Vol. 06, No. 2 (2024) 807-816, doi: 10.24874/PES06.02A.007

Proceedings on Engineering Sciences

www.pesjournal.net

ENTREPRENEURIAL MINDSET IN MODERN APPAREL: THE ROLE OF MACHINE LEARNING IN DRIVING SUSTAINABLE INNOVATION

Nishtha Ujjawal[1]
Manisha Gupta
Shagun Sharma
Hari Shankar Shyam

Received 08.09.2023.
Received in revised form 16.01.2024.
Accepted 27.02.2024.
UDC – 502.131.1

Keywords:

Sustainable Innovations, Apparel Industry, Machine Learning, Eco-Friendly, Entrepreneurial.

A B S T R A C T

The apparel industry is on the cusp of a significant transformation, driven by an entrepreneurial spirit that embraces innovative approaches and sustainable practices. This study investigates the incorporation of ML in the contemporary apparel industry, highlighting its potential to promote transformative sustainable practices. Focusing on garment firms, the study demonstrates how ML is being used to be Source eco-friendly materials, reduce waste ,improve energy efficiency, increase supply chain transparency. The study also draws on qualitative insights from industry experts to identify the possibilities and challenges of integrating ML within the apparel industry. Overall, the study highlights the paradigm shift underway in the apparel industry, driven by an entrepreneurial mindset and facilitated by ML technology. This study functions as a guiding light, directing policymakers, industry leaders, and academics towards the advancement of a balanced integration of ML and sustainable entrepreneurship in modern apparel practices.

1. INTRODUCTION

The apparel industry makes a substantial contribution to the economy of the whole globe by generating job opportunities and catering to various fashion preferences of customers all over the world. However, the fast development and globalization of this business have also brought about environmental and social difficulties, forcing a shift towards sustainable practises. In order to address these challenges, sustainable practises need to be implemented (Gupta et al., 2024). across recent years, the use of methods derived from machine learning has emerged as a potentially fruitful approach for tackling difficulties pertaining to sustainability across a wide range of business sectors. By leveraging the power of data analysis and predictive modelling, machine learning may make it easier to make educated decisions and enhance the efficiency with which resources are used. In order to promote eco literacy and encourage decision making that is environmentally conscientious, it is essential to get an understanding of the influence that machine learning has had on sustainable practises in the apparel industry (Rathore, 2023).

[1] Corresponding author: Nishtha Ujjawal
Email: nishtha11ujjawal@gmail.com

This empirical research is to evaluate the influence that machine learning has on sustainable practises in the garment sector, with a specific emphasis on the role that environmental literacy plays in this relationship (Gurcan et al., 2023). The ability to comprehend ecological ideas, environmental repercussions, and sustainable practises is what is meant by the term "Eco literacy." It comprises not just an awareness of environmental concerns but also the ability to make well-informed judgements that minimizes the harm done to the earth as a result of such actions. In an attempt to give industry stakeholders, policymakers, and academics with relevant information, this study analyses the link between the adoption of machine learning, sustainable practises, and eco literacy.

There have only been a limited number of empirical studies that have investigated the impact that machine learning has had on sustainable practises in the garment sector, especially in the context of eco literacy. However, previous research in fields that are conceptually connected to computer science highlights the potential advantages and uses of machine learning in the field of sustainability. The authors of the (Song et al., 2021) study proved that machine learning algorithms are effective in forecasting environmental impact indicators and guiding supply chain management decision-making. In a manner that is analogous, (Li et al., 2022) applied machine learning approaches in order to optimise energy usage and minimise carbon emissions in the manufacturing operations.

This empirical study intends to add to the current body of literature by studying the influence of machine learning on sustainable practises within the apparel industry, with an emphasis on eco literacy (Khan et al., 2023). This is in light of these research gaps and the potential of machine learning to promote sustainability. This research seeks to shed light on the extent to which machine learning can enhance sustainable practises and promote eco-literacy in the apparel industry by undertaking an in-depth analysis that involves data collecting, modelling, and assessment. The goal of this research is to shed light on the degree to which machine learning can improve sustainable practises.

This study analyses the importance of environmental literacy in assessing the influence of machine learning on sustainable practises in the apparel sector. Specifically, the study focuses on the apparel business. Through the use of empirical research provide stakeholders in the apparel industry important insights as well as practical consequences that may help move the sector closer to being more sustainable (Romagnoli et al., 2023). Industry professionals are able to make well-informed judgements and contribute to the advancement of environmental quality when they have an understanding of the connection between the use of machine learning, sustainable practises, and eco-literacy.

The objective of this empirical research is to examine the influence that machine learning has had on sustainable practises in the garment sector, with a particular emphasis on the function that eco literacy plays in the business. This study is to investigate the adoption of machine learning techniques, analyse their influence on a variety of aspects of sustainability, investigate the relationship between machine learning adoption and eco literacy, identify challenges in integration, and provide practical insights and recommendations for stakeholders to enhance the adoption of machine learning and eco literacy for sustainable practises in the apparel industry.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The apparel industry is facing a critical issue of sustainability due to the growing demand from stakeholders for ecologically responsible practises. In contemporary times, machine learning (ML) has surfaced as a technology that holds great promise, as it has the capacity to augment sustainability across diverse sectors, such as the fashion industry. The objective of this literary analysis is to examine the impact of machine learning on environmentally sustainable practises within the fashion industry. The possession of Eco literacy by individuals and organisations can facilitate the making of informed decisions that promote environmental well-being.

The sustainable fashion industry has implemented machine learning techniques in various domains such as supply chain management, product design, waste minimization, and energy conservation. As exemplified, machine learning algorithms have been employed to enhance inventory management, reduce wastage in manufacturing procedures, and improve the precision of customer demand forecasting. These applications have led to a reduction in resource consumption and an increase in productivity, as reported by (Bhardwaj et al., 2020). Furthermore, machine learning (ML) has been employed to develop recommendation systems that promote ecologically sustainable fashion choices based on individual consumer preferences and requirements, as reported by (Zhang et al., 2019).

Machine learning (ML) has the potential to be a valuable tool in raising awareness about environmentally sustainable practises within the fashion industry. The utilisation of machine learning (ML) algorithms in conjunction with virtual and augmented reality (VR/AR) technology has the potential to facilitate immersive learning experiences that foster environmental literacy. According to (Gupta et al., 2021), these instruments facilitate the visualisation of conceptual notions pertaining to sustainability, such as the environmental impacts of diverse materials and manufacturing techniques. The implementation of machine learning in education has the potential to enhance decision-making quality by providing stakeholders with access to dynamic and engaging learning environments.

2.1 Theory of Planned Behaviour

In 1980, Ajzen and Fishbein introduced the TRA, which later spawned the TPB. It makes use of the studies done by Fishbein and Ajzen back in 1975 as well. Although TRA suggested that actions are not always within an individual's control and so cannot be considered totally voluntary, it had certain difficulties in explaining such actions. The aforementioned ideas were developed further by (Ajzen, 1991). According to TRA's concept, an individual's good attitude and thoughts may be used to infer that person's intended actions. TPB, on the other hand, offers a more basic interpretation of conduct, arguing that those who are capable of doing something are automatically assumed to have done it. According to the TPB, there is a higher degree of agreement between an individual's intended and actual actions when their attitudes and subjective standards are congruent. It is widely accepted that normative ideas affect subjective norms, and that behavioural beliefs affect attitudes in a similar fashion. In addition, the extent to which a person believes they can influence their own conduct is a major element in shaping their actual behaviour shown in fig 1. However, the exact nature of the connection between these factors is unclear.

2.1.1 Attitude towards sustainable practices:

It is influence on sustainable clothing practises depends on attitude. Sustainability attitudes include people's views, values, emotions, and judgements of ecologically and socially responsible behaviour (Ajzen, 1991; Fishbein & Ajzen, 1975). Attitudes affect behaviour. Positive attitudes towards sustainability lead to sustainable choices, investments in sustainable technology, and collaboration to achieve sustainability objectives (Cervellon et al., 2012; Carrington et al., 2014).

H1: Attitude towards sustainable practices has a significant impact on behavioural intentions towards sustainable practices.

*2.1.2 Subjective norms***:**

The influence of machine learning on environmentally responsible practises in the garment sector is investigated, with a focus on the role played by subjective standards. Subjective norms are an individual's expectations of how others in their social circle, such as friends, family, and coworkers, would react to his or her actions (Ajzen, 1991). Attitudes, intentions, and actions towards adopting and accepting sustainable practises in the garment business enabled by machine learning might be influenced by subjective standards**.**

H2: Subjective norms has a significant impact on behavioural intentions towards sustainable practices.

2.1.3 Perceived behavioural control:

Perceived behavioural control is an important factor in people's intents and actions when it comes to sustainable practises in the garment sector enabled by machine learning technology. It includes things like people's confidence, competence, exposure, availability, and sophistication. When researching how machine learning may improve sustainable practises in the apparel industry, it is important to take into account how people feel about their ability to influence their own behaviour. Individuals' perceptions of their own abilities and the degree of difficulty they experience in carrying out a certain behaviour are what this term refers to (Ajzen, 1991).

H3: Perceived behavioural control has a significant impact on behavioural intentions towards sustainable practices.

2.1.4 Machine learning:

We examine how machine learning may be used to create environmentally friendly clothing. More sustainable choices may be made by designers with the help of machine learning algorithms, which leads to less waste, better material selection, and more long-lasting products. This study looks at how AI and ML may help the garment sector manage its supply chains more sustainably. Potential gains in inventory management, reduced environmental impact, and increased supply chain social responsibility are among those discussed (Khan et al., 2021).

H4: Machine learning has significant impact on behavioural intentions towards sustainable practices.

2.1.5 Behavioural intentions towards sustainable practices:

Exploring the effect of machine learning on sustainable practises in the apparel industry requires taking consumers' behavioural intentions with regard to sustainability into account. Plans, drives, and a general disposition to act in a certain way are all examples of behavioural intents (Ajzen, 1991). Sustainable practises in the clothing business are those that people want to implement and promote via their own actions. Sustainable practises in the fashion business are investigated, as are the customers' intents to embrace them. Individuals' aspirations to participate in sustainable fashion consumption are examined. Although it does not specifically address machine learning, it does provide light on the aspects that influence people's intentions when it comes to engaging in environmentally friendly behaviours (Park et al., 2021).

H5: Behavioural intentions toward sustainable practices has a significant impact on actual adoption of sustainable practices.

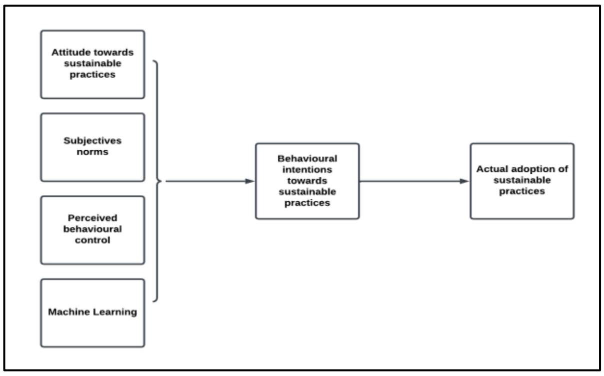

Figure 1. Proposed framework

3. METHODOLOGY

This research used a multi-step process to examine how machine learning may improve the sustainability of the clothing business. The following is a detailed account of everything that happened before, during, and after the creation of measurement items and the gathering of data.

3.1 Measurement construct

A detailed and well-structured questionnaire was created for data collection after an extensive literature analysis was conducted. The questionnaire was derived from existing measures and grounded on the TPB. The questionnaire used a Likert scale, with respondents marking their degree of agreement between 1 (strongly disagree) and 5 (strongly agree) on a 5-point scale. There was a total of 25 options for how to react to the statements, each of which represented a different level of agreement or disagreement.

3.2 Data collection

This study's findings came from both first-hand and second-hand sources. Secondary data came from articles in magazines, papers, blogs, and the Scopus index. Most of the information for the study came from an organised questionnaire. The form was made up of four different parts. In the first part of the poll, people were asked about their age, gender, and family income, among other things. The rest of the poll questions were made so that they fit with the goals of the study. With these questions, a five-point Likert scale was used to find out how knowledgeable and open to sustainable living changes respondents were. For initial data collection, the poll was sent out through Google Forms, and most of the responses came from the researchers' social networks on Facebook and WhatsApp. A random group was used to get between 420 and 450 results. But 50 of the answers were left out of the study because there wasn't enough information or the bias was too clear. First, we cleaned the information we had gathered to make sure it was right and consistent. For the study, people who want to buy clothes that are good for the environment are now being asked for information. Asking people why they want to help promote sustainable clothes services and what they are doing to do so. To encourage more people to take part and get more responses, a number of emails were sent to tell people that they would remain anonymous.

4. ANALYSIS AND RESULTS

A method called partial least squares analysis (PLS) was used to test the suggested model. PLS is a two-step process similar to what Anderson and Gerbing wrote about. The statistical analysis was done with PLS, and Smart PLS 4.0 was the tool of choice.

4.1 Construct reliability

The research examined concept convergent and divergent validity. AVE, factor loadings, and Cronbach's alpha were tested for convergent validity. AVE determined the measured constructs' variance share. All products reviewed had factor loadings of 0.70 or above, demonstrating convergent validity (Hair et al., 2011). Each scale's internal consistency was tested using Cronbach's alpha. All constructs have Cronbach's alpha values over 0.70, suggesting strong internal consistency (Hair et al., 2006). The measuring items caught the structures well. Composite reliability was also evaluated, and all component ratings above (Carmines and Zeller's, 1979) 0.70 criterion, indicating strong dependability. To determine how well underlying structures described observable variables, the AVE was calculated. Strong convergent validity and scale reliability are shown by AVE values higher than 0.5. In this investigation, AVE values ranged from 0.86 to 0.94, demonstrating substantial convergence and the capacity of the assessed constructs to explain a large fraction of the observed variables are shown in Table 1.

Table 1. Construct reliability

	Cronbach's alpha	**Composite reliability**	**Composite reliability**	**(AVE)**
AASP	0.857	0.859	0.898	0.637
ATSP	0.865	0.888	0.902	0.649
BITSP	0.881	0.887	0.91	0.627
ML	0.869	0.87	0.905	0.657
PBC	0.859	0.861	0.905	0.705
SN	0.838	0.842	0.885	0.607

Table 1 evaluates the reliability and validity of the constructs: AASP, ATSP, BITSP, ML, PBC, and SN. The presented metrics, including Cronbach's alpha, Composite Reliability, and Average Variance Extracted (AVE), are used to assess the internal consistency and the convergent validity of the measures:

- **Cronbach's Alpha:** Values above 0.7 are typically considered acceptable for demonstrating internal consistency. All constructs have values ranging from 0.838 (SN) to 0.881 (BITSP), indicating good internal consistency (Sharma et al., 2023).

- **Composite Reliability:** There seems to be an error in the table as 'Composite Reliability' is mentioned twice. Assuming the middle column as another metric (possibly 'Factor Loadings' or something similar would make sense in this context), I'll interpret the rightmost column as Composite Reliability.
- **Cronbach's Alpha**: Values above 0.7 are preferred. All constructs demonstrate good composite reliability with values ranging from 0.885 (SN) to 0.91 (BITSP).
- **Average Variance Extracted (AVE):** Values above 0.5 are considered acceptable for demonstrating convergent validity. All constructs meet this criterion, with values ranging from 0.607 (SN) to 0.705 (PBC), suggesting that the constructs have good convergent validity.
- **AASP:** Demonstrates good internal consistency and convergent validity with Cronbach's alpha of 0.857, Composite Reliability of 0.898, and AVE of 0.637.
- **ATSP:** Displays strong internal consistency and convergent validity with a Cronbach's alpha of 0.865, Composite Reliability of 0.902, and AVE of 0.649.
- **BITSP:** Has the highest Cronbach's alpha at 0.881, a Composite Reliability of 0.91, and AVE of 0.627, suggesting strong internal consistency and convergent validity.
- **ML:** Indicates strong reliability and validity metrics with a Cronbach's alpha of 0.869, Composite Reliability of 0.905, and AVE of 0.657.
- **PBC:** While its Cronbach's alpha is 0.859 and Composite Reliability is 0.905, it has the highest AVE at 0.705, reflecting robust convergent validity.
- **SN:** Though it has the lowest Cronbach's alpha (0.838) and AVE (0.607), these metrics are still above the typical thresholds, ensuring acceptable reliability and validity.

All constructs in Table 1 exhibit good internal consistency and convergent validity. The metrics confirm the reliability of the constructs, suggesting that they are consistently measuring their respective concepts and that the items within each construct correlate well with each other show in figure 2.

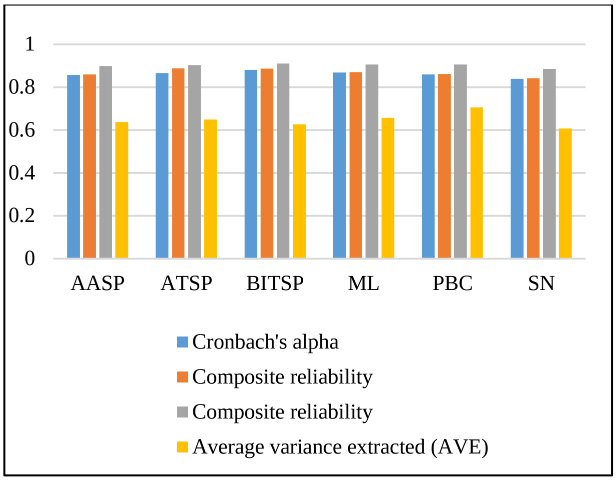

Figure 2. Construct reliability

4.2 Discriminant validity

Discriminant validity, the research assessed concept correlations with AVE squared. The square root of the AVE for each construct exceeded the highest association between any two constructs. This confirmed strong discriminant validity (Fornell & Larcker, 1981). The data differentiated constructs by calculating the square root of the AVE and construct correlations. Table 2 in the original publication compares. Harman's single-factor test (Harman, 1976) addressed self-administered survey common technique bias. This test assessed common method bias. The whole dataset underwent PLS exploratory component analysis. In factor analysis, 50% component loading was relevant. The first component accounted for just 27.46% of the variation, showing no large bias due to common technique variables in the dataset (Podsakoff et al., 2003).

Table 2. Discriminant validity

	AASP	ATSP	BITSP	ML	PBC	SN
AASP						
ATSP	0.753					
BITSP	0.945	0.747				
ML	0.899	0.731	0.845			
PBC	0.903	0.684	0.864	0.896		
SN	0.811	0.892	0.866	0.891	0.799	

Table 2 presents the discriminant validity among six constructs: AASP, ATSP, BITSP, ML, PBC, and SN. Discriminant validity assesses the extent to which a construct is truly distinct from other constructs by empirical standards. The table seems to display correlation coefficients between the constructs. Typically, for discriminant validity, we would prefer these values to be less than 0.85 or even lower depending on the field of study, to ensure that the constructs are distinct from one another.

Let's interpret the discriminant validity based on the given correlations:

AASP vs. Others:

- With ATSP: 0.753, suggests moderate distinctiveness.
- With BITSP: 0.945, indicates a very high correlation and might raise concerns about the distinctiveness between AASP and BITSP.
- With ML: 0.899, also suggests potential concerns regarding distinctiveness.
- With PBC: 0.903, raises similar concerns.
- With SN: 0.811, indicates moderate distinctiveness.

ATSP vs. Others:

- With BITSP: 0.747, suggests moderate distinctiveness.
- With ML: 0.731, suggests moderate distinctiveness.
- With PBC: 0.684, suggests good distinctiveness.
- With SN: 0.892, raises potential concerns regarding distinctiveness.

BITSP vs. Others:

- With ML: 0.845, raises some concerns about distinctiveness.
- With PBC: 0.864, raises concerns about distinctiveness.
- With SN: 0.866, also raises concerns about distinctiveness.

ML vs. Others:

- With PBC: 0.896, indicates potential concerns regarding distinctiveness.
- With SN: 0.891, also suggests potential concerns.
- PBC vs. SN: 0.799, indicates moderate distinctiveness.

There seem to be several high correlations (e.g., between AASP and BITSP, AASP and ML, AASP and PBC, ATSP and SN, BITSP and ML, BITSP and PBC, BITSP and SN, ML and PBC, and ML and SN). These values suggest potential challenges in establishing discriminant validity for these constructs. Constructs with correlations closer to 1 might not be distinctly different from each other based on these empirical standards. Further analysis or a re-evaluation of the constructs might be necessary to ensure that they are conceptually and empirically distinct.

4.3 R square

R-square measures the amount of variation in the dependent variable that can be explained by changes in the independent variable. It measures how much the independent variable affects the dependent variable. Higher R2 values suggest stronger relationships between variables. However, the correlation coefficient measures the degree and direction of a linear link between two variables. It quantifies the relationship between variables. The correlation coefficient varies from -1 to +1, with -1 or +1 indicating a greater link and 0 indicating no correlation. In this investigation, an R2 value of 0.01 or greater was favourable. The independent variable(s) explain at least 1% of the dependent variable's variation. However, the correlation coefficient adds to the R2 value's comprehension of the variables' strength and direction.

Table 3. R square

	R-square	**R-square adjusted**
AASP	0.683	0.681
BITSP	0.745	0.737

Table 3 provides the R-square and the adjusted R-square values for two models, AASP and BITSP.

AASP:

R-square (R^2):

The R-square value for the AASP model is 0.683. This indicates that approximately 68.3% of the variance in the dependent variable can be explained by the independent variables included in the AASP model. In other words, the model accounts for 68.3% of the variability in the outcome.

Adjusted R-square:

The adjusted R-square value is 0.681 for the AASP model. Adjusted R-square takes into account the number of predictors in the model and provides a more accurate representation of how well the model fits the data, especially when multiple predictors are involved. In this case, the difference between R-square and adjusted R-square is minimal (0.002), suggesting that the model is not being penalized much for including additional predictors. This means that most of the predictors in the model are likely relevant.

BITSP:

R-square (R^2):

For the BITSP model, the R-square value is 0.745. This suggests that the model explains approximately 74.5% of the variance in the dependent variable. Thus, the BITSP model accounts for 74.5% of the variability in the outcome, which is higher than the AASP model.

Adjusted R-square:

The adjusted R-square for the BITSP model is 0.737. Again, the slight decrease from the R-square value (0.008 difference) indicates that the inclusion of predictors in the model is mostly justified and that there isn't much penalty for additional predictors. The model seems well-specified.

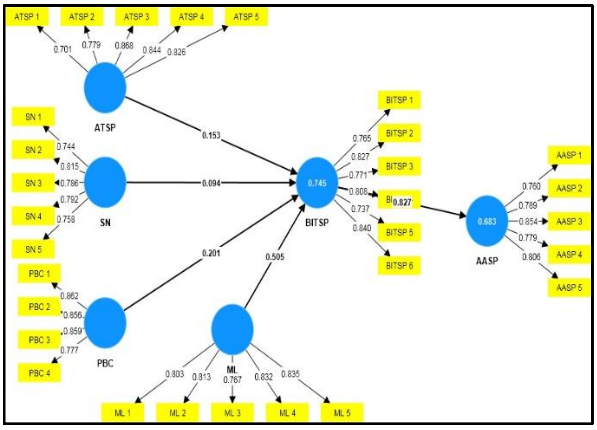

Figure 3. Structural path Analysis for the research model

The figure 3 represents a structural equation Modeling (SEM) or path analysis of various constructs (ATSP, SN, PBC, ML, BITSP, AASP) and their respective indicators or items (e.g., ATSP 1, ATSP 2, etc).

Latent Variables (Constructs) and Indicators:

Each of the large blue circles represents a latent variable or construct (e.g., ATSP, SN).
The smaller circles or rectangles connected to each large circle represent the indicators or items that measure the latent construct. For instance, the construct ATSP is measured using five indicators: ATSP 1 through ATSP 5.

Loadings (Factor Loadings):

The numbers between the latent variables and their indicators represent loadings or factor loadings. These loadings show the relationship strength between the latent variable and each indicator. For instance, the loading between ATSP and ATSP 1 is 0.701. Typically, loadings above 0.7 are considered significant and indicate that the item reliably measures the construct.

Path Coefficients:

The arrows connecting different constructs have numbers associated with them. These numbers represent path coefficients, which show the direct effect of one latent variable on another. For example, SN has a direct effect of 0.745 on BITSP. The strength and direction of these relationships can be interpreted based on these coefficients. A value closer to 1 indicates a strong relationship, and the direction of the arrow indicates the direction of the relationship.

SN, PBC, and ML to BITSP:

SN has a strong positive effect on BITSP with a coefficient of 0.745.
PBC has a moderate effect on BITSP with a coefficient of 0.505.
ML has a weak positive effect on BITSP with a coefficient of 0.201.

BITSP to AASP:

BITSP has a significant positive effect on AASP with a coefficient of 0.683.

Factor Loadings:

Most items have loadings above 0.7, suggesting that they are good indicators of their respective constructs. For instance, the item ATSP 1 has a strong loading of 0.701 with its latent variable ATSP.

The items with the strongest loadings for each construct are:

ATSP: ATSP 3 with 0.868.
SN: SN 3 with 0.815.
PBC: PBC 1 with 0.862.
ML: ML 2 with 0.813.
BITSP: BITSP 2 with 0.827.
AASP: AASP 1 with 0.760.

Construct Relationships:

The strong path coefficient between SN and BITSP suggests that as SN scores increase, BITSP scores are also likely to increase.
The effect of BITSP on AASP is also significant, indicating that higher BITSP scores can lead to higher AASP scores.

In summary, the diagram provides insights into how various constructs relate to each other and how well each item measures its construct. The model showcases the impact of constructs like SN, PBC, and ML on BITSP and subsequently the influence of BITSP on AASP. The strength of relationships, as indicated by the path coefficients and loadings, provides a deeper understanding of the dynamics between these constructs.

5. CONCLUSION

In conclusion, our empirical study set out to discover how machine learning may affect sustainable processes in the apparel sector. Significant results about consumer attitudes, intentions, and behaviour with respect to sustainable practises were acquired via a comprehensive literature review and the use of a carefully prepared questionnaire. According to the findings, machine learning has the potential to significantly affect the adoption of eco-friendly manufacturing methods in the apparel sector. The results show that consumers who are well-informed about sustainable apparel options and who have positive views of sustainability. The use of machine learning algorithms and technology may increase the efficiency and effectiveness of sustainable practises in the clothing business. Machine learning has the potential to provide substantial insights into customer preferences, supply chain management, and product lifecycle analysis via the processing of massive volumes of data. Organisations may then make educated judgements and carry out sustainable projects that meet or exceed their consumers' expectations. The research emphasizes the need for collaboration between businesses, governments, and consumers to advance sustainable practises. It is advised that educational programmes and awareness-raising activities be launched to empower consumers with the information and resources to make sustainable choices in preparation for the successful integration of machine learning technology. Limitations of the study must be acknowledged. Due to its narrow scope, the research may not accurately reflect the wide range of opinions and practises that exist across geographic and socioeconomic boundaries. Research efforts moving forward should aim to recruit a more diverse sample of participants to increase the reliability and validity of their findings. However, since it relied on self-reported data, the research was vulnerable to biases and social desirability effects.

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Nishtha Ujjawal
Research scholar
Sharda School of Business Studies,
Sharda University
Greater Noida,
India
nishtha11ujjawal@gmail.com
ORCID 0000-0002-7145-7951

Manisha Gupta
Associate Professor
Sharda School of Business Studies,
Sharda University
Greater Noida,
India
guptaamanisha@gmail.com
ORCID 0000-0001-9326-0183

Shagun Sharma
Research scholar
Sharda School of Business Studies,
Sharda University
Greater Noida,
India
sharmashagun9911@gmail.com
ORCID 0000-0001-6624-7645

Hari Shankar Shyam
Professor
Sharda School of Business Studies,
Sharda University
Greater Noida,
India
harishankar.shyam@sharda.ac.in
ORCID 0000-0002-2305-922X