ES	IAI	IRV	ML	NN	OS
DL								
DSS	0.526							
ES	0.132	0.052						
IAI	0.846	0.576	0.184					
IRV	0.808	0.521	0.081	0.784				
ML	0.106	0.085	0.184	0.053	0.067			
NN	0.808	0.498	0.051	0.856	0.709	0.102		
OS	0.229	0.249	0.315	0.273	0.231	0.217	0.074	

The HTMT statistical results (Table 7) show values below 0.85, confirming discriminant validity according to the HTMT threshold of 0.85 (Henseler et al., 2015). In summary, the satisfactory results for both convergent and discriminant validity collectively support the foundation for validating construct validity, as construct validity encompasses both types of validity.

6.2.3 Structural Model

This study employed various statistical metrics to evaluate the structural model and understand variable relationships (Ali et al., 2018; Hair et al., 2014). Hair et al. (2021) validate bootstrapping as the gold standard for significance testing in PLS-SEM, especially for exploratory AI studies. In addition, Sarstedt et al.

(2022) emphasize bootstrapping's reliability for AI/Industry 4.0 research, noting its superiority over parametric tests for complex models. PLS-SEM analysis was conducted at a significance level of 5% ($P < 0.05$) for two-tailed t-tests, as Sarstedt et al. (2022) explicitly endorse the use of two-tailed t-tests (at $p < 0.05$) for hypothesis testing in PLS-SEM, including bootstrapped confidence intervals. Following established statistical conventions (Hair et al., 2019), null hypotheses (H_0) were rejected when p-values derived from bootstrapped t-tests fell below 0.05 ($p < \alpha$), indicating statistically significant relationships between constructs. Conversely, p-values exceeding 0.05 ($p > \alpha$) warranted retention of H_0, suggesting insufficient evidence for hypothesized effects.

6.2.4 Model Fit

The model fit has been assessed by **Standardized Root Mean Square Residual (SRMR) and** R^2. In this case, the model fit is acceptable, as indicated by the R^2 value of 0.533. Hair et al (2014) argued that the R^2 value more than 0.50 represents the moderate relationship for model fit. Additionally, the SRMR value is 0.06 which is less than 0.08. Hair et al (2014) claimed that SRMR value should be less than 0.08 to ensure the model fit of PLS SEM. In this case, the SRMR value also indicates how well the PLS-SEM model fits the independent and dependent variables.

Table 8: Outputs of the Structural Model for Testing Hypothesis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|) (β)	P values	Decision
DL -> IAI	0.173	0.172	0.084	2.058	0.040	Supported
DSS -> IAI	0.127	0.131	0.058	2.201	0.028	Supported
ES -> IAI	0.082	0.083	0.042	1.975	0.048	Supported
IRV -> IAI	0.196	0.197	0.06	3.261	0.001	Supported
ML -> IAI	-0.014	-0.015	0.049	0.282	0.778	Not Supported
NN -> IAI	0.356	0.351	0.075	4.756	0.000	Supported
OS -> IAI	0.06	0.063	0.041	1.469	0.142	Not Supported

The standardized beta coefficients (β) quantify the strength and direction of relationships between AI technologies and apparel industry outcomes, while significance levels (p-values) confirm their statistical reliability. The extraordinarily high t-statistics for IRV→IAI ($t=3.261$, $p=0.001$) and NN→IAI ($t=4.756$, $p<0.001$) demonstrate these technologies have both strong effect magnitudes ($\beta=0.196$ and 0.356 respectively)

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7. Discussion on Findings

The study examines the differential impacts of artificial intelligence (AI) tools on Bangladesh's apparel industry, conceptualizing their benefits as multi-dimensional exogenous constructs and their aggregate influence as a single-dimensional endogenous construct termed Intelligent Apparel Integration (IAI). Contrary to expectations, generic machine learning (ML) applications demonstrate no statistically significant effect ($\beta = 0.282$, *p* > 0.05), suggesting limitations in their current deployment or adaptability within the sector. In contrast, specialized AI technologies exhibit robust positive associations with IAI: expert systems ($\beta = 1.975$, *p* < 0.05), decision support systems ($\beta = 2.201$, *p* < 0.05), image recognition and vision ($\beta = 3.261$, *p* < 0.01), deep learning ($\beta = 2.058$, *p* < 0.05), and neural networks ($\beta = 4.756$, *p* < 0.001) all achieve significance, with t-statistics for IRV (3.261) and NN (4.756) surpassing critical thresholds for *p* < 0.01 and *p* < 0.001, respectively (Hair et al., 2023). The latter's t-value, coupled with a negligible probability of chance (*p* < 0.0001), underscores neural networks' exceptional role in driving industry transformation. Standardized coefficients (IRV: $\beta = 0.196$; NN: $\beta = 0.356$) further corroborate these tools' moderate-to-strong practical relevance, particularly in automating and optimizing garment production processes. With an R^2 of 0.533, the model explains 53.3% of IAI's variance, indicating substantial predictive power (Hair et al., 2014). These findings collectively suggest that while broad ML frameworks remain peripheral, targeted AI adoption— especially neural networks, computer vision, and decision-support tools—holds significant potential to enhance operational efficiency and global competitiveness in Bangladesh's ready-made garment industry.The study identifies strong positive correlations among five AI tools—Expert Systems, Decision Support Systems, Image Recognition and Vision, Deep Learning, and Neural Networks—in their impact on the Bangladeshi apparel industry. In contrast, Machine Learning and Optimization Systems showed no significant correlation. These findings align with earlier research (Sharmin, 2022; Hassani et al., 2020) and suggest that effectively utilizing AI in supply chain management, design, and production can help Bangladesh maintain its competitive edge in the global market. AI-enabled clothing design has reduced costs, increased efficiency, and addressed issues of human accuracy and quality variance, while predictive analytics can enhance demand forecasting, reduce overproduction, and promote sustainability in the sector. Surprisingly,The study reveals that Machine Learning and Optimization Systems have a limited impact on the Bangladeshi apparel industry. Despite AI's potential for solving complex problems, these tools do not significantly influence the sector.

8. Practical Implications

The study's findings present critical insights for industry stakeholders by delineating which AI technologies offer measurable benefits versus those requiring cautious implementation. For manufacturers, the strong performance of

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expert systems ($\beta = 1.975$, $p < 0.05$) underscores their value in automating compliance processes and customer service operations, directly addressing pain points in labor regulation adherence and export market responsiveness. The significant impact of Decision Support Systems ($\beta = 2.201$, $p < 0.05$) highlights their transformative potential for supply chain management, enabling data-driven procurement and logistics decisions that could enhance Bangladesh's competitiveness against regional rivals.

Optimization algorithms emerge as vital tools for tackling chronic inefficiencies, particularly in production scheduling and inventory management. Their implementation could substantially reduce fabric waste and idle capacity—key cost factors in an industry operating on thin margins. While deep learning shows promise for quality control ($\beta = 2.058$, $p < 0.05$), the rejection of related hypotheses suggests manufacturers should focus on tailored applications, such as defect detection models trained on localized production issues rather than generic computer vision solutions.

The lack of significant impact from generic machine learning and neural networks carries important implications for technology investment strategies. This finding suggests that industry stakeholders—including factory owners, trade associations, and government bodies—should prioritize proven technologies while adopting a measured approach to emerging tools. For policymakers, these results emphasize the need for targeted AI literacy programs and infrastructure development to support effective adoption of high-impact systems like DSS and expert systems.

Collectively, these insights provide a framework for strategic AI integration that aligns technological capabilities with the sector's operational realities. The findings caution against broad, indiscriminate technology adoption while identifying specific areas where AI can deliver immediate, measurable benefits to Bangladesh's apparel industry. This evidence-based perspective enables stakeholders to make informed decisions that balance innovation with practical implementation challenges.

9. Limitations & Future Agenda of the Study

This research has several limitations that warrant consideration. First, the sample size of 300 respondents may not fully represent Bangladesh's apparel sector, potentially affecting generalizability. Second, reliance on self-reported surveys introduces possible response biases. Third, the limited number of referenced studies and restricted access to current industry data may have constrained the depth of analysis. A notable conceptual limitation emerges from the findings on Machine Learning (ML). While ML as a broad category showed no significant impact ($\beta = 0.282$, $p > 0.05$), its subsets—Deep Learning (DL) and Neural Networks (NN)—demonstrated strong effects ($\beta = 2.058/4.756$, $p < 0.05$). This inconsistency suggests potential construct misclassification, as the study does not clarify whether "ML" excluded DL/NN or encompassed all ML paradigms. Future research should explicitly define these constructs to enhance

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interpretability. Additionally, the dynamic nature of both AI technologies and the apparel industry means findings may require periodic reassessment. While the study focused on AI's role, other unexamined variables could also influence sectoral growth. Beside, pproximately half of the literature were not specific to Bangladesh's apparel industry, suggesting potential limitations in the study's contextual relevance and theoretical grounding. This underscores the need for more targeted, domain-specific references in future AI/ML research on this sector. These limitations highlight opportunities for more comprehensive future research with expanded datasets and clearer theoretical frameworks.

10. Conclusion

This study systematically examined the impact of seven AI tools on Bangladesh's ready-made garment (RMG) sector. The analysis revealed significant positive correlations for Expert Systems, Decision Support Systems (DSS), Image Recognition, Deep Learning, and Neural Networks with operational improvements, while Machine Learning and Optimization tools showed negligible or negative effects. These findings highlight the need for strategic adoption of domain-specific AI technologies—particularly DSS and neural networks for supply chain optimization and quality control—rather than generic ML applications. By prioritizing high-impact tools identified in this research, Bangladesh’s apparel industry can enhance efficiency, competitiveness, and adaptability in global markets. Future studies should explore longitudinal AI implementation outcomes in this sector.

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