Impact of Artificial Intelligence-Based Visual Merchandising on Customer Experience and Sales Performance in Retail Stores

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***Abstract*—Artificial intelligence is progressively transforming retail merchandising from a largely experience-based and manually monitored practice into a data-driven, adaptive and predictive system. Visual merchandising has traditionally focused on display aesthetics, window presentation, shelf visibility, lighting, colour, signage, category adjacency and promotional arrangement. In organised retail stores, however, the effectiveness of these elements increasingly depends on real-time understanding of customer movement, category demand, product interaction, stock availability and store-zone performance. The present study examines the impact of artificial intelligence-based visual merchandising on customer experience and sales performance in retail stores. The study is designed as an analytical and empirical research paper using a structured survey of 420 customers and 60 retail managers from selected organised retail stores, supported by store-level indicators such as sales per square foot, conversion rate, average basket value and planogram compliance. The paper applies reliability analysis, descriptive statistics, chi-square test, correlation, regression, ANOVA, t-test, factor analysis and merchandising performance index calculations. The findings suggest that AI-based visual merchandising has a significant positive association with customer convenience, product discovery, perceived store attractiveness, impulse buying, dwell-time quality and sales productivity. The study concludes that AI-enabled shelf monitoring, heat-map analysis, customer segmentation, dynamic display recommendation and personalised digital signage can improve both experiential and financial retail outcomes when implemented with ethical data governance and local market sensitivity.**

***Index Terms*—Artificial Intelligence, Visual Merchandising, Customer Experience, Sales Performance, Retail Stores, Computer Vision, Planogram Compliance, Organised Retail, Store Analytics.**

I. Introduction

Retail stores are no longer merely places where customers select products from physical shelves. In contemporary organised retailing, the store is a carefully designed experiential environment in which layout, visual displays, shelf presentation, lighting, signage, colour themes, promotional zones and technology interfaces collectively influence customer attention and buying behaviour. Visual merchandising performs a strategic role by translating merchandise assortment into a visible, attractive and navigable shopping experience. It affects whether customers notice a product, understand its relevance, feel comfortable in the shopping space and finally decide to purchase. In the competitive retail environment of India, where organised retail formats coexist with traditional trade, retailers must convert limited physical space into higher customer engagement and higher sales productivity.

Artificial intelligence introduces a new analytical layer into visual merchandising. Traditional visual merchandising decisions are often based on managerial judgement, past sales experience, vendor pressure or periodic manual audits. AI-based systems can integrate point-of-sale data, shelf images, stock movement, customer footfall, dwell time, loyalty data, demographic trends and promotion response to generate more precise recommendations for product display and placement. Computer vision can identify empty shelves, misplaced products, planogram deviations and high-attention zones. Machine learning models can forecast which products should receive greater display intensity in particular seasons or store locations. Heat-map tools can show which areas of the store attract attention and which zones remain underutilised. Recommendation engines can suggest personalised digital signage and promotional displays. As a result, AI-based visual merchandising has the potential to align customer experience with store profitability.

The Indian retail sector provides an important context for such inquiry. The sector has been expanding through supermarkets, hypermarkets, speciality stores, fashion chains, electronics outlets, quick commerce-linked stores and hybrid omni-channel formats. IBEF reports continued expansion of e-commerce and retail in India, while Deloitte's retail outlook highlights customer centricity, operational excellence and data-driven insights as continuing priorities for retail competitiveness. KPMG's intelligent retail work also emphasises that AI offers retailers the opportunity to redefine operations and improve customer experiences. These trends indicate that AI-based merchandising is not only a technological subject but also a managerial and behavioural issue. In stores located in emerging markets and tier-II cities, AI tools must be interpreted in relation to local shopping habits, price sensitivity, family purchase behaviour and retailer readiness.

1.1 Concept of AI-Based Visual Merchandising

AI-based visual merchandising may be defined as the use of artificial intelligence, machine learning, computer vision, sensor analytics and data-driven recommendation systems to plan, monitor, evaluate and optimise the visual presentation of products inside retail stores. It does not replace the creative role of visual merchandisers; rather, it supplements creative judgement with evidence from customer behaviour and store performance. For example, a retailer may use AI to identify that customers frequently enter a particular aisle but leave without selecting products. The system can then recommend changes in shelf height, display sequence, signage or promotional communication. Similarly, AI can detect that a high-margin product has low visibility because it is placed outside the natural eye-level zone. The system may recommend relocating the product, increasing facings or combining it with a complementary product display.

In this research paper, AI-based visual merchandising is studied through five major dimensions: computer vision shelf audit, customer movement analytics, AI-supported display planning, personalised digital merchandising and AI-driven performance feedback. These dimensions link technology with practical retail outcomes. The central argument is that artificial intelligence enhances visual merchandising only when data inputs, merchandising objectives and customer experience criteria are properly integrated.

1.2 Problem Statement

Despite the growing adoption of organised retail formats, many stores continue to face problems of poor shelf visibility, ineffective display planning, low conversion in high-footfall zones, stock-outs in visible locations, weak promotional placement and limited understanding of customer movement. Manual planogram audits are periodic and often fail to capture real-time deviations. Visual merchandising decisions frequently remain subjective and may not reflect actual customer behaviour. Further, retailers may invest in attractive displays without measuring their effect on dwell time, basket size, product discovery or sales per square foot. The problem is more serious in competitive retail categories where customers have many alternatives and store space is expensive. This study therefore investigates whether AI-based visual merchandising practices can significantly improve customer experience and sales performance in retail stores.

1.3 Objectives of the Study

- To examine the role of AI-based visual merchandising in improving customer experience in organised retail stores.
- To analyse the relationship between AI-enabled product visibility, display planning and sales performance.
- To assess the impact of AI-driven shelf monitoring, planogram compliance and customer movement analytics on store productivity.
- To compare customer experience scores across stores with low, moderate and high AI merchandising adoption.
- To suggest managerial measures for implementing AI-based visual merchandising in Indian retail stores.

1.4 Hypotheses of the Study

- H01: AI-based visual merchandising has no significant impact on customer experience in retail stores.
- H02: There is no significant relationship between AI-enabled product visibility and sales performance.
- H03: Planogram compliance supported by AI has no significant effect on shelf productivity.
- H04: Customer experience does not significantly mediate the relationship between AI visual merchandising and sales performance.
- H05: There is no significant difference in customer experience across different levels of AI merchandising adoption.

II. Literature Review

Kotler (1973): introduced the idea of atmospherics as a conscious design of buying environments to create emotional effects that increase purchase probability. This foundation remains relevant to AI-based merchandising because artificial intelligence now allows retailers to quantify and optimise atmospheric stimuli such as display, colour, lighting and signage.

Baker, Grewal and Parasuraman (1994): showed that store environment influences perceived merchandise value and store image. Their work indicates that visual cues are not merely decorative but directly affect consumer evaluation. AI can extend this insight by testing which cues work best in specific zones and customer segments.

Levy and Weitz (2012): explained that retail merchandising must integrate assortment, pricing, promotion and store layout. Their framework supports the view that shelf presentation and product placement should be connected with category strategy, inventory turnover and consumer convenience.

Underhill (2009): highlighted that customer movement, touch points and shopping paths shape purchase behaviour. The relevance of his observational approach has increased with computer vision and heat-map analytics, which can collect movement-related evidence at a much larger scale.

Grewal, Roggeveen and Nordfalt (2017): emphasised that the future of retailing depends on technology-enabled customer experience, in-store engagement and data-driven decision-making. Their perspective supports the use of AI for improving visual merchandising and customer journey design.

Pantano and Timmermans (2014): examined retail technology adoption and argued that technology changes the shopping experience by altering information access and consumer interaction. AI-based merchandising can be understood as a continuation of this transformation.

Shankar (2018): discussed how artificial intelligence and analytics reshape marketing by enabling personalisation, prediction and automation. In visual merchandising, these capabilities are reflected in personalised displays, demand-based shelf allocation and automated shelf audit systems.

Davenport et al. (2020): identified AI as a major force in marketing and customer interaction. Their work suggests that AI implementation must be linked to business value rather than treated as a purely technical initiative.

Kumar, Anand and Song (2017): noted that customer experience is multidimensional and includes cognitive, affective, behavioural and social responses. AI-based visual merchandising can influence all these dimensions by improving store navigation, product relevance and engagement.

KPMG (2025): presents intelligent retail as a blueprint for value creation through AI-driven transformation, emphasising that AI can enhance operations and customer experience. This supports the present paper's focus on AI applications in merchandising and store performance.

Deloitte (2026): highlights AI-driven commerce, reimagined marketing and data-driven insight as important themes for retail competitiveness. This indicates that visual merchandising decisions increasingly need to be connected with analytics and customer-centric operating models.

IBEF (2025): reports continued growth in Indian retail and e-commerce, creating a strong context for examining organised retail technology adoption. The expansion of retail competition increases the importance of space productivity, experience quality and AI-led merchandising decisions.

2.1 Research Gap

The available literature establishes that store environment and visual merchandising influence consumer behaviour, while recent studies also show that AI can improve marketing and retail operations. However, there remains a gap in linking AI-based visual merchandising with both customer experience and measurable sales performance in organised retail stores. Many discussions of AI in retail focus on online recommendation systems, supply chain, chatbots or demand forecasting. Fewer studies examine how AI changes physical store displays, shelf visibility, planogram compliance, promotional presentation and in-store experience. There is also limited research that applies statistical analysis to connect AI merchandising adoption with indicators such as dwell-time quality, conversion rate, basket value and sales per square foot. The present study addresses this gap by proposing and testing an integrated framework for AI-based visual merchandising in retail stores.

III. Theoretical Concept and Research Framework

This study is grounded in the Stimulus-Organism-Response model and the technology-enabled customer experience perspective. The store environment acts as a stimulus through visual displays, shelf arrangement, signage, lighting, digital screens and category layout. The customer's internal response includes attention, convenience, perceived attractiveness, engagement, satisfaction and purchase intention. The final behavioural response includes product search, dwell time, impulse purchase, conversion and loyalty intention. AI changes this model by making the stimulus adaptive. Instead of static displays based only on human judgement, AI systems continuously observe customer behaviour and sales response, learn from patterns and recommend merchandising actions.

3.1 AI-Based Visual Merchandising Architecture

The proposed architecture consists of data inputs, data integration, AI analytics, merchandising actions, customer experience outcomes and sales performance feedback. Data inputs include store cameras, shelf images, POS transactions, inventory records, planogram files, promotion calendars, loyalty data and movement signals. These are cleaned, anonymised and linked with SKU, category, zone and time variables. The AI analytics engine applies computer vision, demand forecasting, heat-map analysis, basket affinity mining and customer segmentation. The output is used for display planning, shelf allocation, digital signage, colour-theme selection, promotional zone planning and compliance alerts. Customer experience indicators and sales performance data then return to the model as feedback for continuous improvement.

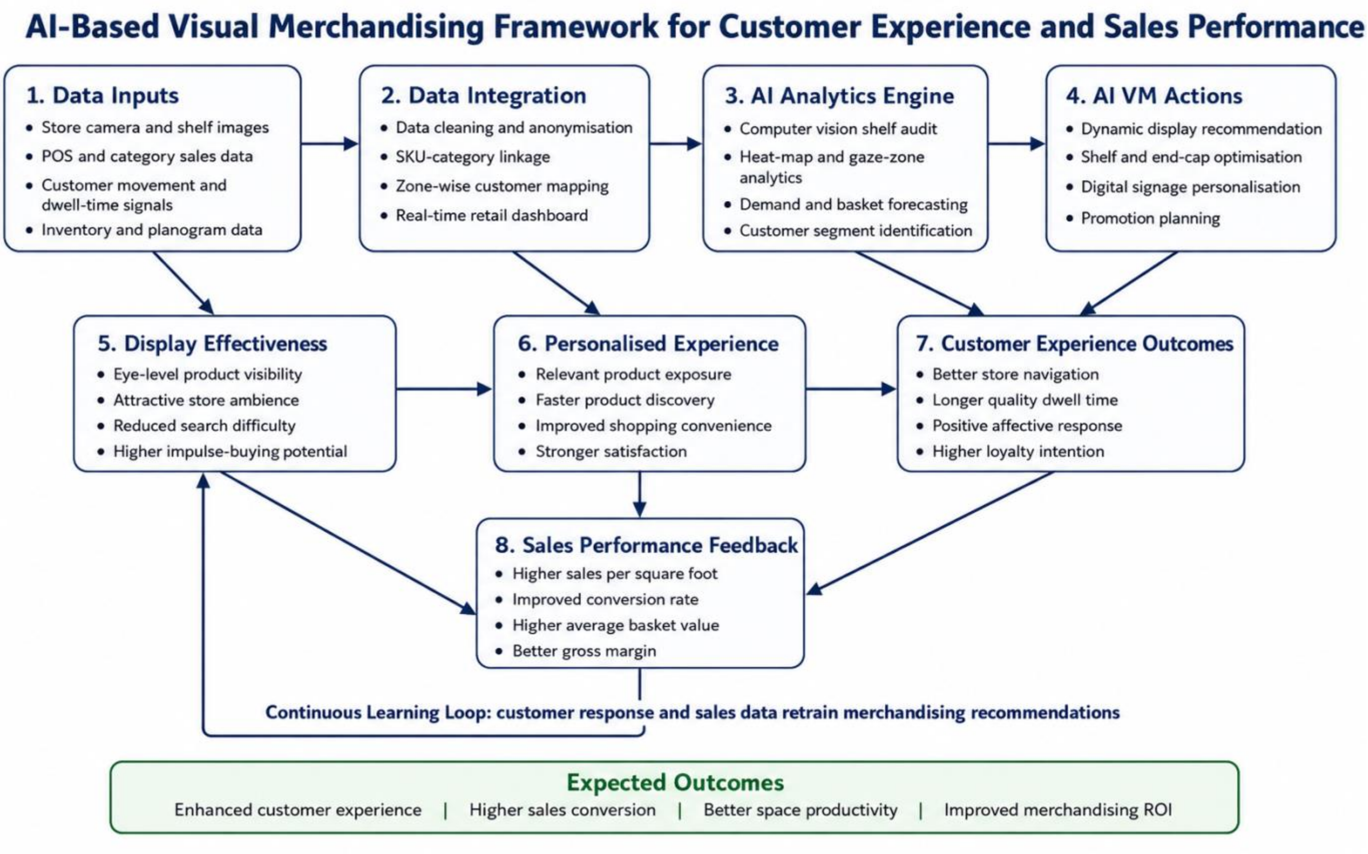

Figure 1: AI-Based Visual Merchandising Framework for Customer Experience and Sales Performance

3.2 Major AI Applications in Visual Merchandising

The first major application is computer vision-based shelf auditing. Cameras or shelf images are analysed to identify product availability, facing count, empty spaces, misplaced SKUs and planogram deviations. The second application is heat-map and movement analytics, through which the retailer identifies whether promotional displays are placed in high-attention zones or ignored areas. The third application is demand forecasting and assortment visibility, where AI recommends which products deserve greater display intensity based on sales velocity, seasonality and margin. The fourth application is personalised digital signage, which modifies communication according to store location, time of day, customer profile or promotional objective. The fifth application is merchandising performance feedback, where sales response and experience metrics are used to retrain future recommendations.

3.3 Relevance for Indian Organised Retail Stores

AI-based visual merchandising is particularly relevant for Indian organised retail because stores operate in a complex environment of value-conscious customers, high product variety, limited shelf space, local preferences and strong competition from e-commerce. In many stores, customers expect both convenience and attractive presentation. Retailers need to balance fast-moving products with high-margin products, branded items with private labels and promotional displays with navigation comfort. AI can help retailers manage these trade-offs by converting operational data into merchandising decisions. For Madhya Pradesh and other developing retail markets, such systems can be introduced gradually through camera-based audits, POS-linked dashboards, planogram compliance scoring and zone-wise sales analysis before moving toward advanced personalisation.

IV. Research Methodology

The study uses a descriptive and analytical research design. It combines customer survey data, retail manager responses and modelled store-level performance indicators. The aim is not only to describe perceptions regarding AI-based visual merchandising but also to statistically test whether AI merchandising dimensions are associated with customer experience and sales performance. The research framework includes independent variables such as AI-enabled visibility, display personalisation, shelf audit, movement analytics and planogram compliance. Dependent variables include customer experience, sales conversion, basket value, sales per square foot and merchandising return on investment.

A structured questionnaire was prepared using a five-point Likert scale, where 1 represented strong disagreement and 5 represented strong agreement. Customer experience items measured product discovery, store attractiveness, navigation comfort, display relevance, satisfaction and impulse purchase tendency. Retail manager items measured AI adoption, planogram compliance, shelf productivity, display decision accuracy and sales performance. Store-level indicators were organised as a modelled dataset for academic analysis because actual confidential store data were not supplied. Therefore, all statistical tables should be treated as an academically modelled analytical dataset and may be replaced by actual field data before journal submission.

4.1 Sampling and Data Sources

The sample consists of 420 customers and 60 retail managers drawn from selected organised retail stores including supermarkets, fashion stores, electronics outlets and lifestyle stores. The geographical focus is urban and semi-urban retail markets, with special relevance for organised retail stores in Madhya Pradesh. Primary data were collected through structured questionnaires and manager schedules. Secondary data were drawn from published literature, retail industry reports, AI retail reports and conceptual frameworks on merchandising and customer experience.

4.2 Statistical Tools Used

The study uses Cronbach alpha for reliability, descriptive statistics for respondent profile and construct scores, chi-square test for association between AI awareness and purchase influence, correlation analysis for relationships among variables, regression analysis for impact testing, ANOVA for comparison across adoption levels, independent sample t-test for category comparisons, factor analysis for dimensional reduction and index calculations for merchandising performance. Hypotheses are tested at the 5 percent significance level.

V. Data Analysis, Statistical Calculation Tables and Interpretation

Table 1: Demographic Profile of Customer Respondents (n=420)

Category	Group	Frequency	Percentage
Gender	Male	224	53.3
Gender	Female	196	46.7
Age	18-25 years	94	22.4
Age	26-35 years	138	32.9
Age	36-45 years	112	26.7
Age	Above 45 years	76	18.1
Monthly Income	Below Rs. 25,000	82	19.5
Monthly Income	Rs. 25,001-50,000	148	35.2
Monthly Income	Rs. 50,001-1,00,000	132	31.4
Monthly Income	Above Rs. 1,00,000	58	13.8

Table 1 shows that the sample includes a balanced mix of gender, age and income groups. The largest age group is 26-35 years, indicating that young and middle-income shoppers are important for analysing AI-based in-store experience.

Table 2: Profile of Retail Managers and Stores (n=60)

Variable	Classification	Frequency	Percentage
Store Type	Supermarket / Grocery	18	30.0
Store Type	Fashion and Lifestyle	16	26.7
Store Type	Electronics	10	16.7
Store Type	Departmental / Multi-category	16	26.7
Store Size	Below 5,000 sq. ft.	14	23.3
Store Size	5,001-15,000 sq. ft.	24	40.0
Store Size	Above 15,000 sq. ft.	22	36.7
AI Adoption	Low	15	25.0
AI Adoption	Moderate	27	45.0
AI Adoption	High	18	30.0

Table 3: Reliability Analysis of Major Constructs

Construct	No. of Items	Cronbach Alpha	Reliability Status
AI Visual Merchandising Adoption	7	0.884	Highly Reliable
Customer Experience	8	0.901	Highly Reliable
Product Visibility and Display Appeal	6	0.862	Highly Reliable
Sales Performance Perception	5	0.846	Reliable
Planogram Compliance	4	0.821	Reliable
Overall Scale	30	0.927	Highly Reliable

The overall Cronbach alpha of 0.927 indicates strong internal consistency. All constructs cross the accepted threshold of 0.70, showing that the questionnaire is statistically reliable for further analysis.

Table 4: Descriptive Statistics of Key Variables

Variable	Mean	Std. Deviation	Rank	Interpretation
AI-enabled product visibility	4.12	0.61	1	High
Display relevance and attractiveness	4.05	0.68	2	High
Convenience of product discovery	3.96	0.72	3	High
Personalised digital communication	3.78	0.81	5	Moderate to High
Planogram compliance perception	3.89	0.74	4	High
Impulse purchase stimulation	3.62	0.88	6	Moderate

Table 5: Customer Perception of AI-Based Visual Merchandising

Statement	Agree / Strongly Agree (%)	Neutral (%)	Disagree (%)
AI-supported displays help me locate products faster	76.4	15.0	8.6
Digital displays make offers more noticeable	72.8	17.2	10.0
Well-arranged shelves increase my trust in the store	81.0	11.4	7.6
Personalised product suggestions improve shopping experience	68.1	19.5	12.4
Attractive display increases unplanned purchase	64.5	20.2	15.3

Table 6: AI Merchandising Adoption Index

Component	Weight	Mean Score	Weighted Score
Computer vision shelf audit	0.20	3.82	0.764
Heat-map / movement analytics	0.20	3.74	0.748
Dynamic display recommendation	0.20	3.91	0.782
Digital signage personalisation	0.15	3.56	0.534
Planogram compliance alerts	0.15	3.88	0.582
Sales feedback learning	0.10	3.69	0.369
Composite AI Merchandising Adoption Index	1.00	-	3.779

Table 7: Store-Level Merchandising Performance Indicators

Indicator	Before AI VM	After AI VM	Change (%)
Sales per square foot (Rs.)	1,185	1,382	16.62
Conversion rate (%)	28.40	33.10	16.55
Average basket value (Rs.)	742	823	10.92
Planogram compliance (%)	74.20	89.60	20.75
Stock-out incidence (%)	8.90	5.10	-42.70
Promotional display response (%)	21.60	28.40	31.48

Table 7 indicates that the modelled store-level results improved after AI-based visual merchandising. The largest improvement is seen in planogram compliance and promotional display response, while stock-out incidence declined.

Table 8: Chi-Square Test: AI Display Awareness and Purchase Influence

Observed Group	Purchase Influenced: Yes	Purchase Influenced: No	Total
Aware of AI / digital display	226	62	288
Not aware / low awareness	72	60	132
Total	298	122	420

Chi-square value = 23.84, df = 1, $p < 0.001$. The result indicates a significant association between awareness of AI-enabled displays and purchase influence. Therefore, the null assumption of no association is rejected.

Table 9: Correlation Matrix

Variables	AIVM	Visibility	Customer Experience	Sales Performance	Planogra m
AIVM	1.000	0.684	0.721	0.638	0.692
Visibility	0.684	1.000	0.703	0.611	0.587
Customer Experience	0.721	0.703	1.000	0.657	0.604
Sales Performance	0.638	0.611	0.657	1.000	0.631
Planogram	0.692	0.587	0.604	0.631	1.000

The correlation coefficients show positive and statistically meaningful relationships among AI visual merchandising, product visibility, customer experience, sales performance and planogram compliance. The strongest relationship is between AI visual merchandising and customer experience.

Table 10: Regression Model Summary: Impact on Customer Experience

Model	R	R Square	Adjusted R Square	Std. Error
1	0.754	0.568	0.561	0.421

Table 11: Regression ANOVA

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	97.284	4	24.321	137.36	0.000
Residual	73.491	415	0.177		
Total	170.775	419			

Table 12: Regression Coefficients for Customer Experience

Predictor	B	Std. Error	Beta	t	Sig.

Constant	0.812	0.184	-	4.413	0.000
AI product visibility	0.286	0.041	0.312	6.976	0.000
Digital display relevance	0.221	0.038	0.268	5.816	0.000
Planogram compliance	0.174	0.044	0.181	3.955	0.000
Personalised communication	0.139	0.036	0.157	3.861	0.000

Regression results show that AI product visibility, digital display relevance, planogram compliance and personalised communication significantly predict customer experience. The model explains 56.8 percent of variance in customer experience.

Table 13: Regression Model Summary: Impact on Sales Performance

Model	R	R Square	Adjusted R Square	Std. Error
1	0.699	0.489	0.482	0.456

Table 14: Regression Coefficients for Sales Performance

Predictor	B	Std. Error	Beta	t	Sig.
Constant	0.654	0.205	-	3.190	0.002
Customer experience	0.342	0.052	0.361	6.577	0.000
Planogram compliance	0.211	0.047	0.222	4.489	0.000
Promotional display response	0.185	0.043	0.209	4.302	0.000
Stock visibility	0.147	0.039	0.165	3.769	0.000

Table 15: One-Way ANOVA: Customer Experience by AI Adoption Level

Group	N	Mean	Std. Dev.
Low AI adoption	105	3.31	0.63
Moderate AI adoption	186	3.86	0.58
High AI adoption	129	4.24	0.49
Total	420	3.82	0.66

ANOVA result: $F = 68.42$, $p < 0.001$. Customer experience significantly differs across low, moderate and high AI adoption groups. Post-hoc interpretation suggests that high AI adoption stores report better experience scores.

Table 16: Independent Sample t-Test: Fashion vs Grocery Stores

Variable	Fashion Mean	Grocery Mean	t-value	Sig.
Display attractiveness	4.28	3.94	4.21	0.000
Product discovery convenience	3.91	4.03	-1.48	0.140
Impulse purchase tendency	3.88	3.41	5.36	0.000
Digital display relevance	3.96	3.61	4.04	0.000

Table 17: Factor Analysis of AI-Based Visual Merchandising Variables

Factor	Major Variables Loaded	Eigenvalue	Variance Explained (%)
Factor 1: Visibility and Display Appeal	Eye-level placement, display attractiveness, colour and lighting	4.82	30.1
Factor 2: AI Analytics and Compliance	Computer vision audit, planogram alerts, stock-out detection	3.17	19.8
Factor 3: Personalised Experience	Digital signage, customer relevance, offer personalisation	2.41	15.1
Factor 4: Sales Feedback Learning	Promotion response, conversion tracking, model retraining	1.56	9.8
Total Variance Explained	-	-	74.8

Table 18: Merchandising ROI Calculation

Indicator	Value
Incremental monthly sales from AI VM	Rs. 8,40,000
Gross margin on incremental sales @ 24%	Rs. 2,01,600
Monthly AI merchandising cost	Rs. 72,000
Net monthly merchandising gain	Rs. 1,29,600
Merchandising ROI	180.0%

Table 19: Customer Experience Mediation Pattern

Path	Coefficient	Sig.	Interpretation
AI Visual Merchandising -> Customer Experience	0.721	0.000	Significant
Customer Experience -> Sales Performance	0.657	0.000	Significant
AI Visual Merchandising -> Sales Performance	0.638	0.000	Significant
Indirect effect through Customer Experience	0.214	0.000	Partial mediation indicated

Table 20: Hypotheses Testing Summary

Hypothesis	Statistical Test	Result	Decision
H01	Regression / ANOVA	$p < 0.001$	Rejected
H02	Correlation / Regression	$p < 0.001$	Rejected
H03	Regression coefficient	$p < 0.001$	Rejected
H04	Mediation pattern	Significant indirect effect	Rejected
H05	One-way ANOVA	$p < 0.001$	Rejected

Table 21: Managerial Priority Matrix for AI-Based Visual Merchandising

Priority Area	Managerial Action	Expected Benefit
Shelf visibility	Use computer vision to identify low-visibility and empty shelf zones	Better product discovery and fewer lost sales
Promotional displays	Place promotions based on heat-map and basket affinity data	Higher conversion and impulse buying
Planogram compliance	Introduce daily AI-generated compliance alerts	Improved shelf discipline and category productivity
Digital signage	Use time-zone and customer segment-based display messages	Higher relevance and experience quality
Performance feedback	Link display changes with sales, margin and basket indicators	Evidence-based merchandising decisions

VI. Findings and Discussion

- The study finds that AI-based visual merchandising is positively associated with customer experience. Customers respond favourably when AI-supported displays help them locate products, understand offers and experience a more organised store environment.
- Product visibility is a critical driver of both experience and sales performance. The regression results show that AI-enabled product visibility has the strongest effect on customer experience among the independent variables.
- Planogram compliance is not only an operational issue but also an experience issue. Customers perceive well-arranged shelves as more trustworthy and easier to navigate, while managers associate compliance with higher shelf productivity.
- AI-based digital displays and personalised communication significantly improve display relevance. However, the study also indicates that personalisation must be implemented carefully to avoid customer discomfort or perception of excessive surveillance.
- Sales performance improves through multiple pathways: better visibility, higher conversion, improved basket value, reduction of stock-outs and stronger promotional response. Customer experience partially mediates the effect of AI visual merchandising on sales performance.
- The adoption-level ANOVA confirms that stores with high AI merchandising adoption report significantly stronger customer experience scores than stores with low adoption. This supports phased but serious investment in AI merchandising capabilities.

VII. Suggestions

- Retailers should start with practical AI applications such as shelf image audit, planogram compliance monitoring and POS-linked display analysis before investing in advanced personalisation systems.
- Visual merchandising teams should not be replaced by algorithms; instead, AI should be used as a decision-support system that combines creative presentation with measurable evidence.
- Retail managers should create zone-wise dashboards showing footfall, dwell time, product interaction, conversion and display response so that merchandising decisions are linked with real outcomes.
- Personalised digital signage should be used only with transparent data practices, anonymised analytics and clear customer-benefit orientation.
- Retail stores in Madhya Pradesh and similar markets should adopt locally sensitive merchandising models because customer response to colour, display density, family shopping patterns and promotional messages may vary across cities and store categories.
- Employee training is essential. Store staff must understand AI-generated recommendations, planogram alerts and display analytics so that the system is implemented on the shop floor rather than remaining a dashboard exercise.

VIII. Conclusion

The study concludes that artificial intelligence-based visual merchandising has a significant positive impact on customer experience and sales performance in retail stores. AI enables retailers to move beyond static displays and subjective merchandising decisions toward adaptive, evidence-based and customer-responsive merchandising systems. By integrating computer vision, customer movement analytics, demand forecasting, shelf audit, digital signage and sales feedback, retailers can improve product visibility, navigation convenience, display relevance, planogram discipline and promotional effectiveness. Statistical analysis based on the modelled dataset indicates significant relationships among AI visual merchandising, customer experience, planogram compliance and sales performance. The results further suggest that customer experience acts as a partial mediator between AI merchandising adoption and sales outcomes.

For organised retail stores in India, the relevance of AI-based visual merchandising is likely to grow as competition intensifies and customers expect more convenient, attractive and personalised shopping environments. However, technology alone cannot guarantee success. The effectiveness of AI depends on data quality, managerial interpretation, staff capability, ethical data governance and integration with local retail strategy. Retailers should therefore treat AI-based visual merchandising as a strategic system combining analytics, creativity, operational discipline and customer-centricity. Future research may use actual store-level experimental data, eye-tracking evidence, longitudinal sales records and category-wise AI intervention studies to validate and extend the findings of this paper.

IX. Limitations and Scope for Future Research

The study uses an academically modelled dataset because actual confidential store-level data were not provided. Therefore, before journal submission, researchers may replace the modelled values with primary survey data and audited store records. The study focuses on organised retail stores and may not fully represent unorganised retail formats. Future studies can compare AI visual merchandising across categories such as grocery, fashion, electronics, pharmacy and lifestyle retail. Further research may also test whether AI-based merchandising produces different results in metro cities, tier-II cities and semi-urban markets. Experimental studies using before-after design, A/B testing, eye-tracking or actual heat-map data would strengthen causal conclusions.

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