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LEVERAGING ARTIFICIAL INTELLIGENCE TO ENHANCE EFFICIENCY AND SUSTAINABILITY IN THE LEATHER INDUSTRY

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Abstract

Every business on the earth is undergoing a change thanks to artificial intelligence (AI); from cyber security and driverless cars to healthcare apps, medicine, and geology, AI is now essential to human survival. AI is growing quickly in the manufacturing sectors as well, since all organizations are embracing digital transformation. India is the world's second-largest manufacturer of leather goods that are shipped outside. However, the nature of the operation remains dubious. There are 144 footwear industries in Tamil Nadu, which is in southern India. These businesses manufacture a variety of shoes for both domestic and international markets. Either synthetic or pure leather was used to make the footwear. Data was gathered from all production managers in the footwear industry using a straightforward random sample technique. The data was gathered using Google Forms and surveys. Python was used to analyse the data and determine the most common system type in this industry. The study ran for six months, from June 2024 to December 2024. Measures to address those barriers must be prioritized by industries. Financial limitations and a lack of trained workers are the biggest barriers to automation, but industries should give these issues top priority for a seamless workflow where environmental rules and change opposition are concentrated.

Keywords: Artifical Intelliegence , Automation, Sustainability, Efficiency ,Leather production

1. Introduction

The range of client needs, technological advancements, and global integration are making today's business scenarios more complex [1].Some of the key factors causing these disparate business conditions are worries about product quality, a wider variety of products, and constantly shifting markets [2]. In order to keep up with these new developments, the leather, leather goods, and footwear production sectors are under extreme pressure to innovate their operational performance. These manufacturing sectors must modernize and automate, It raises production costs even further [3].

This industrial sector needs to operate with excellence in order to respond to market conditions. The pursuit of operational excellence is one strategy that aids this industry in navigating a road toward achieving its goals.

Throughout history, innovation has been the primary driver of rising living standards. However, because it renders traditional technology outdated, the innovation process can be extremely disruptive. The emerging technologies of cloud computing, the Internet of Things (IoT), big data, data science, artificial intelligence (AI), and blockchain have the potential to produce both winners and losers globally. At least 2.5 decades have passed since the invention of several of these technologies [4].

The fashion industry, which is highly segmented and generates a wide range of fashion products, is

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one of the most important sectors globally in terms of investment, revenue, trade, and job generation. Brands need to implement agile supply chain systems to meet consumer. In the wake of this rapid and dynamic change. As which to greatly improve real time predictive analysis, to put forth better product assessments and monitoring, and. Optimize the supply chain, also it is of great value to the apparel. sector. AI for example uses big data to speed up product design and enable dynamic. Forecasting which customer demand will go. Using AI to track stock levels, identify trends in. Consumer data and we will see to it that the time for which they are brought to market is reduced as well as the methods made better and more efficient [5].

Fashion and apparel operations are transforming as a result of artificial intelligence (AI). We see that which is made possible by AI driven technology is process automation leading to faster and better operations, greater in product design and improved customer service. Also AI gives companies very precise customer data which in turn enables them to better understand consumer trends and to create tailored products and services. AI plays in supply chain visibility, consumer demand prediction, design improvement and production process automation. Via use of AI enabled technologies like computer vision and natural language processing we can see the development of virtual assistants which assist customers in finding what best fits their needs and style [6].

Also, AI based analytics can identify which products consumers prefer.Enabling companies to tailor their products. In terms of which, artificial intelligence.AI is a powerful tool which has the ability to transform the F&A sector.Powered by technology companies are able to perform which is faster, more efficient, and at a lower cost. Also AI allows companies to better serve their customers and.offer customized goods and services [7].

AI technology will certainly continue to transform the fashion and apparel world down the road. Artificial Intelligence (AI) has been playing a big role in the fashion industry as tech improves. For fashion companies, AI can help to enhance consumer experiences, accelerate production cycles, improve product performance and quality, reduce costs, and optimize their supply chain through changes to manufacturing and product delivery. There are also uses of AI that serve clients with goods and/or services, identify flaws or irregularities in clothing or textiles, as well as automate activities such as pattern recognition. Insight and customer trends With customer behavior and insight as well, AI can be used to improve the customer experience. AI can also help fashion businesses to leverage the data they collect from consumers (e.g., trends, tastes) for decision-making in production and design [8].

Even virtual fitting rooms that can make a full recommendation to clients about what clothes will fit them best and how to accessorize can be programmed with AI. The garment industry has also discovered the usefulness of the AI. AI can reduce costs, improve product shape and performance, automate processes and streamline the customer experience. AI and fashion combined can revolutionize the industry and enhance the chances of success for fashion brands like never before. Thus far, AI has been applied to the clothing and fashion industry. AI-enabled systems can generate predictive analytics about consumer choice patterns and fashion trends. as it is capable of addressing limitations of classical mathematical models. This is also the case in the fashion and garment sectors [9].

AI-based solutions offers brands with predictive insights into their consumer's preferences and fashion trends.AI has become synonymous with tying companies together around the world. AI is now part of our daily life and is driving several tasks from prediction, search, search engine optimization, predictive analytics, automated customer assistance and automated customer service. Companies have profited from AI’s capacity to accelerate data processing, upgrade customer service systems and enhance operational efficiency. Furthermore, AI-based applications could be exploited to reduce both money and time spent on repetitive tasks (such as data entry and data analysis, etc), reducing hiring costs of human labour [10].

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Furthermore, companies can leverage AI-based platforms to know the needs and wants of their clients and offer personalized services which will in turn instil client loyalty. As AI can make better and faster decisions and enhance the user experience, it is not going to disappear and will affect companies more and more [11].

Many businesses are leveraging AI to enhance precision and automate a number of tasks within their operations and production process. AI-based analytics also promise great potential in predictive management, forecasting and decision-making. Artificial intelligence will still drive the fashions industry future, and its importance to companies is increasing more and more [12].

AI has the complete capacity to transform how businesses run, manage their operations, enhance customer satisfaction, and maintain expenses under control. AI will continue to play a significant role in operations and manufacturing in the future, even though there is still a great deal of room for greater integration. In the upgrading world it is extremely important because the fashion industry is unstable and it appears to be hard to react for adjustments in line with the newest trends and changing customer expectations [13].

2. review of literature

1. Introduction: The Need for AI in Sustainable Leather Production

The leather industry, has began adapting artificial intelligence (AI) technologies more frequently, drawing interest due to their ability to improve a company's sustainability and cut overall operational costs. Leather production is integrated into the global economy through its connection with fashion, automotive, and furniture industries which poses several challenges such as the industry's considerable Environmental footprint from the heavily resource demanding processes of tanning and finishing Sakd finishing [14]. This problem is worsened by the ongoing issue of water scarcity in some areas, adding to the long-term problem of resource depletion . At the same time, evolving consumer needs coupled with the need for agile mass customization is forcing manufacturers to respond immediately [15]. The issue of inefficiencies in leather production which is a result of the multi stage process from raw material acquisition to final delivery is a common issue which in turn puts a strain on the balance between environmental responsibility and economic sustainability [14], [15].

AI presents itself as a solution to these many issues. With its ability to work with large data sets, identify trends and present predictive info AI is putting in place solutions for us. We see in process automation, reduced human error and better decision making that AI is improving the game [16], [17]. Also we have predictive maintenance which via AI is to blame for reduced machine down time and maintenance costs which in the same breath improves production continuity [14], [17]. Also at the same time we have AI based quality control systems which play a role in waste reduction through very accurate defect detection and better resource allocation [18], [14].

Also, AI is increasing future demand forecasting and logistical efficiency and streamlining supply chains which makes the whole leather industry more resilient and sustainable [19], [20]. This review combines latest research on the applications of AI in leather industry, critically assesses their impacts, points out their limitations, and recommends future research directions.

2. AI Applications in Leather Manufacturing Processes

2.1 Automation and Process Optimization

AI-driven automation is reshaping leather manufacturing by enhancing productivity, quality control, and resource efficiency. In early-stage processing, AI algorithms have been deployed to optimize the tanning process through real-time analysis of variables such as chemical concentration, temperature, and time, thereby reducing the use of harmful substances and water [14], [21]. This not only leads to

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a reduction of environmental pollution (see below) but also to an increased occupational safety [14].

Another major breakthrough is image recognition systems based on artificial intelligence that make it possible to fully automatically detect defects in hides and skins. By detecting surface defects (e.g., wrinkles, discoloration, and scratches), such systems enable the more accurate sorting and grading of products, achieving higher product yield and consistency and reducing dependence on manual inspection [18], [21]. With regards to finishing operations, AI can help control the dyeing, coating or embossing of surfaces to ensure uniform aesthetics and minimize rework [21].

In the cutting procedure and sewing techniques, AI-enabled robotics are increasingly used. By means of computer vision, cutting systems maximize the pattern layout of leather while minimizing the waste. Similarly, robotic sewing machines enhance precision, speed, and consistency, while also improving worker ergonomics by alleviating physical strain [15], [16]. Altogether, these innovations contribute to lower production costs, reduced cycle times, and elevated product standards.

2.2 Predictive Maintenance and Fault Detection

AI in leather manufacturing: Call it 'predictive maintenance' of our machinery, in which we can sense future machinery maintenance cycle. Real-time sensor data from equipment — for instance temperature, vibration or energy consumption — can be used to detect anomalies and predict failure of the equipment using AI models [14], [17], [22]. With a preventive strategy, companies can plan maintenance operations before something bad happens, which means unprevented downtime is reduced and the life of the equipment maximized [14], [22].

AI also improves the quality that can be assured by putting the checks in place with a real-time fault-detection. Such systems analyze real-time data for possible deviations indicating potential underlying faults. By early identification of these defects, their timely correction is made possible in order to avoid defective products, saving on resources and enhance the overall process efficiency [17], [18]. Furthermore, they also enhance safer working environments by detecting mechanical hazards well before they become threatening [17].

3.Leveraging AI to Manage Resources Sustainably in Leather Production

3.1 Water and Energy Efficiency

Among the various leather making processes, the tanning process as well as the finishing stage are the most water and energy consuming stages. AI offers practical solutions for maximizing these inputs. AI systems that can monitor and adapt allocation of resources, resources, continue improving system performance while ensuring minimal product quality degradation [14], [22].

For example, if AI-based control systems control water flow and temperature in tanning drums for minimum water and energy uptake while still maintaining performance [14].

Likewise, AI optimization saves energy for energy-hungry operations such as drying and finishing, resulting in reduced electricity use and operational costs [22]. AI-based intelligent monitoring solutions provide up-to-the-minute analysis of energy and water consumption.

These systems recognise waste inefficiency and support rapid adjustments, contributing to a more sustainable and environmentally friendly approach [14], [23].

3.2 Waste Reduction and Recycling

Solid waste production is a concern in the leather industry [1], [24]. Advanced image recognition systems are enabling AI technologies to aid in the automation of sorting, recycling to help minimize waste [18], [24]. These applications improve the granularity of the waste types, increase the accuracy in recycling the waste, increase the throughput of the recycling, and decrease the error condition induced by humans.

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In addition, AI technologies can improve the operation of waste treatment plants by processing data about waste composition and processing conditions. This in turn results in higher energy recovery, lower emissions and a better use of by-products[14]. AI, for instance, can adjust the controls in the anaerobic digestion systems to improve biogas production and promote circular production.

4. AI in Supply Chain Management for the Leather Industry

4.1 Demand Forecasting and Inventory Management

Efficient management of the supply chain is vital for the economic and environmental viability of leather processing [15], [19], [20]. AI forecast support tools process historical sales, market data, and macroeconomic indices and forecast a demand more accurately [15], [20]. It allows manufacturers to optimize inventory levels, minimize excess inventory and minimize the risks of overproduction and waste [19], [20]. Accurate prediction also enables the companies to better match their production with consumer taste, providing responsiveness without sacrificing efficiency.

4.2 Supply Chain Optimization and Traceability

AI helps to streamline logistics and improve transparency in the supply chain, too. Transport routes, fuel usages and time of deliveries are all the time tested for delivering costs, optimal delivery arrival time and low emissions by the algorithms to decrease the cost and delivery lag [19]. When employed with blockchain, AI enhances traceability across the supply chain including raw material sourcing, final product distribution [20], [25].

This dual-system design results in a tamper proof, transparent ledger for all transactions and process steps. Materials can be also traced back to its origin, results in safe and authentic products [25]. These developments increase operational transparency and also provide consumers with confidence backed by verifiable information about the environmental and social credentials of leather articles [25], [20].

5. Challenges and Limitations of AI Implementation in the Leather Industry

Although the opportunities are clear, there are still challenges preventing widespread use of AI in the leather industry. One limitation is the availability and quality of the data. The absence of uniform data collection models and differences in operation methods between tanneries, make it difficult to train and to apply AI models [21], [20], [8].

Cost of AI implementation, now low hanging fruit for small and medium enterprises (SMEs), cost of AI adoption stands as an additional frustration. The implementation of such systems can be cost prohibitive due to the high cost of cutting edge hardware, specialized software, and trained personnel [15], [20]. Further, investment required for reliable data infrastructure and management systems is an additional investment [20].

Workforce-related challenges further complicate adoption. It is expensive and challenging to design, implement and maintain AI systems effectively due to a lack of AI expertise and technical capacity in organizations [15]. Upskilling current employees requires time and resources, potentially disrupting existing workflows.

Finally, we also need to think about how data is private and biased. Sensitive operational data may create legitimate privacy and related security risks. In addition, if AI systems are trained with partial or distorted data, its results would produce bias or unfairness [26]. To ensure the leather industry uses AI responsibly and equitably, it must address these ethical issues.

Three research questions were developed keeping these things in mind.

Analysing the challenges to automation for attaining sustainable leather production

Identifying the cause and effect interactions among the identified challenges

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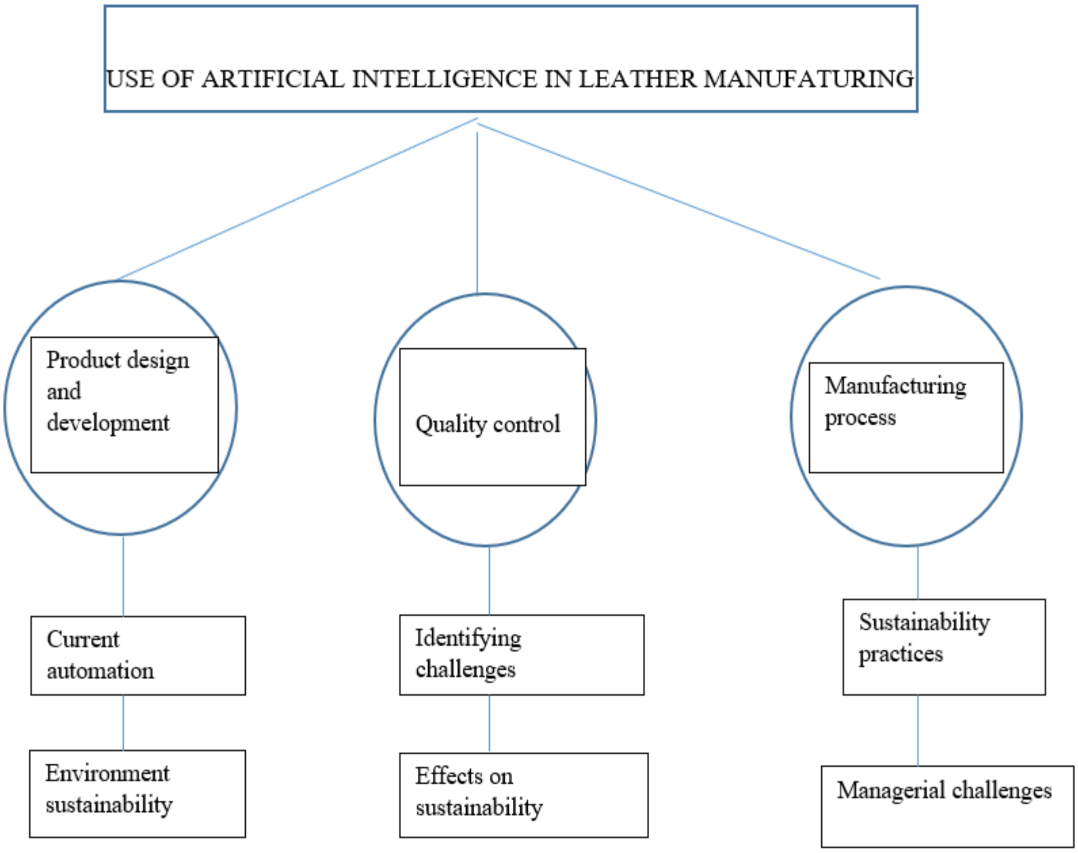
Recommending managerial and practical implication for executing

3. Framework



4. Methodology

The literature, which concentrated on economies that had gone through economic crises in one form or another, provided the study's many criteria. In order to investigate the consequences of the nation's adoption of artificial intelligence to improve sustainability and efficiency, this study used a mixed-method approach. After being extracted from the literature, the factors affecting the obstacles and strategies were empirically examined. To determine the particular challenges that each industry faced and how to address them in light of introducing artificial intelligence to the sector, a qualitative method was adopted. To close the gap between the challenges and solutions identified in the body of current literature, a qualitative approach was used following the quantitative method.

The descriptive research study was conducted in Vellore District, Tamil Nadu. Data gathering and analysis took roughly six months. 125 employees provided primary data, and research journals and other pertinent sources provided secondary data. To gather data, the researcher employed a straightforward mean sampling technique, which involved creating a questionnaire with 17 items based on existing literature. To ascertain the link between the independent and dependent variables, the data were computed using a Python program.

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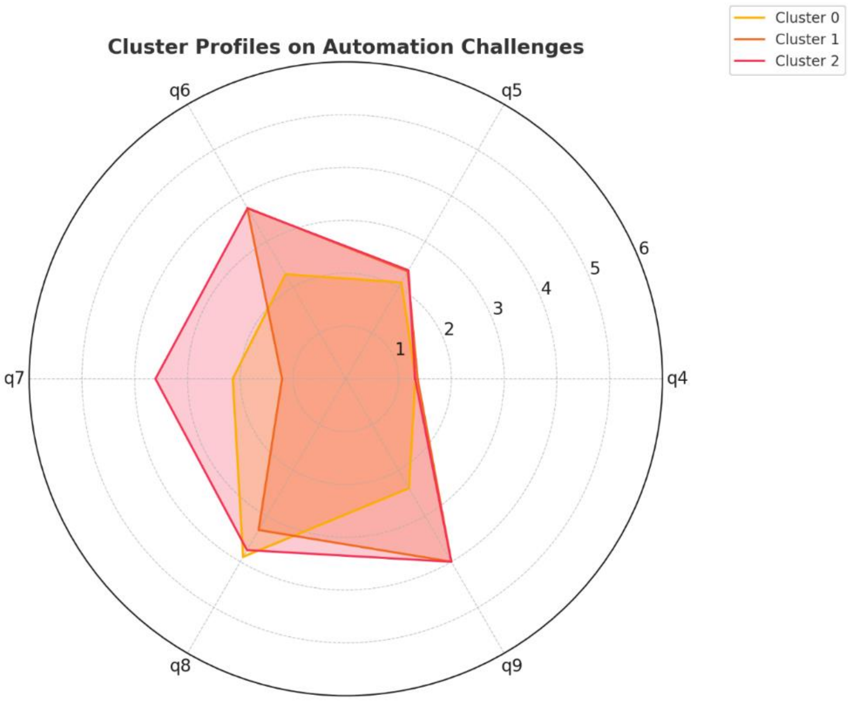
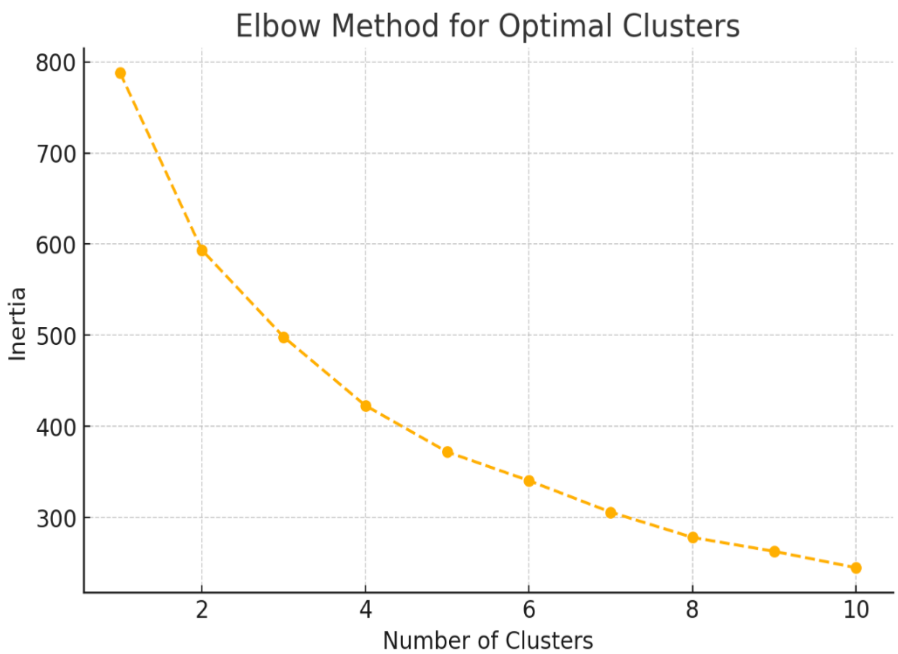
5. Dataanalysis And Intepretation

5.1Analysing the challenges to automation for attaining sustainable leather production





Cluster Results

Table 5.1.1 presents the cluster centers, illustrating the mean ratings across the six factors for each cluster. The cluster sizes are also included to indicate the proportion of respondents in each group.

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Table 5.1.1. Cluster Centers and Sizes

Factor	Cluster 0	Cluster 1	Cluster 2
Q4	1.32	1.36	1.31
Q5	2.11	2.35	2.37
Q6	2.29	3.74	3.73
Q7	2.14	1.21	3.61
Q8	3.89	3.31	3.75
Q9	2.39	4.00	4.00
Cluster size	28	72	51

Key Findings

- **Cluster 0**: Moderate ratings across most factors, emphasizing environmental sustainability (q8) but with lower ratings for cost-benefit considerations (q6).
- **Cluster 1**: Highest ratings for process efficiency (q6) and sustainability outcomes (q9), with minimal concern for external challenges (q7).
- **Cluster 2**: Balanced ratings, with a focus on external challenges (q7) while maintaining high ratings for sustainability outcomes (q9).

Radar Plot Visualization

The radar plot (**Figure 1**) visually represents the cluster profiles, providing insights into the differences in factor ratings across the three clusters.

Figure 1. Cluster Profiles on Automation Challenges

(Refer to the radar plot generated earlier, showing the profiles for Clusters 0, 1, and 2 across factors q4 to q9.)

Implications for Automation and Sustainability

1. **TechnologicalAdvancements**:
For **Cluster 2**, addressing automation challenges (high q7 ratings) is key to building confidence and ensuring adoption.

2. **EconomicFeasibility**:
Clusters across the board rated cost-benefit effectiveness (q6) as crucial, suggesting that automation strategies must demonstrate clear economic advantages.

3. **SustainabilityPrioritization**:
The high ratings for sustainability outcomes (q9) across Clusters 1 and 2 highlight the importance of aligning automation strategies with environmental goals.

4. **Cluster-Specific Strategies**:

- **Cluster 0**: Focus on highlighting sustainability benefits to offset cost concerns.
- **Cluster 1**: Promote success stories of automation in sustainability to reinforce positive perceptions.
- **Cluster 2**: Address specific technological and external challenges to build trust and adoption.

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Figures and Statistical Analysis

Cluster Distributions

Table 5.1.2 provides the cluster distributions, showing the percentage of respondents in each cluster.

Table5.1. 2. Cluster Distribution

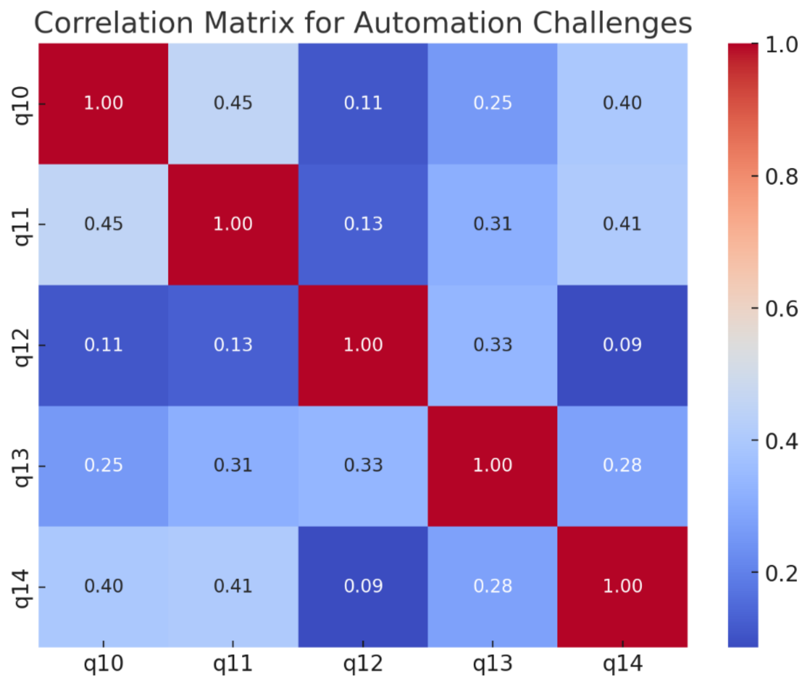
Cluster	Number of Respondents	Percentage
Cluster 0	28	18.5%
Cluster 1	72	47.7%
Cluster 2	51	33.8%

Conclusions

This study highlights the varying perceptions of automation for sustainable leather production. While clusters display optimism regarding automation's sustainability benefits, concerns about external barriers and economic feasibility remain significant. Policymakers and industry stakeholders must prioritize tailored strategies to address these challenges and promote automation adoption.

Future research could explore the integration of specific automation technologies with sustainability metrics and investigate their economic and environmental impacts.

5.2 Identifying the cause and effect interactions among the identified challenges



Correlation Analysis

Table 5.2.1 presents the Pearson correlation coefficients among the variables (q10 to q14). The correlation matrix highlights the strength and direction of relationships between the identified challenges.

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Table 5.2.1. Correlation Matrix of Automation Challenges

Factor	Q10	Q11	Q12	Q13	Q14
Q10: Organisational challenges	1.000	0.451	0.109	0.255	0.397
Q11: Financial constraints	0.451	1.000	0.126	0.312	0.407
Q12: Environmental regulations	0.109	0.126	1.000	0.335	0.086
Q13: Resistance to change	0.255	0.312	0.335	1.000	0.277
Q14: Skilled workforce shortages	0.397	0.407	0.086	0.277	1.000

Key Findings:

1. **Strong Correlations**:

o Organizational challenges (q10) strongly correlate with financial constraints (q11, r = 0.45) and skilled workforce shortages (q14, r = 0.40), suggesting these are primary drivers of implementation difficulties.

2. **Moderate Correlations**:

o Resistance to change (q13) moderately correlates with financial constraints (q11, r = 0.31) and environmental regulations (q12, r = 0.33), indicating interplay between internal and external factors.

3. **Weaker Correlations**:

o Environmental regulations (q12) have minimal direct impact on organizational challenges (q10), highlighting their isolated nature.

Regression Analysis

A multiple linear regression model was employed to quantify the impact of explanatory variables (q11 to q14) on organizational challenges (q10). The results are summarized in Table 5.2.2.

Table 5.2.2. Regression Results for Organizational Challenges

Factor	Coefficient	Impact (Direction)	Significance
Q11: Financial constraints	0.284	Positive	Significant
Q12: Environmental regulations	0.017	Positive	Insignificant
Q13: Resistance to change	0.059	Positive	Insignificant
Q14: Skilled workforce shortages	0.179	Positive	Significant

- **R-Squared**: 0.26, indicating that 26% of the variance in organizational challenges can be explained by the model.

Key Findings:

- Financial constraints (q11) and skilled workforce shortages (q14) exert the most significant impact on organizational challenges, with positive coefficients of **0.284** and **0.179**, respectively.

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- Environmental regulations (q12) and resistance to change (q13) have minimal impact, suggesting these factors might be indirectly influencing challenges through other variables.

Visualization of Relationships

Figure 2 displays the correlation heatmap, visually emphasizing the relationships between the variables.

Figure 2. Correlation Heatmap of Automation Challenges

(Refer to the heatmap generated earlier.)

Discussion

1. **Impact of Financial Constraints**: Financial constraints strongly correlate with and significantly impact organizational challenges. This suggests that budget limitations hinder investments in automation technology and workforce training, leading to broader implementation difficulties.

2. **Role of Workforce Shortages**: Skilled workforce shortages emerge as a critical challenge, both in correlation and regression analyses. This highlights the need for targeted efforts to build technical expertise and reduce resistance to automation.

3. **Regulatory and Behavioral Factors**: While environmental regulations and resistance to change showed moderate correlations, their direct impact on organizational challenges is limited. These factors may act as intermediaries, exacerbating financial and workforce issues.

4. **Actionable Insights**:

○ Addressing financial barriers through incentives or subsidies could reduce organizational challenges.

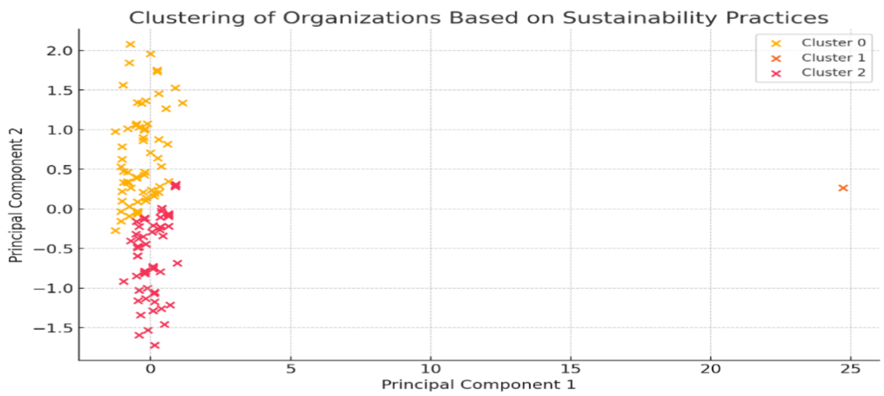
○ Workforce development programs focusing on technical upskilling can alleviate shortages and resistance to automation.

○ Policymakers and organizations should integrate regulatory frameworks that encourage innovation while ensuring environmental compliance.

Conclusion

This analysis reveals the interplay between financial, workforce, regulatory, and behavioural factors in shaping automation challenges. Addressing financial constraints and workforce shortages should be prioritized, as they significantly impact organizational difficulties. Future research could explore causal pathways and intervention strategies to mitigate these challenges and promote sustainable automation adoption.

5.3 Recommending managerial and practical implication for executing



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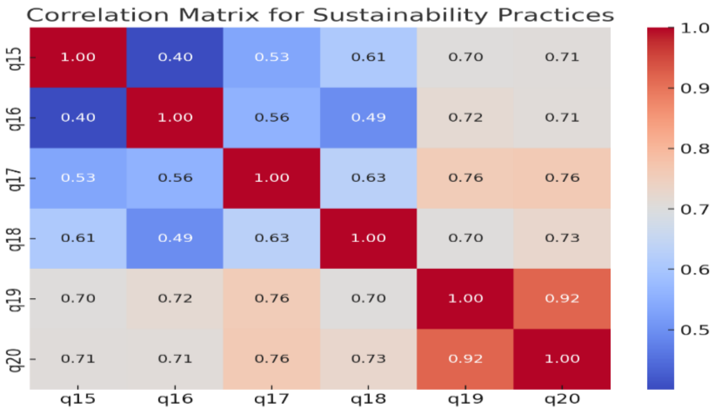

This section presents the analysis of organizational responses regarding sustainability practices, budget allocation, environmental considerations, alignment challenges, employee training, and the need for organizational support. Using Principal Component Analysis (PCA) and clustering, key factors and organizational groups were identified.

Principal Component Analysis (PCA)

PCA was used to reduce dimensionality and identify key components influencing sustainability practices. The results are summarized in **Table 1**.

Table 5.3.1. Principal Component Analysis Results

Principal Component	Explained Variance (%)	Key Variables
PC1	72.4	Training for employees, environmental impact, organisational support requirements
PC2	10.4	Budget allocation, challenges in aligning sustainability

- **PC1**: Represents variables tied closely to direct organizational efforts, such as training and sustainability support.
- **PC2**: Reflects financial and strategic alignment challenges.

These two components explain **82.8%** of the total variance, indicating that they effectively summarize the dataset.

Clustering Analysis

K-Means clustering on PCA-transformed data resulted in three distinct clusters. **Table 2** summarizes the cluster characteristics.

Table 5.3.2. Cluster Characteristics

Cluster	Number of organisations	Key Characteristics
Cluster 0	74	Moderate focus on training and budget allocation.
Cluster 1	1	Outlier with unique challenges and practices.

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Cluster 2	76	High emphasis on training and organisational support.

Figure 3 visualizes the clustering results in PCA space, highlighting distinct groups of organizations.

Visualization of Clusters

Figure 3. Clustering of Organizations Based on Sustainability Practices

(Refer to the scatter plot displaying clusters in PCA-transformed space.)

Mathematical Insights and Tables

Table 5.3.3 highlights the cluster centers in terms of the original variables to provide quantitative insights.

Table 5.3.3. Cluster Centers Based on Original Variables

Factor	Cluster 0	Cluster 1	Cluster 2
Q15: Sustainability Practices	3.76	5.00	4.12
Q16: Budget Allocation	3.22	5.00	3.85
Q17: Environmental Impact	3.93	5.00	4.56
Q18: Alignment Challenges	3.85	4.00	4.18
Q19: Training	2.78	1.00	3.86
Q20: Support Requirements	3.10	4.00	4.12

Discussion

1. **Cluster 0 (Moderate Performers)**:

o These organizations demonstrate moderate emphasis on training and budget allocation. While sustainability practices are implemented, alignment with goals needs improvement.

o **Recommendation**: Focus on increasing budget allocation for sustainability and enhancing employee engagement through targeted training programs.

2. **Cluster 1 (Outlier)**:

o This organization uniquely faces both high budget allocation and alignment challenges. It exhibits a lack of emphasis on training and support despite strong sustainability practices.

o **Recommendation**: Address training gaps and leverage high budget resources to create a robust sustainability framework.

3. **Cluster 2 (High Performers)**:

o Organizations in this cluster prioritize training and organizational support for sustainability. However, they face challenges in aligning sustainability goals with practices.

o **Recommendation**: Strengthen alignment strategies through collaborative decision-making and dedicated sustainability committees.

Managerial Implications

1. **Training and Capacity Building**:

o High correlation between training and sustainability practices (r = 0.92) underscores the importance of investing in employee skill development. Customized training programs tailored to sustainability needs are crucial.

2. **Budget Optimization**:

o Organizations with moderate budget allocation (Cluster 0) should reallocate financial resources to achieve sustainability objectives effectively.

3. **Strategic Alignment**:

o Alignment challenges (q18) remain consistent across clusters. Implementing cross-functional sustainability teams could enhance goal integration.

4. **Tailored Support for Outliers**:

o Unique challenges faced by the outlier group (Cluster 1) call for specialized interventions, such as regulatory support or partnerships with sustainability consultants.

Conclusion

The analysis identified three organizational groups with distinct sustainability practices and challenges. Recommendations include increased training, optimized budget allocation, and strategies to address alignment issues. These findings provide actionable insights for managers and policymakers aiming to enhance sustainability in organizations. Future studies could explore sector-specific strategies and evaluate longitudinal impacts of these recommendations.

6.Discussion

Since cost-benefit effectiveness techniques must show more economic value and emphasize the need of connecting automation with environmental goals, overcoming automation's obstacles is essential to fostering trust and guaranteeing adoption.

Financial restrictions, talent shortages in the workforce, and the main causes of resistance to change have a modest relationship with each other in the cost-effect interactions.

The organization places a moderate amount of focus on budget allocation and training in its recommendations. They have difficulties, though, in coordinating sustainability objectives with practices.

7. Findings

In order to encourage automation, industries need to give priority to measures that tackle those obstacles. While the most significant obstacle to automation is a skilled workforce shortage and financial constraints, industries should prioritize these factors for a smooth workflow where environmental regulations and resistance to change are concentrated. A training program must be essential.

8. Sugessstion

Future research could examine pathways and intervention strategies to mitigate these challenges, and recommendations for increased training, budget allocation, and alignment issues should be prioritized by policymakers and industry stakeholders. Suggestions for improving efficiency and sustainability should also be prioritized.

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