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From the Editors Desk:

Special Issue – I

Selected Papers from the ***ICSSR Sponsored Two-Day International Research Conference on "Digital Marginalisation and AI Bias: Redefining Business and Society (ICDMAI-BS 2026)"***

It gives us immense pleasure to present **Special Issue – I** of the Quest Journal of Management and Research, comprising selected double blind peer-reviewed papers from the ***ICSSR Sponsored Two-Day International Research Conference on "Digital Marginalisation and AI Bias: Redefining Business and Society (ICDMAI-BS 2026)",*** held on **27–28 February 2026** in hybrid mode.

The conference was organized with the objective of fostering scholarly dialogue on the transformative impact of Artificial Intelligence and digital technologies on contemporary business and society. As AI-driven systems increasingly influence decision-making processes, consumer behaviour, education, governance, and communication, concerns regarding digital exclusion, algorithmic bias, ethical accountability, and equitable access have become central to academic and policy discussions. The conference provided an interdisciplinary platform for researchers, academicians, practitioners, and policymakers to explore these emerging challenges and opportunities.

The papers included in this **Special Issue – I** reflect the growing significance of understanding how digital technologies shape individual, organizational, and societal outcomes. The contributions offer valuable perspectives on consumer behaviour, digital literacy, educational inclusion, citizen empowerment, and algorithmic influence within the broader context of digital transformation.

The issue opens with the paper **"Impact of Cross-Selling and Merchandising Strategies on Customer Basket Size in a Digitally Driven Retail Environment: Evidence from Pantaloons, Akola",** which examines the effectiveness of contemporary retail strategies in enhancing customer engagement and purchase behaviour within digitally enabled retail ecosystems. The study contributes to understanding the evolving relationship between technology-driven retail practices and consumer decision-making.

The second paper, **"Empowering Digital Citizens: Students' Awareness of Bias in AI-Generated News,"** explores students' perceptions and awareness of bias embedded in AI-generated content. As artificial intelligence increasingly mediates information dissemination, the study highlights the critical role of digital literacy and critical thinking in preparing informed and responsible digital citizens.

In **"Digital Marginalization in AI-Powered Education: An Instructional Design Perspective,"** the authors investigate how AI-enabled educational systems may unintentionally reinforce inequalities among learners. The paper emphasizes the importance of inclusive instructional design frameworks that ensure accessibility, fairness, and equitable learning opportunities.

The fourth contribution, **"Digital Awareness and Empowerment of Citizens: Bridging the Divide for an Equitable Society,"** focuses on the role of digital awareness initiatives in reducing inequalities and promoting inclusive participation in the digital economy. The study underscores the need for collaborative efforts among governments, educational institutions, and communities to bridge existing digital divides.

The issue concludes with **"Influence of Algorithms on Consumer Choice and Behaviour: Implications for Bias and Digital Marginalization,"** which critically examines the growing role of algorithms in shaping consumer preferences and purchasing decisions. The paper raises important questions concerning transparency, fairness, and ethical responsibility in algorithm-driven environments.

Collectively, the contributions featured in this Special Issue advance our understanding of the complex interplay between digital technologies, artificial intelligence, and social inclusion. They highlight the opportunities offered by technological innovation while drawing attention to the challenges of ensuring fairness, accessibility, and ethical accountability. The findings presented herein offer valuable insights for researchers, educators, industry practitioners, and policymakers seeking to create more inclusive and responsible digital ecosystems.

We express our sincere gratitude to the **Indian Council of Social Science Research (ICSSR)** for its support in facilitating this international conference and promoting research on issues of contemporary relevance. We also extend our appreciation to all authors, reviewers, keynote speakers, session chairs, members of the organizing committee, and participants whose dedication and scholarly contributions made the conference a resounding success.

As we present **Special Issue – I**, we hope that the research published in this volume stimulates further inquiry, informed policymaking, and meaningful dialogue on the challenges and opportunities associated with digital transformation. The discussions initiated through these contributions are expected to contribute significantly to the development of a more equitable, ethical, and inclusive digital future.

Dr. Kavita Khadse,

Editor & ICSSR International Research Conference Convener

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"Impact of Cross-Selling and Merchandising Strategies on Customer Basket Size in a Digitally Driven Retail Environment: Evidence from Pantaloons, Akola"

*** Prof. Vaishnav Kadu**
**** Ms. Janhavi Dabhade**

Abstract:

The fashion retail industry is undergoing a rapid digital transformation driven by the adoption of data analytics, artificial intelligence, and technology-enabled merchandising practices. These developments are reshaping not only retail performance outcomes but also the inclusiveness of customer engagement across diverse demographic groups. This study examines the influence of cross-selling and visual merchandising strategies on customer basket size at Pantaloons, an organised apparel retailer located in Akola. Particular emphasis is placed on understanding how digitally supported promotional tools and algorithm-based recommendations affect purchasing behaviour and whether such interventions provide equitable benefits to all customer segments. Primary data were collected from 500 walk-in customers through structured questionnaires administered via Google Forms and physical surveys. These data were supplemented by in-store observations and informal interactions with sales personnel and store managers to capture both human-led and technology-assisted selling practices. The findings reveal that proactive staff recommendations, coordinated outfit displays, and visually engaging store layouts significantly contribute to increased basket size and impulse purchases. However, the study also identifies concerns related to uneven access to digital loyalty programs, limited engagement with mobile applications, and potential bias in digitally driven promotional exposure, which tend to disadvantage less tech-savvy and price-sensitive customers. The study concludes that while data-driven and AI-supported merchandising strategies can enhance store-level performance, their sustainable effectiveness depends on inclusive design, transparency, and ethical implementation. The research underscores the importance of responsible digital integration in retail to achieve both commercial growth and social equity in evolving business environments.

Keywords : *Cross-Selling, Digital Retailing, Artificial Intelligence in Retail, Consumer Buying Behaviour, Customer Basket Size, Ethical Retailing.*

1. Introduction

The fashion retail industry is undergoing a significant transformation driven by advances in digital technologies such as omnichannel systems, data analytics, and artificial intelligence. Retailers increasingly depend on data-informed decision-making and technology-enabled merchandising practices to enhance operational efficiency, improve personalisation, and strengthen revenue performance (Brynjolfsson et al., 2013; Davenport & Ronanki, 2018). Within this changing retail landscape, cross-selling and visual merchandising have gained strategic importance as key mechanisms for increasing customer basket size and encouraging impulse buying in physical stores, often supported by digital tools in-

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cluding loyalty programs and personalised promotional offers.

Consumer purchasing behaviour in contemporary retail environments is influenced not only by price and product availability but also by experiential factors associated with the store setting. The servicescape framework proposed by Bitner (1992) explains how physical surroundings function as environmental stimuli that shape customers’ emotional responses and behavioural intentions. Supporting this view, empirical research demonstrates that atmospheric elements such as lighting, colour schemes, music, and spatial layout significantly influence customer dwell time and spending behaviour (Turley & Milliman, 2000). In the context of fashion retail, visually coordinated displays and structured merchandise presentation further enhance brand perception and stimulate impulse-driven purchases (Kerfoot et al., 2003; Park et al., 2006).

Alongside visual cues, cross-selling plays a crucial role in enhancing transaction value by motivating customers to purchase complementary products. Prior studies suggest that data-driven and sequential cross-selling strategies are more effective when aligned with customer needs and behavioural patterns (Kamakura et al., 2003; Li et al., 2005). Relationship-oriented approaches further indicate that personalised recommendations contribute to higher customer lifetime value and stronger long-term relationships (Venkatesan & Kumar, 2004; Kumar & Reinartz, 2016). In physical retail environments, these practices are increasingly embedded within hybrid retail models that integrate human-led selling with digitally enabled touchpoints (Verhoef et al., 2015; Grewal et al., 2017).

However, the advantages of digital retail transformation are not experienced uniformly across all customer segments. Research on the digital divide highlights that inequalities in access, digital skills, and technology usage often intersect with broader social and economic disparities (Selwyn, 2004; Choudrie et al., 2021). In semi-urban and emerging market contexts, limited digital literacy, restricted smartphone access, and higher price sensitivity may prevent certain consumers from fully benefiting from app-based promotions, personalised recommendations, and algorithm-driven merchandising tools (Donner & Tellez, 2008). Moreover, growing concerns related to algorithmic bias and ethical accountability in data-driven systems raise important questions regarding fairness and inclusivity in digitally mediated retail environments (O’Neil, 2016; Martin, 2019; Mehrabi et al., 2021; Boone & Ganeshan, 2021).

Despite extensive research on digital retailing in metropolitan and online settings, empirical evidence from semi-urban organised retail contexts in India remains limited. In particular, the interaction between traditional merchandising strategies and digitally enabled retail tools, examined through the lens of inclusion and ethical digital transformation, has received insufficient scholarly attention. Addressing this gap, the present study investigates Pantaloons, Akola, to examine how digitally supported cross-selling and visual merchandising strategies influence customer basket size. By linking retail performance outcomes with issues of digital marginalisation and ethical retailing, the study contributes to both academic discourse and managerial decision-making in emerging market retail environments.

2. Review of Literature

2.1 Cross-Selling and Customer Basket Size

Cross-selling has emerged as an important managerial approach for increasing the value of individual transactions, strengthening customer lifetime value, and improving overall profitability. Prior studies emphasise that cross-selling initiatives are more successful when they are tailored to customers’ preferences and situational buying needs, rather than relying on aggressive product-promotion tactics

(Kamakura et al., 2003; Li et al., 2005). Research within the relationship marketing domain further highlights that customised product suggestions enhance customer trust and foster repeat purchasing behaviour (Venkatesan & Kumar, 2004; Kumar & Reinartz, 2016). Additionally, empirical findings suggest that both data-supported sequential recommendations and salesperson-driven cross-selling positively influence basket size, with human interactions in physical retail settings remaining particularly effective due to their ability to respond flexibly to real-time customer signals (Grewal et al., 2017).

2.2 Visual Merchandising

Visual merchandising plays a critical role in shaping how customers perceive a store, form impressions about the brand, and engage in impulse purchasing. Well-designed product displays improve perceived product value and strengthen brand memory, while consumers' emotional reactions to the retail environment often trigger spontaneous buying decisions (Park et al., 2006). The servicescape perspective highlights that physical store conditions influence customer moods and behavioural responses (Bitner, 1992), and research shows that atmospheric factors such as lighting arrangements, colour schemes, and spatial design affect both the time customers spend in the store and their overall expenditure (Turley & Milliman, 2000). In addition, systematically arranged merchandise encourages shoppers to explore multiple product categories, thereby supporting complementary purchases (Kerfoot et al., 2003).

2.3 Digital Retail, Algorithmic Bias, and Digital Marginalisation

The ongoing digital shift in retail has led to widespread adoption of artificial intelligence–driven applications and omnichannel systems aimed at improving overall customer experience (Davenport & Ronanki, 2018; Verhoef et al., 2015). Nevertheless, the advantages of these digital innovations are not shared equally, as differences in technology access, digital competence, and literacy continue to limit participation, particularly within semi-urban retail settings (Brynjolfsson et al., 2013; Choudrie et al., 2021). Ethical challenges also emerge from algorithmic decision-making, as data-based retail systems may disproportionately target technologically engaged or high-spending customers, thereby deepening patterns of exclusion (O'Neil, 2016; Martin, 2019; Mehrabi et al., 2021). As a result, scholars increasingly advocate for hybrid retail approaches that integrate digital technologies with human-led interactions to promote more inclusive and equitable customer engagement (Lamberton & Stephen, 2016).

2.4 Research Gap

Although prior research has extensively examined cross-selling, visual merchandising, and digital retail practices independently, there is a noticeable lack of integrated empirical studies focusing on semi-urban organised retail settings in India. This shortfall underscores the need for systematic investigation into how hybrid retail approaches affect customer basket size while simultaneously addressing issues of digital exclusion and ethical responsibility.

2.5 Literature Synthesis

Existing studies demonstrate that cross-selling and visual merchandising play an important role in enhancing customer basket size, particularly when supported by personalisation, sequential recommendation strategies, and engaging store environments (Kamakura et al., 2003; Kerfoot et al., 2003; Li et al., 2005). Store layout, atmospheric elements, and coordinated displays influence consumer emotions and impulse buying behaviour, while both data-driven and salesperson-led cross-selling practices contribute to increased transaction value (Bitner, 1992; Turley & Milliman, 2000; Park et al., 2006; Grewal et al., 2017). Research on digital retailing and omnichannel integration further highlights the growing influence of technology-enabled tools on customer decision-making and overall retail performance (Brynjolfsson et al., 2013; Verhoef et al., 2015; Davenport & Ronanki, 2018).

However, uneven technology adoption and variations in digital literacy raise concerns related to digital marginalisation, particularly in semi-urban and emerging market contexts (Selwyn, 2004; Donner & Tellez, 2008; Choudrie et al., 2021). Studies on algorithmic bias also caution that data-driven systems may unintentionally reinforce exclusion by favouring digitally active or high-value customers (O'Neil, 2016; Martin, 2019; Mehrabi et al., 2021). While these themes have largely been examined independently, limited integrated research exists within semi-urban organised retail settings, highlighting the need for empirical studies on hybrid retail strategies that balance commercial performance with inclusive and ethically responsible customer engagement.

3. Research Methodology

3.1. Research Design

A descriptive–analytical research design was utilised to study customer perceptions and behavioural responses to cross-selling and merchandising in retail, focusing on natural shopping behaviour. The methodology facilitated systematic examination of factors like basket size, staff influence, visual merchandising, and digital engagement. Techniques such as percentage analysis and cross-tabulation were applied to uncover relationships among key variables, yielding insights into customer behaviour in a digitally driven retail environment.

3.2. Research Objectives

1. To examine the impact of cross-selling and visual merchandising strategies on customer basket size and impulse buying behaviour at Pantaloons, Akola, in a digitally driven retail environment.
2. To assess the role of digital tools in supporting merchandising strategies and evaluate issues of digital marginalisation and algorithmic bias in promotional exposure, loyalty benefits, and customer inclusion.

3.3. Sampling Technique

The study employed a convenience sampling method to select respondents from Pantaloons in Akola, focusing on walk-in customers available for participation immediately after their purchases. This method was chosen for its suitability given operational constraints, time efficiency, and the exploratory nature of consumer behaviour research in retail.

3.4. Sample Size and Universe

- **Sample Size:** 500 respondents
- **Sample Universe:** Walk-in customers of Pantaloons, Akola.
- The study analysed 500 customers at Pantaloons, encompassing various demographics such as age, gender, occupation, and income, which strengthened the findings on basket size formation in digital retail.

3.5. Data Collection Method

Primary data were collected using a structured questionnaire comprising closed-ended, multiple-choice, and Likert-scale questions, administered through both physical surveys and Google Forms. The instrument assessed customer responses to digital in-store features, cross-selling prompts, and merchandising displays. In addition, contextual insights into customer movement patterns and engagement with promotional elements were obtained through in-store observations and informal interactions.

3.6. Data Analysis

The data were analysed using descriptive statistical tools, including percentage analysis and cross-tabulation, utilising Microsoft Excel and Google Sheets to organise and interpret the findings. This methodology enabled the identification of relationships between merchandising strategies and customer basket size.

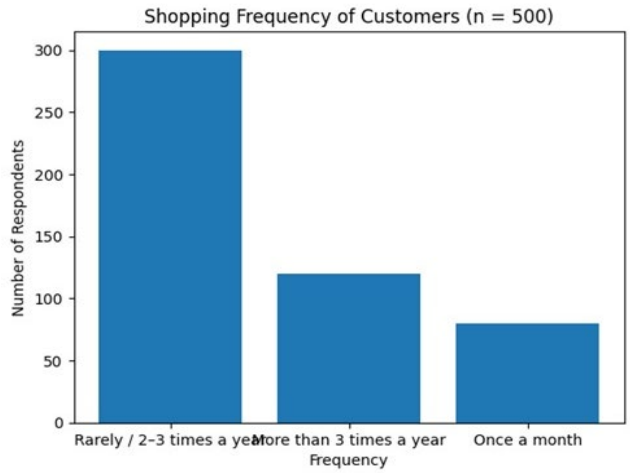
4. Data Analysis and Interpretation

Aspect	Category	Frequency	Percentage (%)
Gender	Male	292	58.4
	Female	192	38.4
	Not disclosed	16	3.2
Age Group	Below 20	125	25.0
	21–30	267	53.4
	31–40	92	18.4
	41–50	16	3.2
Location	Akola City	367	73.4
	Nearby Town/ Village	83	16.6
	Other	50	10.0
Total		500	100

Table 4.1: Demographic Analysis of Customer

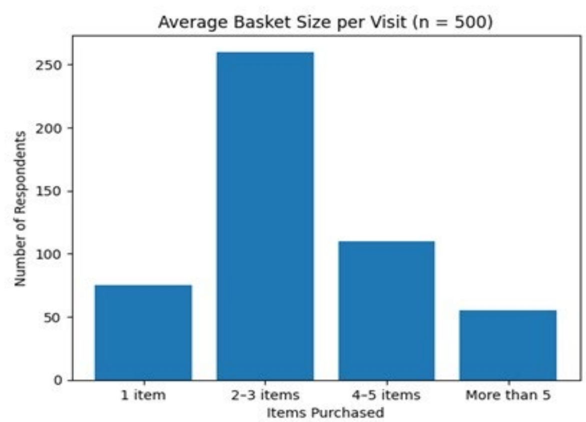
A study of 500 responses revealed that 58.4% of customers at Pantaloons, Akola, were male, while 38.4% were female. The age group with the

Highest representation was 21–30 years (53.4%), followed by those under 20 (25.0%) and aged 31–40 (18.4%). Furthermore, 73.4% of respondents were local residents, indicating strong market penetration in Akola, with 16.6% from nearby areas and 10% from other regions, reflecting effective regional outreach.



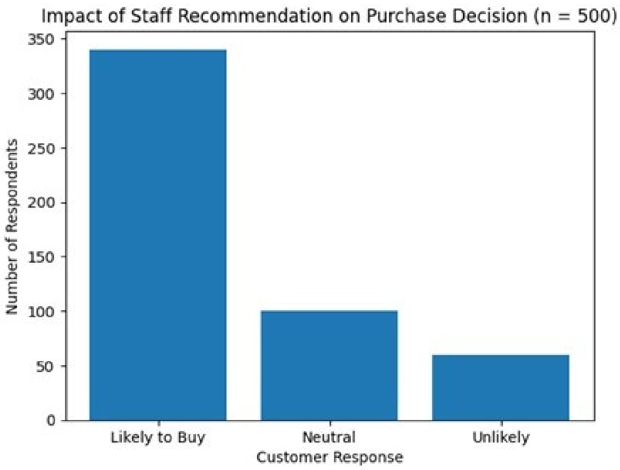
4.2: Shopping Frequency of Customers

Shopping frequency at Pantaloons is predominantly low, with most customers shopping rarely or two to three times a year, indicating occasion-driven visits. This emphasizes the need for strategies to maximize basket size during these limited interactions, such as effective cross-selling, attractive displays, and timely promotions, to enhance transaction value.



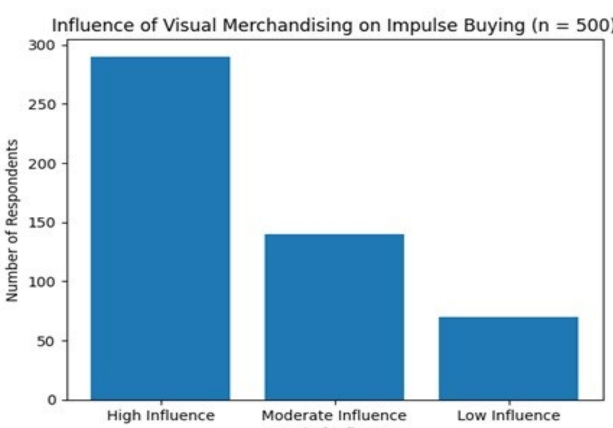
4.3: Customer Basket Size and Purchase Volume.

Customer basket size is a key indicator for evaluating merchandising and cross-selling strategies. At Pantaloons, the majority of customers typically purchase two to three items, while fewer buy four to five items or just one. This moderate basket size indicates significant opportunities for upselling and add-on selling. Customers are willing to buy additional items when effectively presented with complementary products, emphasising the potential of cross-selling initiatives, bundled offers, and coordinated product displays to enhance basket value in a digital retail setting.



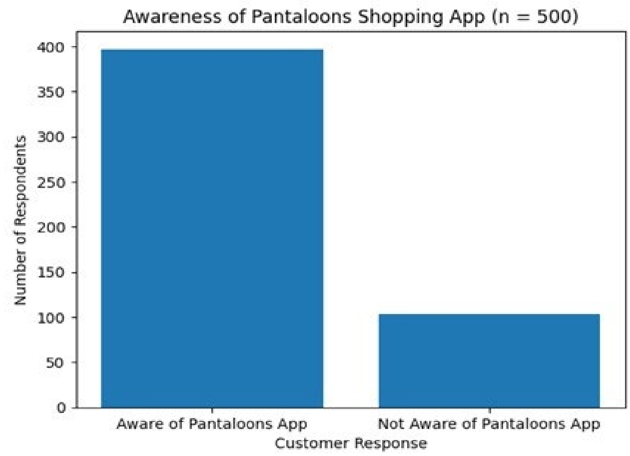
4.4: Impact of staff Recommendation on Purchase decision

Sales staff significantly influence customer purchasing decisions in physical retail, with many customers likely to buy additional products when recommended by staff. The findings highlight human-led cross-selling as effective for increasing basket size, even amidst rising digital tool usage. Personal interaction mitigates decision-making uncertainty and promotes product utility, enhancing overall shopping satisfaction.



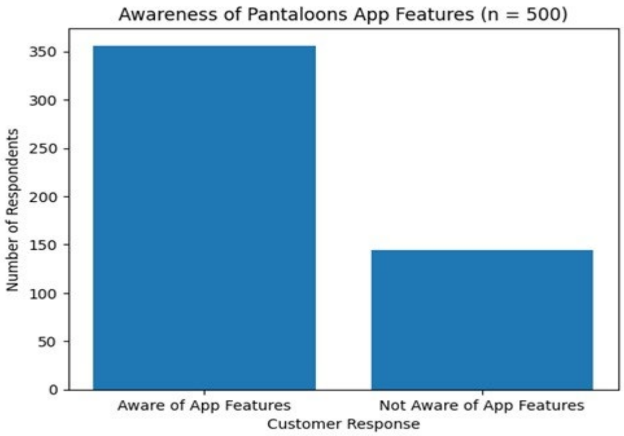
4.5: Influence of Visual Merchandising on Impulse Buying

Visual merchandising serves as a crucial sensory and cognitive influence on in-store purchasing behaviours, significantly impacting impulse buying through store layout, mannequin styling, and product displays. Effective merchandising enhances decision-making by simplifying choices, inspiring outfit combinations, and prolonging customer dwell time, especially when integrated with digital retail strategies, thereby fostering experiential shopping and promoting incremental basket growth..



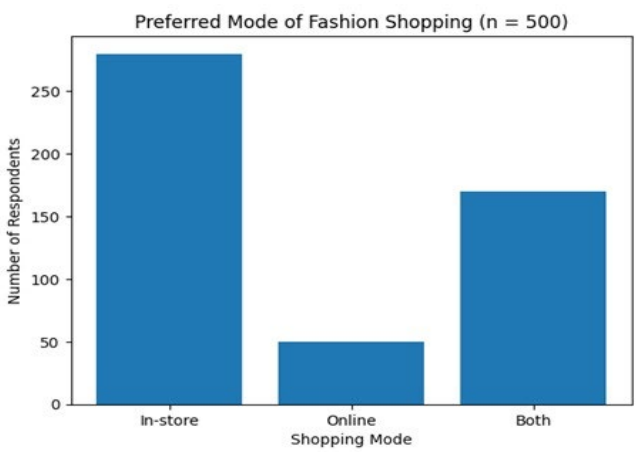
4.6: Awareness of Pantaloons Shopping App

The analysis indicates that while many customers know about Pantaloons' mobile shopping app and its exclusive offers, this awareness does not guarantee active use of the app for shopping. The findings highlight that despite a strong digital presence, customer engagement and app utilisation for decision-making are lacking. To enhance its impact on customer basket size, the brand needs to implement targeted engagement strategies and reinforce app usage in-store.



4.7: Awareness of Pantaloons App Features

Despite high awareness of the Pantaloons shopping app, specific functionalities like quick delivery and loyalty integration are less recognised. This results in a functional awareness gap, limiting digital cross-selling and personalised merchandising efforts. Customers unaware of these features are less likely to make complementary purchases, reducing the app's potential for basket expansion. The findings suggest a form of digital marginalisation that affects customer engagement with technology-driven retail benefits.



4.8: Preferred Mode of Fashion Shopping

The results reveal a strong preference for in-store shopping, with a notable inclination for hybrid shopping that combines online and in-store channels. A smaller segment favours exclusively online shopping, highlighting the enduring importance of physical retail environments for fashion purchases that require touch and trial. The findings suggest that digital tools complement, rather than replace, in-store experiences, enhancing the effectiveness of cross-selling and merchandising strategies when integrated with human interaction and visual merchandising in physical stores.

5. Conclusion

This study examined the impact of cross-selling and merchandising strategies on customer basket size at Pantaloons, Akola. The findings show that basket value is influenced by economic factors, in-store experience, and digital tools, with customers typically purchasing two to three items per visit. Human-led cross-selling and visual merchandising encourage impulse buying, while low usage of digital tools indicates a gap between awareness and engagement. Price sensitivity remains a key constraint, highlighting the need for value-oriented and integrated retail strategies.

6. Contribution of the Study

This study contributes empirical evidence from a semi-urban organised apparel retail context in India by integrating cross-selling and visual merchandising with issues of digital marginalisation and ethical digital transformation. The findings highlight the role of hybrid retail models, where human-led selling complements digital merchandising to enhance customer basket size while supporting inclusive engagement. Managerially, the study offers practical insights for balancing revenue growth with responsible use of digital retail tools.

7. Suggestions and Recommendations

Recommendations to enhance basket size in Pantaloons' digital retail environment include training sales associates in cross-selling, enhancing visual merchandising, implementing bundled offers and personalised digital coupons, optimising communication of loyalty program benefits, expanding product assortments, improving trial room management, and leveraging digital tools to improve omnichannel integration.

8. Limitations and Future Scope

This study has limitations that suggest future research avenues, notably its reliance on a single-store case study of Pantaloons, Akola, which may affect the general applicability of its findings. Convenience sampling and self-reported data may lead to response bias. The descriptive analysis limits causal inference between merchandising strategies and customer basket size. Future research could overcome these issues by employing comparative designs across different cities and formats, utilising inferential statistical methods like regression analysis or structural equation modelling, and incorporating real-time transaction data alongside behavioural models to enhance analytical rigour in digital retail contexts.

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Empowering Digital Citizens: Students Awareness of Bias in AI-Generated News

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Abstract:

This study investigates how young college students perceive and identify with news content generated through Artificial Intelligence(AI). Using focus group discussions as the primary method, the research explores audience attitudes, trust and engagement with AI produced news. The discussions provide insights into how students negotiate authenticity, credibility and personal connection when consuming AI-generated news. Findings aim to contribute to the broader understanding of audience-media relationships in the digital age, highlighting both opportunities and challenges of integrating artificial intelligence into news production.

Keywords : *AI-generated news, audience perception, focus groups, media credibility, digital journalism, student engagement*

1. Introduction

The way news reaches people today has changed drastically because of Artificial Intelligence (AI). AI tools are now being used at almost every stage of news production, from writing articles automatically to selecting top stories for homepages to summarising long reports in real time. While the productive advantages of AI for news organisations are well known, there is a rising concern that AI-generated news content may carry biases that consumers cannot easily detect. Such hidden bias is a major issue for a democracy as people must have access to fair, balanced, and transparent information in order to participate in a meaningful way.

This study, titled "Empowering Digital Citizens: Student Awareness of Bias in AI-Generated News," aims to improve students' ability to act as responsible and informed digital citizens by enabling them to identify, evaluate and react to biases in news content generated by AI systems. The study has been designed as an exploratory qualitative investigation at SNDT Women's University, Mumbai. Focus group discussions were conducted with women university students to learn more about their news consumption habits, awareness of AI in news production, ability to spot bias in AI-generated content, views about trusting AI-generated news, and opinions on being prepared for digital citizenship. By bringing forward the voices of women university

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students a group that is simultaneously among the most active digital news consumers and the most underrepresented in AI and journalism scholarship this study makes the argument that awareness of algorithmic bias is not just some technical skill but a fundamental dimension of digital citizenship and democratic empowerment in today's India.

1.2 The study has the following five research objectives:

1. To explore students' news consumption patterns and their trust level in broadcast and digital news media.
2. To assess students' awareness and knowledge of Artificial Intelligence tools currently used in news creation and distribution.
3. To examine students' ability to identify and critically evaluate bias in AI-generated news content.
4. To understand the factors influencing students' trust or distrust in AI-generated news compared to human-written journalism.
5. To investigate students' perspectives on digital citizenship preparedness and the responsible integration of AI in Indian news media.

2. Review of Literature

2.1 AI and Its Growing Role in News Production

Over the past decade, the media sector has seen a significant rise in the use of artificial intelligence. About 75% of news organisations worldwide have implemented news writing automation, according to a review of 127 research studies by Sonni et al. (2024). Major international organisations such as the Associated Press, The Washington Post, Reuters and Bloomberg now operate automated reporting systems capable of producing large volumes of articles with minimal human involvement (Graefe, 2016; Carlson, 2015). Within India, leading publications including The Times of India and Hindustan Times have begun experimenting with AI-assisted tools for headline creation, story recommendation and content production (Aneez et al., 2016; Chadha, 2017). Cools and Diakopoulos (2024) identified sixteen distinct applications of generative AI tools across the news production cycle in European newsrooms, while Pavlik (2023) argued that generative AI constitutes a qualitatively different shift that demands new approaches to media education. Breazu and Katsos (2024), who examined editorial perspectives generated by ChatGPT-4, found that the system maintained structural biases from its training corpus even when showing more balance than some biased documents.

2.2 Audience Perceptions and Trust in AI-Generated News

Clerwall (2014) demonstrated that readers were unable to reliably differentiate between machine-written and human-authored articles, indicating that automated content can pass through audience evaluation undetected. Graefe et al. (2018) confirmed that while automated articles received slightly lower readability scores, they were rated similarly to human-written pieces on credibility and expertise. Waddell (2018) showed that when readers became aware of machine authorship, their credibility assessments declined, though a follow-up study found that bias perceptions were reduced when news was attributed to a journalist and algorithm working in tandem (Waddell, 2019). A meta-analytic synthesis by Graefe and Bohlken (2020) concluded that automated news showed no significant difference from human-written content in credibility perceptions, though readability differences were substantial. Within India, the Reuters Institute Digital News Report 2025 (Newman et al., 2025) reported that 44% of Indian respondents expressed comfort with AI-generated news the highest proportion globally yet 71% simultaneously reported uncertainty about trusting AI-produced online content (Ipsos, 2024). This paradox suggests that Indian audiences are exposed to AI-mediated information but may lack the critical frameworks needed to evaluate it properly.

2.3 Algorithmic Bias and Its Implications for News Content

Because AI systems are trained on historical datasets that reflect pre-existing societal inequalities, the content they produce can prolong or even increase biases related to gender, caste, region, religion and socioeconomic status (Broussard et al., 2019; Porlezza & Schapals, 2024). A landmark investigation by UNESCO (2024) examined outputs from leading large language models and found that women were disproportionately represented in domestic and caregiving roles, while men were associated with professional and leadership positions. Unlike traditional editorial bias where audiences can identify the known ideological orientation of a particular media organisation, algorithmic bias is embedded within training data, model architecture and optimisation functions in ways that are invisible to the average consumer (Carlson, 2018; Dörr, 2016). Diakopoulos (2019) stressed that transparency and accountability in automated news systems are essential for maintaining democratic information environments.

2.4 Digital Citizenship, AI Literacy and the Indian Media Landscape

The concept of digital citizenship encompasses the norms, skills and knowledge required for responsible and critical participation in digital environments (Ribble, 2015). In the context of AI-generated news, digital citizenship extends beyond basic digital literacy to include algorithmic literacy the understanding that automated systems produce and choose content carefully, that such content may carry biases, and that citizens have the right and responsibility to critically evaluate their media consumption (Polizzi & Taylor, 2024). India's distinctive multilingual media landscape, rapid digital adoption among young people, a large vernacular news ecosystem and distinct cultural norms around both technology and gender make Western research findings difficult to apply directly (Kohli-Khandekar, 2013; Rao, 2019). Belladi (2025) argued that digital technologies including AI are fundamentally reshaping the relationship between media, state, and civil society in India.

2.5 Research Gap

Several interconnected gaps in the existing literature make this study necessary. Most research on audience perceptions of AI-generated news has been conducted in Western, English-speaking contexts, with limited attention to developing countries. While technical studies have documented how AI produces gender-biased content (UNESCO, 2024), no study has examined how young women as news consumers perceive, identify and respond to such biases. Qualitative approaches like focus group discussions are underutilised in this field, with most existing research relying on experimental and survey-based designs. India's distinctive media landscape means that findings from Western studies require contextual validation (Kohli-Khandekar, 2013). This study addresses these gaps through an exploratory qualitative investigation with women university students at SNDT Women's University, Mumbai.

3. Methodology

This study adopted an exploratory qualitative research design using focus group discussions (FGD) as the primary data collection method. The qualitative approach was chosen because the research objectives required in-depth understanding of students' perceptions and reasoning regarding AI-generated news (Creswell & Poth, 2018). The study is situated within an interpretivist epistemological framework, which recognises that students' opinions are influenced by their sociocultural environments, family influences, educational backgrounds and media habits (Lincoln & Guba, 1985). FGDs were preferred over individual interviews as they enable participants to interact, challenge and build upon each other's ideas through collective deliberation (Krueger & Casey, 2015; Gill et al., 2008).

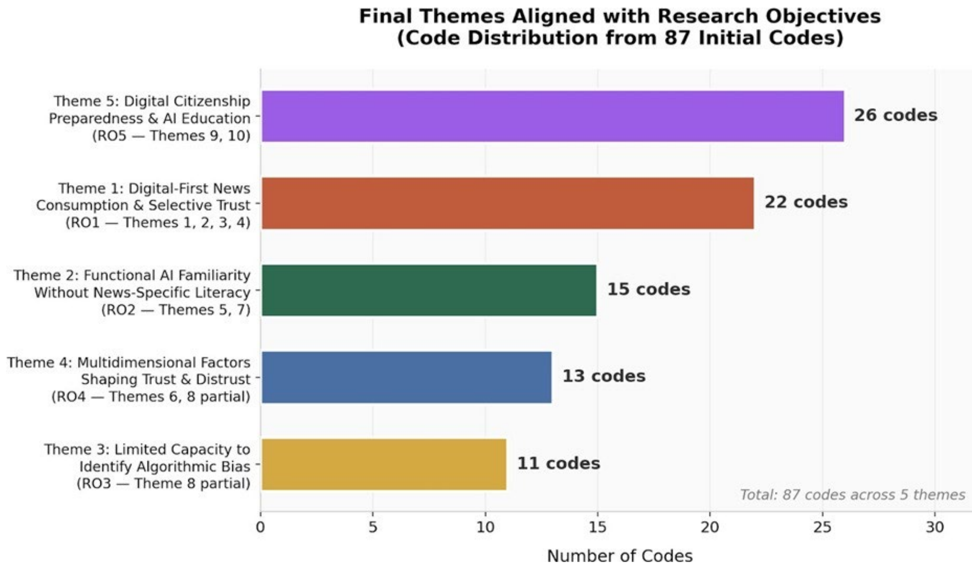
Both FGDs were conducted at SNDT Women's University using a semi-structured discussion aligned with the five research objectives. The discussions were moderated by the co-researcher (Miss Ankita Mhaskar) with the research guide (Dr. Rohit Pawar) present. Sessions were audio-recorded with informed consent and transcribed using Transkriptor software, followed by manual verification for accuracy. The data was analysed using Braun and Clarke's (2006) six-phase reflexive thematic analysis framework, implemented in QDA Miner Lite software. The process involved familiarisation through repeated reading of both transcripts, systematic line-by-line coding generating 87 initial codes, grouping codes into 10 candidate themes, reviewing and consolidating into 5 final themes aligned with the research objectives, defining and naming each theme, and producing the analytical report with supporting participant quotations.

The study has several limitations: the small sample size (13 participants) limits generalisability; both FGDs were relatively brief (9–11 minutes); the English-language instruction may have constrained expression for Hindi and Marathi-speaking participants; and the single-institution, Mumbai-based setting means students from other geographic contexts may hold different perceptions. Despite these limitations, the study provides valuable exploratory insights into an under-researched area.

4. Thematic Analysis

Thematic analysis of the two focus group discussions generated 87 initial codes which were grouped into 10 candidate themes, then consolidated into 5 final themes aligned with the research objectives. The 10 initial themes were: (1) Social Media Dominance in News Consumption, (2) Family and Cultural Influences on News Habits, (3) Selective and Conditional Trust in News Sources, (4) Active Verification and Fact-Checking Behaviour, (5) Widespread AI Tool Familiarity but Limited News-Specific Use, (6) Deep Scepticism Toward AI-Generated News, (7) Deepfakes, Misinformation, and AI Misuse Concerns, (8) Conditional Acceptance of AI in News Production, (9) Human-AI Collaboration as the Preferred Future Model, and (10) Urgent Need for AI Literacy and Education.

The consolidation rationale was as follows: Themes 1–4 (Social Media Dominance, Family/Cultural Influences, Selective Trust, and Fact-Checking Behaviour) were merged into Final Theme 1, addressing news consumption patterns and trust. Themes 5 and 7 (AI Tool Familiarity and Deepfakes/Misinformation Concerns) were merged into Final Theme 2, capturing students' AI awareness and knowledge. Codes from Theme 8 relating to bias perception, plus codes on critical evaluation capacity from Theme 6, were regrouped into Final Theme 3. Theme 6 (Deep Scepticism) and trust-related codes from Theme 8 were merged into Final Theme 4. Themes 9 and 10 (Human-AI Collaboration and AI Literacy & Education) were merged into Final Theme 5, addressing digital citizenship preparedness and responsible AI integration.



5. Findings

Thematic analysis of the two focus group discussions (N=13) at SNDT Women's University, Mumbai, yielded 87 codes consolidated into five themes aligned with the research objectives. Findings are presented below with direct participant evidence from FGD-1 (8 non-media students) and FGD-2 (5 media and communication students).

5.1 Digital-First News Consumption and Selective Trust in Media Sources (RO1)

All nine FGD-1 participants identified Instagram Reels as their primary news source, supplemented by Google News and YouTube, with daily Instagram usage of 3–4 hours. FGD-2 participants consumed news more purposefully through Inshorts (15–30 minutes daily), television channels (NDTV, News18) and professional sources such as Bloomberg. "Three hours or four hours Instagram" (Student 5, FGD-1). Family practices shaped FGD-2 participants' habits, with several participants following fixed time slots for television news on regional Marathi channels. Trust was conditional and source-specific: both groups trusted established brands (NDTV, Hindustan Times, Times of India) but distrusted unverified Instagram pages, government channels and content perceived as propagandistic. Active verification, such as reading beyond headlines and cross-checking sources, was practised primarily by FGD-2 participants.

5.2 Functional AI Familiarity Without News-Specific AI Literacy (RO2)

All 13 participants were familiar with ChatGPT and Gemini, with FGD-2 students confirming daily use. However, no participant in either group had ever used an AI-based news application. When prompted, participants identified AI applications in journalism: FGD-2 students recognised AI's role in summarising, framing and editing news content; FGD-1 students identified AI-generated videos, photos and articles. Both groups were aware of deepfake technology, but only FGD-2 participants could cite specific examples. Student 3 (FGD-2) described a deepfake video of actor Dharmendra circulated on WhatsApp that her father had forwarded believing it to be real. When FGD-1 students were asked to recall specific AI-generated news encounters, none could do so. This reveals a clear gap: students possess functional AI competence for academic tasks but lack algorithmic literacy regarding AI's role in news production and curation.

5.3 Limited Capacity to Identify Algorithmic Bias in AI-Generated News (RO3)

Participants conceptualised AI as data-driven and therefore largely objective. Student 1 (FGD-1) suggested AI systems operate from factual databases rather than subjective judgment: “They mostly go out of data…factual things in database.” Some recognised that AI follows popularity and trending metrics, which could bias content selection, but no participant spontaneously identified other bias mechanisms. The concept of developer bias influencing AI output was acknowledged when introduced during discussion, but participants had not considered this possibility independently. Students described AI content as inherently seeming fake but this suspicion was directed at AI content as a category rather than at identifiable patterns of algorithmic bias an inability to distinguish between different forms of bias that represents a critical deficit in algorithmic literacy as defined by Polizzi and Taylor (2024).

5.4 Multidimensional Factors Shaping Trust and Distrust in AI-Generated News (RO4)

When asked directly whether they would trust news produced entirely by AI, all participants refused. Four specific factors drove this distrust: perceived inauthenticity of AI content, association of AI-generated material with misinformation, limitation of AI content to entertainment rather than serious news, and difficulty of verifying AI-produced information. “People have fear…AI generated means misleading” (Student 4, FGD-2). However, participants articulated strict conditions for acceptable AI use in journalism: content must be factual and verified, must not spread misinformation, must carry source attribution and labelling, and must be subject to human oversight. Student 4 (FGD-2) specifically called for bibliographic references in AI-generated content and insisted on human verification of all AI-produced data. Participants also preferred human presenters over AI anchors.

5.5 Digital Citizenship Preparedness and the Imperative for AI-Integrated Education (RO5)

Both groups endorsed a human-AI collaboration model for journalism: AI handling editing, proofreading and content creation, while humans retain anchoring, field reporting and editorial judgment. Full AI replacement of journalists was unanimously rejected. Both groups acknowledged that AI awareness among Indian citizens is critically insufficient and notably admitted their own prior lack of awareness about AI in news production. A generational divide was identified: corporate workers possess greater AI awareness than homemakers, and younger people are more familiar with AI than older generations. “Even we weren’t as aware that AI is being used in news” (All Students, FGD-1). Participants’ educational recommendations were specific: AI should be a dedicated subject in schools; instruction should be practical rather than theoretical; curricula should include prompt engineering, deepfake identification and source verification; and the emphasis should be on mindful use rather than dependency. FGD-2 participants additionally called for public awareness campaigns on AI misinformation.

6. Conclusion

This study spoke with 13 women students at SNDT Women’s University, Mumbai, about how they engage with AI and news. Non-media students rely almost entirely on Instagram for news, spending 3 to 4 hours daily scrolling reels, while media students take a more deliberate approach through broadcast channels, Inshorts and source verification. All 13 knew about ChatGPT and Gemini, but none had heard of AI-powered news tools like Perplexity. While they use AI every day, they do not understand how it works behind the news they consume and none could spot how AI content might carry hidden algorithmic biases.

Still, there is a hopeful side. No one was willing to blindly trust AI-made news they found it fake-seeming, unreliable and fit only for entertainment. They set clear expectations: accuracy, labelling, sourcing and human involvement before AI can play any acceptable role in journalism. Students preferred a future where AI handles tasks like editing and proofreading while humans remain in charge of anchoring, field reporting and editorial decisions; full replacement of journalists was rejected outright. They also pointed to a generational gap, noting that older family members, especially homemakers, are far more vulnerable to AI misinformation on platforms like WhatsApp. Most importantly, students from both groups said they want schools and colleges to teach them how to verify AI-generated content, identify deepfakes and use AI mindfully. That demand shows that young Indian women are ready to learn; they just need the right support to move from being everyday AI users to truly informed digital citizens.

7. Implications

For educational institutions, the findings demonstrate an urgent need to integrate algorithmic literacy into both media studies and general education curricula at the university level. News organisations must provide clear labelling, source credit and visible human editorial control in order to gain audience trust. Policymakers should create rules to make AI more transparent and raise awareness about algorithmic processes, as citizens do not fully understand how AI is used in news. This study established that awareness of algorithmic bias in AI-generated news is not a technical but an empowerment dimension of digital citizenship in contemporary India. Adding knowledge about AI to the education system will help young Indian women make proper decisions and actively participate in democracy.

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Digital Marginalization in AI-Powered Education: An Instructional Design Perspective

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Abstract:

The rapid integration of Artificial Intelligence (AI) into education is transforming teaching, assessment, and learner engagement through adaptive platforms, predictive analytics, and automated decision-making systems. While these technologies promise personalization and expanded access, they also risk reinforcing existing inequalities. This paper critically examines how digital marginalization emerges within AI-powered educational environments through algorithmic bias, data representation gaps, infrastructural disparities, and culturally misaligned system design. Using a conceptual and thematic review approach, the study analyzes how bias operates across the machine learning lifecycle, disproportionately impacting marginalized learners, particularly in socio- economically and digitally underserved contexts. The paper argues that exclusion in AI-driven education is not merely technological but fundamentally rooted in design and governance failures. It proposes an inclusion-centered instructional design framework integrating culturally responsive pedagogy, Universal Design for Learning, ethical data practices, and participatory design. The study offers actionable strategies for developing equitable AI-enabled learning ecosystems that promote access, fairness, and educational justice.

Keywords : *AI Bias, Digital Marginalization, Educational Technology, Instructional Design, Inclusion, Adaptive Learning*

INTRODUCTION

The use of Artificial Intelligence (AI) in the educational system leads to a new learning approach through the adaptive learning systems, automated graders, and learning prediction that provide a high level of personalization and automation (Vesna, 2025). As described in Roshanaei et al. (2023), the integration of AI in the educational system leads to the promotion of educational equity by providing a unique learning experience and reducing the resource disparities between the different learner groups. Hence, the individual learning pathways, the automated grader and the performance analysis that are some examples of the AI applications in education lead to more efficient pedagogical practices, students' engagement and higher quality of education for all worldwide(Hariyanto et al., 2025).

The speed of technological integration into education has brought numerous challenges, including the danger of digital exclusion and algorithms that perpetuate current forms of social inequality (Vesna, 2025). As AI opens many doors for education, it is crucial to scrutinize of how AI- powered

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ed-tech will be used in the classroom and the ways in which it can exacerbate the current inequalities between students, by embedding such embedded inequalities in the technology itself, during data training and when it is implemented (Boateng & Boateng, 2025; Vesna, 2025). This paper aims to assess the ways in which the integration of ed tech in the classroom can exacerbate current inequalities between students (Boateng & Boateng, 2025; Vesna, 2025) and assess the ways in which instructional design can mitigate some inequalities present in digital learning (Baker & Hawn, 2021; Boateng & Boateng, 2025).

One of the pressing concerns is the lack of diversity and representation in training data. Without having diverse training data, AI systems may perform poorly for minority groups, lead to inaccurate profiling, and limit access to quality education for marginalized populations, which ultimately perpetuates social inequality (Du et al., 2024). Another concern is that the increasing use of AI in education is exacerbating existing digital divide and infrastructure inequalities, leading to the exclusion of disadvantaged groups from AI-assisted learning environments (Roshanaei et al., 2023).

This paper suggests that education leaders and others need to develop instructional design models that mitigate bias in learning technologies (Gabriel, 2024). The paper describes how marginalization can be built into every stage of a machine learning process, from data collection to model training, implementation and assessment, and proposes an inclusion-focused design lens to address these inequalities. The goal of the paper is to identify steps that educators, education leaders, policymakers and EdTech developers can take to ensure that the adoption of AI technologies in education supports the goals of equity and access (Boateng & Boateng, 2025).

LITERATURE REVIEW

The application of Artificial Intelligence (AI) in education represents a major pedagogical shift, bringing both opportunities and challenges. This review synthesizes research across three areas: (a) applications of AI in education, (b) algorithmic bias in educational systems, and (c) the relationship between AI-based learning and the digital divide.

1. AI in Education

AI technologies have increasingly shaped digital learning through adaptive platforms, intelligent tutoring systems, automated grading, and learning analytics (Gutiérrez et al., 2025). These tools aim to personalize learning, enhance engagement, and improve operational efficiency (Hariyanto et al., 2025). Research highlights their role in customizing learning pathways, delivering real-time feedback, and predicting academic performance, contributing to more flexible and scalable learning models (Roshanaei et al., 2023; Vesna, 2025).

Despite these benefits, systemic concerns remain. Key issues include the pedagogical value of AI systems, the balance between human teaching and automation, and long-term implications for learners. Personalization may limit exposure to diverse perspectives and reduce meaningful human interaction (Gabriel, 2024). The rise of generative AI and large language models has expanded content creation possibilities while raising concerns around quality, ethical use, and equitable access (Gabriel, 2024). Moreover, limited research examines the long-term cognitive and well-being impacts of AI- mediated learning environments (Nivins et al., 2024)

2. Algorithmic Bias in AI Systems

Algorithmic bias is an increasing concern in AI-driven education (Baker & Hawn, 2021; Boateng & Boateng, 2025). Bias can emerge at the data, algorithm, or application level within the machine learning pipeline (Boateng & Boateng, 2025). Educational datasets often lack demographic diversity, resulting in systems that inadequately serve minority learners (Du et al., 2024; Roshanaei et al., 2023). This can produce unfair assessments, inaccurate learner profiling, and restricted educational opportunities (Du et al., 2024).

Assessment platforms illustrate these risks. Systems trained on narrow socio-economic or linguistic datasets may misinterpret student performance, creating what is termed “bias in the absence of bias” (Du et al., 2024). The opacity of algorithmic processes further complicates detection, as links between data inputs and outcomes remain unclear. Given their use in high-stakes contexts such as admissions, grading, and learning access, biased systems can have lasting academic consequences (Boateng & Boateng, 2025).

Current mitigation strategies emphasize inclusive datasets, transparent system design, and algorithmic audits. However, scalable and context-specific bias detection frameworks remain underdeveloped.

3. Digital Divide and Educational Inequality

AI integration in education is closely linked to digital inequality. Disparities persist in access to infrastructure, digital skills, and technological resources (Roshanaei et al., 2023; Vesna, 2025). Learners from low-income households, rural regions, minority communities, and disability groups face barriers in accessing AI-enabled learning systems.

Unequal infrastructure further limits institutional adoption. Under-resourced schools often lack financial and technological capacity to implement AI-driven personalization (Vesna, 2025). Additionally, socially biased datasets may reinforce gender and cultural inequalities within learning environments (Roshanaei et al., 2023).

Digital marginalization extends beyond device ownership to include digital literacy gaps, limited critical participation, cultural misrepresentation, and weak data protections (Pawluczuk, 2020). Although policy reforms and inclusive technology models have been proposed, comprehensive strategies addressing AI-driven digital inequality remain limited (Edeni et al., 2024; Fadden et al., 2024; Sun, 2024).

METHODOLOGY

This paper outlines the criteria for source selection, data extraction procedures, and analytical techniques used to identify key variables and research gaps. The methodology aims to examine how algorithmic bias manifests in AI-enabled educational technologies and how it affects marginalized learner groups. The review follows established literature review guidelines to ensure objectivity, relevance, and methodological rigour.

A systematic search strategy was adopted based on the protocol proposed by Chembe, Kimuyu, and Muleya-Mutshke (2023). Keywords including artificial intelligence in education, algorithmic bias, and digital marginalization were used to retrieve relevant scholarly literature. Searches were conducted across major academic databases, including Scopus, Web of Science, IEEE Xplore, and ACM Digital Library, to ensure comprehensive coverage of peer-reviewed articles, conference papers, and technical reports.

Following the initial search, titles and abstracts were screened to assess relevance to AI applications in education. Full-text articles were subsequently evaluated against predefined inclusion and exclusion criteria, focusing on studies examining the emergence, impact, and mitigation of algorithmic bias affecting marginalized learners (Chembe et al., 2023). This screening process enabled identification of dominant themes and research gaps relating to fairness and equity in AI-driven education.

The refined corpus underwent thematic analysis. Findings were categorized according to bias typologies, learner impacts, and proposed mitigation strategies to develop a structured understanding of equity challenges in AI-supported learning environments (Barnes & Hutson, 2024). This synthesis informed policy and instructional design recommendations grounded in current research discourse (Roshanaei et al., 2023).

Further analysis examined bias across the machine learning lifecycle (Baker & Hawn, 2021). Evidence indicates that non-diverse training datasets contribute to unfair predictions, biased assessments, and inequitable learning recommendations (Du et al., 2024; Fraidan, 2024). Legacy datasets often reproduce historical inequalities linked to socio-economic status, race, and gender (Eden et al., 2024).

The review also considered emerging risks associated with generative AI and large language models. Bias detection remains complex due to evolving natural language evaluation standards and cultural contextualization challenges (Gabriel, 2024). Bias may also stem from developer assumptions, system design choices, and reliance on historical performance metrics (Egunjobi & Adeyeye, 2024; Boateng & Boateng, 2025).

Overall, this systematic methodological approach enables a comprehensive examination of bias sources and mechanisms in AI-based educational systems while identifying intervention points for inclusive instructional design.

FINDINGS

This study investigates the integration of Artificial Intelligence in education, examining its impact on teaching, learning, and the broader educational ecosystem. It evaluates AI-driven personalized learning platforms, particularly their instructional benefits in adapting learning materials to learner capabilities while also assessing their potential to reinforce existing social inequalities (Ayeni et al., 2024; Chilambarasan, 2025; Bura & Myakala, 2024).

The study further explores ethical challenges associated with AI adoption, including data privacy, algorithmic transparency, and surveillance concerns, all of which influence trust and responsible technology use (Barnes & Hutson, 2024; Faruqui et al., 2024). It also analyses how AI systems may perpetuate digital exclusion through biased implementation and unequal technological access (Ayeni et al., 2024). According to Gupta et al. (2025), inequalities in digital skills and infrastructure between different socio-ecoomic classes may further exacerbate the digital exclusion.

Evidence suggests that adaptive systems may inadvertently reproduce inequality by limiting underperforming learners to lower-level content and reinforcing stereotypical learning pathways (Chinta et al.). Bias may emerge across data collection, model design, and deployment, reflecting broader societal inequalities related to gender, race, and socio-economic status (Caccavale et al.). Without systematic auditing, such systems risk perpetuating historical disparities (Roshanaei et al.).

Accordingly, the literature calls for instructional design frameworks that embed equity and inclusivity across the AI lifecycle, from data generation to system deployment (Denny et al.). Holistic approaches integrating technical, pedagogical, and socio-ethical considerations are essential to mitigating digital exclusion (Daher; Roshanaei et al.). Culturally responsive design, accessibility integration, and continuous algorithmic auditing are critical to ensuring socially empowering AI systems.

Addressing digital marginalization requires examining bias throughout the machine learning pipeline, including training data selection, evaluation processes, and deployment practices (Baker & Hawn, 2021). Large Language Models present additional challenges, as biases may persist despite model refinement and can intensify when fine-tuned using limited or unrepresentative datasets. Developer homogeneity further compounds risk, embedding unexamined cultural assumptions into AI systems (Egunjobi & Adeyeye, 2024).

Overall, instructional design emerges as a key intervention point for mitigating AI-driven inequities.

Embedding ethical principles, AI literacy, and culturally responsive pedagogy within AI learning environments can reduce marginalization and promote equitable outcomes. Continuous monitoring, inclusive data governance, and accountability frameworks remain essential to ensuring AI systems are fair, transparent, and inclusive for all learners.

DISCUSSION

This paper examines how digital marginalization is constructed within AI-supported learning environments through the interaction of technical and social factors embedded across the machine learning lifecycle. Bias emerging during data acquisition, model development, or implementation can perpetuate unequal learning experiences (Ifenthaler et al., 2024). Although often framed as technical flaws, such biases reflect pre-existing social inequalities that become encoded within algorithmic systems (Rane et al., 2023; Roshanaei et al., 2023). Consequently, AI integration may reinforce disparities related to disability, race, ethnicity, gender, socio-economic status, and language rather than mitigate them (Stephenson & Harvey, 2022).

Equity challenges are evident in multiple AI applications. Assessment systems trained predominantly on dominant-group datasets may generate biased feedback, inaccurate evaluations, and restricted learning pathways for marginalized learners (Boateng & Boateng, 2025; Barnes & Hutson, 2024). Similarly, adaptive platforms may deliver less challenging content to learners labelled as low- achieving, reinforcing deficit perceptions and limiting progression (Chinta et al., 2024). Historical learner data further sustains discriminatory decision-making under the guise of algorithmic neutrality (Egunjobi & Adeyeye, 2024).

Bias also manifests in language and measurement systems. AI tools that standardize expressions of knowledge may misinterpret students using non-dominant linguistic styles or learning approaches (Chinta et al., 2024). Automated scoring systems frequently disadvantage such learners through embedded measurement bias (Baker & Hawn, 2021). Predictive analytics may additionally produce false correlations, leading to unjust risk profiling or misconduct flagging, particularly within AI proctoring environments (Du et al., 2024)

Digital marginalization is further intensified through access disparities and surveillance practices (Alvarez-Icaza & Huerta, 2024). Infrastructure limitations, device access, and digital literacy gaps affect the equitable functioning of AI learning tools across socio-economic contexts (Roshanaei et al., 2023). Surveillance technologies and monitoring systems risk undermining learner autonomy and may result in disproportionate disciplinary outcomes for marginalized groups (Du et al., 2024; Bešić et al., 2025).

Addressing these risks requires a shift from reactive bias correction to proactive, inclusion- centered design. Key strategies include representative dataset development, subgroup algorithmic audits, and transparent decision-making processes (Baker & Hawn, 2021; Barnes & Hutson, 2024). Co-design approaches involving marginalized learners enhance contextual relevance and reduce cultural stereotyping (Kayyali, 2025; Siddiqi, 2025). Continuous monitoring remains essential, as bias may re-emerge post-deployment when systems encounter new contexts (Roshanaei et al., 2023).

A human-centered approach is therefore critical in high-stakes educational AI. Human-in-the- loop systems enable educators to interpret, challenge, and moderate algorithmic decisions, mitigating risks associated with opaque systems (Sun, 2024). Models that position AI as augmenting rather than replacing educators further support equitable learning outcomes (Bešić et al., 2025).

Framing digital marginalization as a design and governance issue highlights instructional design as a key intervention point. Through inclusive frameworks, ethical oversight, and participatory development, AI-enabled education can move toward equitable learning experiences rather than reproducing systemic inequalities.

CONCLUSION

This study critically examined the rapid integration of Artificial Intelligence (AI) in education through the lens of digital marginalization and increasing inequality. While AI technologies offer benefits such as personalization, accessibility, and operational efficiency, their implementation often lacks sufficient equity safeguards, disproportionately affecting marginalized learners and developing contexts (Adıgüzel et al., 2023; Raza et al., 2025). The review identified algorithmic bias, data imbalance, infrastructural disparities, and digital skill inequalities as key mechanisms through which AI-driven systems may reinforce rather than reduce educational inequities (Roshanaei et al., 2023).

Bias was found to operate across the machine learning lifecycle, from data curation to system deployment, shaping assessment practices, learner profiling, and access to opportunities. Structural concerns including data imbalance, cultural bias, and governance limitations further demonstrate that AI functions as a socio-technical system reflecting broader power relations rather than as a neutral educational tool (Baker & Hawn, 2021; Rane et al., 2023; Roshanaei et al., 2023).

To address these risks, the study supports an inclusion-centered instructional design approach that integrates culturally responsive pedagogy, linguistic diversity, ethical data practices, accessibility principles, and algorithmic transparency (Deckker & Sumanasekara, 2025; Kayyali, 2025). This requires diverse training datasets, regular auditing, and participatory redesign processes involving marginalized communities (Barnes & Hutson, 2024).

The findings further emphasize the importance of human oversight and teacher autonomy within AI-enabled learning environments. A human-centered pedagogical framework positions AI as complementary to educators rather than a replacement, ensuring alignment with inclusive educational goals (Bešić et al., 2025; Sun, 2024). Ongoing teacher training, AI literacy development, and governance frameworks are essential for responsible integration (Roshanaei et al., 2023; Daher, 2025). Achieving equitable AI-powered education demands coordinated action among policymakers, educators, developers, and institutions. Investment in inclusive infrastructure, culturally sensitive system design, and robust data governance is necessary to bridge digital divides and prevent technological inequalities (Alvarez-Icaza & Huerta, 2024).

Ultimately, the future of AI in education will be shaped not solely by technological capability but by intentional, equity-driven design. When guided by principles of accessibility, fairness, and social justice, AI has the potential to contribute to more inclusive and transformative educational systems.

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Digital Awareness and Empowerment of Citizens: Bridging the Divide for an Equitable Society

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Abstract:

Digital technologies have ostensibly democratised access to information and services; however, they have simultaneously entrenched and transformed existing social inequalities into resilient digital forms. This research report offers a comprehensive critical synthesis of the scholarly landscape concerning digital awareness and citizen empowerment. This analysis adopts a wider perspective. Drawing on central theories Jan van Dijk's Resources and Appropriation Theory, Amartya Sen's Capability Approach, and Richard Heeks' Adverse Digital Incorporation it makes a clear argument: simply having internet access isn't sufficient. True digital empowerment requires more. Individuals need critical literacy, meaningful agency, and real structural opportunities. Mere connectivity alone doesn't ensure any of this.

This report delves into three key digital governance models. First is India's "Scale Model," where the government develops large-scale infrastructure like Digital India and Aadhaar, always navigating the promise of improved welfare alongside worries about surveillance. Next is Estonia's "Trust Model," which is built on radical transparency and gives citizens control over their data through decentralized frameworks. The European Union's "Rights Model" is defined by strict regulations and a dedication to digital constitutionalism.

India takes center stage in this analysis. The report thoroughly explores how the Jan Dhan-Aadhaar-Mobile (JAM) trinity has impacted lives at times for the better, at times not. It also investigates Bhashini's efforts to make digital services available in multiple languages and questions the true implications of the Digital Personal Data Protection Act (DPDP) 2023 for privacy. Here's the key takeaway: in the absence of robust safeguards and an emphasis on meaningful, substantive outcomes, digital inclusion can have unintended consequences. Rather than empowering marginalized groups, these systems may end up treating them as data points or surveillance subjects, instead of enabling them as active participants. Ultimately, the report goes beyond critique. It offers concrete policy and academic recommendations to move past a solely technocratic approach. The aim: to progress from simply enabling digital access to genuinely broadening people's real capabilities and freedoms.

Keywords : *Digital empowerment, digital divide, adverse digital incorporation, Digital India, algorithmic governance, capability approach, data protection, Estonia X-Road, Bhashini, digital citizenship, resources and appropriation theory, ICT4D.*

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1. Introduction

1.1 The Digital Paradox: Ubiquity Versus Inequality

Look around in the early twenty-first century, and you'll see something strange: technology is everywhere, but that hasn't made things fair. Sure, digital infrastructure has exploded broadband, mobile phones, cloud computing, AI, all that. People once imagined the internet would tear down old barriers like class and geography. Everyone would have a shot at the same opportunities, right? Turns out, not so much. (Collins, 2008; Kuttan & Peters, 2003; Ranganathan, 2011)

The numbers from the 2020s tell a different story. Look at the numbers from the 2020s and you'll notice a different story. Billions go online every day, but the true benefits of digital life aren't available to everyone. New technology doesn't eliminate old inequalities it often reflects them, and sometimes even makes them worse. The so-called "deepening divide" is about more than just who owns a smartphone. (Lamberti et al., 2023; Kang et al., 2024; Kolotouchkina et al., 2024)

Because of that, researchers are focusing less on how much infrastructure exists, and more on who really has control, agency, and the skills to navigate the digital world. If you want to fully take part in society now whether it's working, accessing services, or exercising your rights you need more than just a connection. You need digital know-how and power. This isn't just about adopting new gadgets; it's about changing how people, governments, businesses, and the public interact at a basic level. (Mossberger et al., 2007; Deja et al., 2024; Zhu et al., 2025)

India is a prime example. The government's big digital drives like "Digital India" and "India Stack" have connected millions more people. But that doesn't mean everyone's sharing the benefits. Research shows just getting people online doesn't make things fair. For many on the margins, the digital world brings new risks: more surveillance, having their data mined, or being left out by biased algorithms. So, digital tools can open doors but they can also build new walls. (Mohapatra et al., 2025; Romke, 2013; Wang & Si, 2024; Arya & Pradeep Kumar, 2025)

1.2 Conceptual Delineation: The Awareness-Literacy-Empowerment Nexus

To really understand how people, use digital technology, you have to tease apart three ideas: digital awareness, digital literacy, and digital empowerment. They build on each other, but they also loop back and interact in real life.

Start with digital awareness. This is the base layer. It's not just knowing that tech exists. It's about seeing the big picture recognizing how digital spaces work, what they offer, and where the dangers lurk. You get that the internet isn't just a place to scroll for fun; it's a tool for learning, speaking up, getting services, and more. But you also spot the risks, like privacy leaks, scams, or running into legal trouble. If people don't see both the upsides and the hazards, they'll probably never bother to pick up real digital skills. (Wang & Si, 2024; Kang et al., 2024; Van Le & Tran, 2024)

Now, digital literacy is where things get practical. It's the toolkit. You've got to handle devices, bounce around different software, and actually do stuff online, from searching for information to making your own content and knowing what's okay to share. Researchers talk about "medium-related skills" (like using a phone or app) and "content-related skills" (like sorting fact from fiction online). In places like the Global South, there's another hurdle: much of the internet runs on English, which leaves many folks struggling just to get their foot in the door. (Aziz & Hossain, 2024; Deja et al., 2024; Jung et al., 2025; Zhu et al., 2025)

Then there's digital empowerment the top of the pyramid. It's both a process and a result. You start making real choices you couldn't make before: landing a job, booking healthcare, holding officials to account. Empowerment means turning digital tools into something that genuinely changes your life, moving you from just scrolling and consuming to actually shaping your own path online. (Mohapatra et al., 2025; Arya & Pradeep Kumar, 2025; Saha et al., 2024; Brian et al., 2024)

1.3 Scope and Analytical Approach

This review pulls together ideas from across different fields, government policies, and actual case studies. While India is the main focus, there's plenty of comparison with places like Estonia, the European Union, and Rwanda to keep the view global. The analysis draws on Van Dijk's Resources and Appropriation Theory, Sen's Capability Approach, and Heeks' Adverse Digital Incorporation framework to stitch together a full picture of digital empowerment. (Kolotouchkina et al., 2024; Yang et al., 2024; Lamberti et al., 2023)

Here's how it's laid out: Section 2 breaks down the main theories. Section 3 maps out the big themes. Section 4 puts India side by side with other countries. Section 5 takes a hard look at how things have played out in India specifically. After that, you'll find a rundown of what researchers are missing, a look at how development and digital tech are tangled up together, and finally, some ideas for where policy and research should go next. (Mossberger et al., 2007; Romke, 2013; Collins, 2008)

2. Conceptual and Theoretical Framework

2.1 Resources and Appropriation Theory (Van Dijk)

Van Dijk's Resources and Appropriation Theory pushes back against the idea that technology alone shapes society. Instead, it sees access to technology as a step-by-step process, shaped by real-world social forces. Things like age, gender, caste, and education don't just exist in the background they drive real gaps in who gets what: time, know-how, money, connections, and cultural capital. These gaps show up in four main ways:

- **Motivational access:** Do people actually want to use tech? Fears, cultural expectations, and whether the tech even matters to them all play a part.
- **Material access:** Who actually has the devices and a working internet connection?
- **Skills access:** Can people use digital tools well? Do they know how to find, judge, and use information?
- **Usage access:** Are people using these tools often? Are they doing a lot with them, or just the basics? Is it actually meaningful for them?

It's a cycle. People with more resources use digital tools to get ahead, while those with less get left further behind. That's why so many "universal access" programs don't reach the people who need them most. (Lamberti et al., 2023; Kang et al., 2024; Alexandrov et al., 2017)

2.2 The Capability Approach (Sen & Nussbaum)

Sen's Capability Approach flips the conversation. It's not just about whether people have tech it's about what they can actually do with it. Personal background, social rules, and the environment all decide if digital tools lead to real empowerment.

Think about a woman with a phone. If her community frowns on women using technology, that phone doesn't open doors for her. Or take a student with a smartphone but no digital literacy the device doesn't help much with learning. So, empowerment isn't one-size-fits-all. You have to look beyond simple access and dig into the context. (Arya & Pradeep Kumar, 2025; Saha et al., 2024; Deja et al., 2024)

2.3 Adverse Digital Incorporation (Heeks)

Heeks' Adverse Digital Incorporation framework calls out a big myth: just being part of the digital world isn't always good. Sometimes, when marginalized groups get “included,” it’s not for their benefit.

- **Exploitation:** Platforms squeeze value out of people think gig workers hustling for low pay.
- **Surveillance:** Some tech just tracks and controls people, like biometric ID systems that watch more than they help.
- **Dependency:** People come to rely on shaky digital systems for basic needs, which can backfire fast.

This approach asks harder questions. It’s not about how many people are online, but about what that connection actually means for their lives. Sometimes, inclusion isn’t progress it’s another way of keeping people down. (Romke, 2013; Van Le & Tran, 2024; Collins, 2008)

2.4 Digital Capital (Bourdieu Adapted)

Building on Bourdieu’s capital theory, digital capital looks at how digital skills and access turn into economic, social, or cultural advantages. It’s not just about having access, though. Digital habitus the attitudes and instincts we pick up shapes how people move through the digital world. Privileged folks often know how to play the game, finding ways to benefit and get ahead online. Meanwhile, others with the same access still struggle to make it work for them. This gap shows up as a “third-level divide” the difference in outcomes, not just opportunities. (Mossberger et al., 2007; Deja et al., 2024; Zhu et al., 2025)

3. Thematic Literature Analysis

3.1 Digital Literacy as Mediating Variable

Digital literacy sits right in the middle of the access-empowerment link. It’s not just about knowing how to use devices, but also about thinking strategically online. Education really shapes who picks up these skills and who doesn’t. When literacy programs are woven into the community think libraries and telecenters they tend to last longer. “Infomediaries” (those folks who help others bridge the digital gap) make a real difference here. (Aziz & Hossain, 2024; Deja et al., 2024; Wang & Si, 2024; Jung et al., 2025)

3.2 Socio-Demographic Inequality Patterns

Digital divides don’t exist in a vacuum they echo old, familiar inequalities:

- **Gender:** Women run into extra roadblocks. Lower incomes, less literacy, barely any free time, and sometimes, outright cultural barriers keep them from getting online, especially on mobile.
- **Geography:** Rural communities still struggle with weak infrastructure, which just makes everything harder.
- **Caste:** Here, the digital world can actually amplify old biases algorithmic discrimination, hate speech, and even exclusion from online spaces are all too common. (Arya & Pradeep Kumar, 2025; Saha et al., 2024; Barra et al., 2024; Lamberti et al., 2023)

3.3 Digital Governance and Administrative Transformation

Digital governance changes how people interact with public services. The “Digital-Era Governance” model puts citizens at the center. India’s JAM Trinity (Jan Dhan-Aadhaar-Mobile) is a good example: it lets the government send benefits directly to people. But it’s not all smooth when biometrics or data don’t match up, some people just vanish from the system. They become “digitally invisible,” cut off from basic help. (Mohapatra et al., 2025; Romke, 2013; Yang et al., 2024; Van Le & Tran, 2024)

3.4 Psychological Mediators: Trust and Self-Efficacy

People are more likely to use technology when they trust it, find it useful, and know they can handle it. Estonia nails this with “trust by design” the system itself builds confidence. But in places where trust is low and adoption feels forced, people see digital tools less as empowering, and more like surveillance. (Kang et al., 2024; Deja et al., 2024; Lamberti et al., 2023)

3.5 Misinformation and Digital Resilience

Critical media literacy is key to fighting misinformation and digital echo chambers. Even as people get better at using tech, most still lack real critical skills, so they're easy targets for manipulative content. You see the fallout in real life misinformation-driven violence isn't rare, especially in places like India. (Aziz & Hossain, 2024; Zhu et al., 2025; Alexandrov et al., 2017)

4. India in Global Comparative Perspective

4.1 India: The Scale and Sovereignty Model

India's digital push runs on a massive, centralized system. Think India Stack, JAM Trinity, UPI all designed to deliver welfare and drive financial inclusion through state-run platforms. It's efficient, sure, but there's a catch: surveillance risks. Some call it "surveillance humanitarianism," pointing out that these systems sometimes leave out the most vulnerable, hitting them hardest. (Mohapatra et al., 2025; Romke, 2013; Van Le & Tran, 2024)

4.2 Estonia: The Trust & Decentralization Model

Estonia does things differently. Their X-Road platform lets data flow between agencies without piling everything into one big database. People can see who's accessed their data, which builds trust and gives citizens real control. But here's the thing: Estonia's small and pretty cohesive. Would this work in a bigger, more divided country? That's still up in the air. (Yang et al., 2024; Wang & Si, 2024; Lamberti et al., 2023)

4.3 The European Union: The Rights and Regulation Model

The EU goes all-in on rules and rights. Laws like GDPR, the Digital Services Act, and the AI Act are there to protect privacy and give people control over their data. With the EU's market clout, these rules often shape global standards. But not everyone's a fan some see it as "regulatory imperialism," especially when these strict frameworks get copied in places that don't have the same resources or context. (Lamberti et al., 2023; Collins, 2008; Kolotouchkina et al., 2024)

4.4 Rwanda: The Policy-Praxis Gap

Rwanda puts a lot of effort into its digital transformation. There are gender quotas, investments in tech, and a government that's hands-on. Still, deep-rooted patriarchal attitudes make it tough for women to really benefit from these digital advances. Digital fixes help, but they can't replace the need for deeper social change. (Saha et al., 2024; Arya & Pradeep Kumar, 2025; Barra et al., 2024)

Table 1: Comparative Digital Governance Models

Feature	India (Scale Model)	Estonia (Trust Model)	EU (Rights Model)
Primary Goal	Welfare Delivery, Financial Inclusion	Efficiency, Transparency	Privacy, Market Regulation
Key Mechanism	Centralized Stack (Aadhaar, UPI)	Decentralized Exchange (X-Road)	Legislation (GDPR, DSA, AI Act)
Citizen Role	Beneficiary / Data Point	Partner / Data Owner	Rights Holder / Data Subject
Trust Source	State Guarantee / Coercion	Radical Transparency (Audit Logs)	Legal Remedy / Courts

Dominant Risk	Exclusion Errors, Surveillance	Cyber-security (Interdependency)	Innovation Stifling, Complexity

(Mohapatra et al., 2025; Yang et al., 2024; Lamberti et al., 2023; Romke, 2013; Collins, 2008).

5. India: A Critical Deep Dive

5.1 The Aadhaar Paradigm: Inclusion vs. Legibility

Aadhaar gives millions an official identity. In practice, that opens doors to financial services and helps stop benefits from leaking away. But if you look closer, especially from an ADI point of view, Aadhaar makes people "legible" to the state, forcing them to prove who they are again and again. When the tech fails say, the biometrics don't match people lose access to basic services. That's not a small glitch; it's what some call "technological violence." And with all data pulled into one central system, the government gets a wide-angle view of its citizens. People become transparent to the state, but when things go wrong, they have few places to turn. (Mohapatra et al., 2025; Romke, 2013; Van Le & Tran, 2024)

5.2 Linguistic Inclusion: The Bhashini Initiative

Bhashini aims to break down barriers to the internet by using voice-first AI in local languages. For people who struggle with reading, this changes the game. Early numbers show real interest. But there's a catch: translation can miss the mark, losing meaning along the way. And English still acts as the gatekeeper to good jobs and economic mobility. So, while Bhashini opens a door, it doesn't change the deeper power structures that keep some voices out. (Aziz & Hossain, 2024; Zhu et al., 2025; Deja et al., 2024)

5.3 Legal Frameworks: The DPDP Act 2023

India's DPDP Act tries to put a data protection framework in place, but it comes with big loopholes. The state can sidestep many rules, locking in surveillance powers with little oversight from the courts. Rules like "deemed consent" let data be used without people actually agreeing, forcing citizens into a trade-off between privacy and basic welfare a classic Faustian bargain. The law clamps down on corporate misuse, but when it comes to what the state does with your data, you're still exposed. (Collins, 2008; Lamberti et al., 2023; Yang et al., 2024)

5.4 Caste and the Digital Sphere

Caste privilege doesn't stop at the keyboard. Online, upper-caste groups use their digital know-how and networks to get ahead. Meanwhile, Dalit and marginalized voices run into algorithmic bias, harassment, and outright exclusion. The dream of a casteless internet? Still out of reach. The same barriers just show up in new forms. (Lamberti et al., 2023; Kang et al., 2024; Kolotouchkina et al., 2024)

6.1 The "Access is Not Empowerment" Consensus

Everyone agrees now: just giving people internet access isn't enough. The real issues go deeper skills and outcomes matter more than simply being online. When you only boost connectivity, without helping people build the right skills, you set them up for trouble. Marginalized groups often end up tracked or exploited, not truly empowered. (Kuttan & Peters, 2003; Alexandrov et al., 2017; Deja et al., 2024; Aziz & Hossain, 2024)

6.2 The Empowerment-Surveillance Tension

Here's where things get messy: the state's role in digital empowerment is full of contradictions.

- **The Empowerment Thesis:** Take India's "Scale Model." The government says if you want benefits delivered fast and without fraud, you have to let yourself be seen. Surveillance, they argue, is just part of the deal.
- **The Privacy Antithesis:** In the EU, the "Rights Model" flips this on its head. They see privacy as essential for empowerment. Without it, citizens can't really control their lives or participate

freely in politics.

- **The Trade-off Synthesis:** In practice, especially in developing countries, people face a harsh trade-off a "Faustian bargain." They give up privacy and data rights just to get basic welfare. Administrative efficiency comes at the price of civil liberty.

The evidence is clear: in many developing countries, people end up sacrificing privacy for welfare, often losing key civil liberties along the way. (Mohapatra et al., 2025; Lamberti et al., 2023; Collins, 2008; Van Le & Tran, 2024)

6.3 The Fallacy of "Technological Solutions for Sociological Problems"

Technology alone can't fix deep social problems. Look at Rwanda: digital policies haven't broken down gender barriers. In India, language remains a massive hurdle despite tech initiatives. Technology reflects and amplifies what's already there. It can't, by itself, change the underlying social structures. (Saha et al., 2024; Arya & Pradeep Kumar, 2025; Aziz & Hossain, 2024)

7. Research Gaps

- Longitudinal Impact of Adverse Incorporation: Empirical data on the long-term trajectories of adversely incorporated populations is scarce. (Lamberti et al., 2023; Kang et al., 2024
- Intersectional granularity regarding caste, gender, and geography is lacking in India. (Arya & Pradeep Kumar, 2025; Saha et al., 2024; Barra et al., 2024)
- Algorithmic governance in the Global South has received limited research attention regarding the interaction between algorithms and local prejudices. (Kolotouchkina et al., 2024; Van Le & Tran, 2024; Yang et al., 2024)
- Rigorous evaluation is needed to assess the efficacy of voice-first interfaces in relation to Bhashini's impact on functional literacy and empowerment. (Zhu et al., 2025; Aziz & Hossain, 2024; Jung et al., 2025)

8. Analytical Discussion

The digital divide has moved beyond its old definition. Today, it's digital inequality, deeply woven into national ideas of progress. Digital tools can make public services more accessible, but they also risk reducing people to passive recipients rather than active citizens. Estonia and the EU reject this passivity. Simply knowing how to use technology isn't enough.

Digital awareness must reach further, knowing how to use technology. It has to grow into political consciousness. People need not only to use digital systems but also to question them, even refuse them when they threaten their rights. So, algorithmic awareness and understanding data rights these aren't side issues. They're the next battlegrounds.

9. Policy & Academic Recommendations

9.1 Policy Recommendations

- Change the Data Protection and Privacy Act so the state takes its data responsibilities seriously, and require independent audits of algorithms.
- Build "human-in-the-loop" systems to catch biometric failures and make sure real people can step in during welfare delivery.
- Bring literacy programs directly into community spaces. Don't just teach technical skills focus on rights, too, so people know what they're entitled to.
- Make Bhashini a tool for legal empowerment. Translate important justice documents into local languages so people actually understand them.

9.2 Academic Recommendations

- Adopt decolonial, participatory action research methodologies centred on Global South perspectives.

- Prioritise research examining the harms associated with digital inclusion, specifically surveillance, stress, and exploitation.
- Promote comparative South-South studies to develop indigenous digital development theories.

10. Conclusion

The transition from digital access to genuine citizen empowerment requires more than expanding infrastructure or connectivity; it demands a structural rethinking of how digital technologies are embedded within social, legal, and governance systems. Digital India and similar large-scale initiatives have extended government services farther than ever before. These projects have made it simpler to reach citizens and deliver services, but one thing often gets overlooked: genuine citizen agency and the difficult reality of inequality. If people are brought into digital systems without enough protections, real choices, or the skills to use them effectively, they are not truly empowered their problems are just moved online. People end up trapped in systems they don't fully grasp, monitored by algorithms, and forced to follow rules they never created.

If digital empowerment is to be meaningful, we have to abandon this top-down model. Instead, we should prioritize approaches that actually build people's capacities and place them at the center not only as users, but as active agents with real choices.

Researchers consistently point out that the digital divide is more than just a matter of who has internet access and who does not. The issue is more complex. The work of van Dijk, Sen, and Heeks all indicates the same thing: connectivity alone isn't sufficient. What truly matters is whether people possess the necessary skills, trust in institutions, legal rights, and the freedom to convert access into real benefits. Digital empowerment is fundamentally about expanding what people are able to do and who they can become not simply about getting them online.

In the realm of digital governance and ICT4D, digital literacy is not just useful it is crucial. When people know how to find information, communicate online, and interpret data, they are more likely to secure jobs, participate in public life, and feel empowered. Yet, significant gaps persist. These gaps exist across income levels, regions, gender, and age groups. Global research continues to show that without proper devices, training, or support, individuals are left behind. On the positive side, targeted initiatives whether for college students, older adults, or marginalized communities can genuinely improve confidence, engagement, and effective technology use. Institutions like libraries, universities, and community centers are vital here. They are not merely optional they are necessary for lifelong digital learning and for bridging these divides. Intersectional inequalities continue to shape the digital landscape in significant ways. Gender disparities influence who adopts technology and who can participate in entrepreneurship. Where individuals live and their economic circumstances determine whether they benefit from digital governance or are left behind. Some governments intervene China's regional digital pilot initiatives, for instance, show that state-driven strategies can reduce territorial divides, but only when supported by strong institutions and active markets. In urban areas, smart governance is more than just deploying technology; it requires ensuring digital tools are accessible, user-friendly, and designed around the actual needs of people. This is what produces genuine, shared public value.

When comparing governance models, the construction of institutions becomes a crucial factor in determining who is empowered. India's approach, focused on scale and rapid implementation such as JAM and Aadhaar brings millions into welfare systems. The benefits are clear, but so are the dangers: concerns about privacy, surveillance, and data control persist. Estonia follows another route, centering on trust and granting citizens real authority over their information. The European Union relies on rights-based regulation, making privacy and digital constitutionalism central. Across these approaches, one message stands out: true empowerment is not just about the technology. Legal protections and transparent governance are equally important. India's DPDP Act and language-access efforts like Bhashini are positive moves, but they require stronger enforcement, wider inclusion, and greater accountability to be effective.

Research on digital financial inclusion reveals a similar pattern. Expanding ICT can empower users but only if people understand how to use these tools, if regulations are strong, and if institutions provide support. Without these safeguards, digital finance can worsen exclusion and increase vulnerability.

The trend is clear. Digital inclusion based solely on access without attention to literacy, rights, or participation can actually intensify inequalities. Creating a genuinely empowering model requires more: legal protections, strategies that address intersecting inequalities, strong digital literacy, and meaningful opportunities for citizen involvement. Digital transformation is not just about connecting people. It is about ensuring they have the skills, protections, and institutional backing to use digital tools in ways that matter for their lives. Empowerment is rooted in this foundation a combination of ethics, capability, and rights, not just connectivity.

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Influence of Algorithms on Consumer Choice and Behavior: Implications for Bias and Digital Marginalization

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Abstract:

Artificial Intelligence (AI)–driven algorithms have become integral to modern marketing practices, significantly influencing how consumers discover products, evaluate alternatives, and make purchase decisions. Recommendation systems, targeted advertisements, and personalized content increasingly shape consumer exposure and choice architecture. While these algorithmic tools enhance efficiency and relevance, they also raise critical concerns related to bias, transparency, and digital marginalization. This study examines the influence of algorithms on consumer choice and behavior, with particular emphasis on how algorithmic marketing impacts consumer autonomy and fairness in digital marketplaces. The research adopts a mixed-method approach, incorporating both primary and secondary data. Primary data is collected through a structured questionnaire administered to consumers to assess their awareness, reliance, and perceptions of algorithm-driven recommendations across digital platforms. Secondary data is sourced from academic journals, industry reports, and existing literature on algorithmic bias, consumer behavior, and ethical AI in marketing. Descriptive and inferential statistical tools are used to analyze the data and identify patterns in consumer responses. The findings indicate that while consumers benefit from personalized recommendations, many remain unaware of the extent to which algorithms influence their choices. The study also highlights concerns regarding reduced exposure to alternatives, potential reinforcement of biased content, and exclusion of digitally marginalized groups. The paper concludes with managerial implications for marketers, emphasizing the need for transparent, ethical, and inclusive algorithmic marketing practices. The study contributes to the ongoing discourse on responsible AI by bridging marketing strategy with societal and ethical considerations in the digital age.

Keywords : *Algorithmic Marketing, Consumer Behavior, Digital Marginalization, Algorithmic Bias, Artificial Intelligence.*

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INTRODUCTION

The rapid advancement and widespread adoption of Artificial Intelligence (AI) technologies have fundamentally transformed the contemporary digital marketplace. Algorithm-driven systems now play a central role in shaping consumer experiences across digital platforms, influencing how individuals search for information, discover products, evaluate alternatives, and ultimately make purchase decisions. From e-commerce websites and streaming services to social media platforms and search engines, algorithms have become deeply embedded in everyday consumer interactions. These systems are primarily designed to improve efficiency, relevance, and personalization; however, their pervasive presence has generated growing academic and managerial interest in understanding their broader behavioral and societal implications.

Algorithms operate by analyzing large volumes of consumer data, identifying patterns, and predicting user preferences to curate personalized content and recommendations. Such mechanisms significantly alter the traditional decision-making environment by structuring consumer choice architecture. Rather than being exposed to a neutral or exhaustive set of options, consumers increasingly encounter algorithmically filtered information that prioritizes certain products, services, or messages. While this personalization enhances convenience and reduces information overload, it simultaneously raises concerns regarding reduced choice diversity, repetitive exposure, and potential manipulation of consumer preferences. These dynamics challenge conventional assumptions of rational consumer decision-making and highlight the need to critically examine algorithmic influence.

An equally important concern relates to algorithmic bias and fairness. Algorithmic systems are not inherently neutral; they are shaped by training data, design assumptions, and optimization objectives, which may unintentionally produce skewed or discriminatory outcomes. In marketing contexts, biased algorithms may influence visibility, product recommendations, and promotional targeting, thereby affecting consumer perceptions and access to alternatives. Such outcomes can contribute to digital marginalization, where certain consumer segments may experience restricted exposure, unequal opportunities, or systematic exclusion within digital ecosystems. These issues are particularly relevant in discussions surrounding ethical AI and responsible digital transformation.

From a consumer behavior and marketing strategy perspective, understanding how consumers perceive algorithmic systems is of critical importance. Consumers may derive substantial benefits from personalized recommendations, yet remain only partially aware of the underlying mechanisms guiding content selection. This creates a complex psychological and behavioral interplay involving awareness, trust, reliance, and perceived influence. Trust in algorithm-generated suggestions may enhance decision efficiency, but excessive reliance may also reduce active information search and evaluation. Similarly, awareness of algorithmic functioning does not necessarily diminish influence; instead, it may reshape consumer interpretations and attitudes.

Against this backdrop, the present study, titled “Influence of Algorithms on Consumer Choice and Behavior: Implications for Bias and Digital Marginalization,” seeks to examine consumer perceptions and behavioral responses to algorithm-driven recommendations. The research focuses on key constructs including consumer awareness, reliance, trust, perceived influence, bias perceptions, and attitudes toward ethical algorithm usage. By integrating behavioral and ethical considerations, the study contributes to the expanding discourse on algorithmic marketing, digital consumer psychology, and responsible AI-enabled business practices. The findings aim to offer both theoretical insights and managerial implications relevant to marketers operating in increasingly algorithm-mediated environments.

LITERATURE REVIEW

Existing research has extensively examined the growing role of algorithms and AI- driven systems in shaping consumer behavior within digital environments. Scholars have particularly focused on personalization mechanisms, recommendation systems, consumer trust, decision automation, and ethical concerns arising from algorithmic influence. As digital platforms increasingly mediate consumer interactions, academic attention has shifted toward understanding both the functional benefits and potential behavioral consequences of algorithm- driven ecosystems.

Study 1 – Algorithmic Personalization and Consumer Decision-Making

Xiao, B., & Benbasat, I. (2007).

E-commerce product recommendation agents: Use, characteristics, and impact.

MIS Quarterly, 31(1), 137–209.

Prior studies highlight that algorithmic recommendation systems significantly influence consumer decision processes by reducing information overload and enhancing perceived relevance. Research suggests that personalized recommendations improve user convenience, decision efficiency, and overall engagement, thereby increasing purchase likelihood and platform dependency. However, scholars caution that excessive personalization may narrow consumer choice sets, reduce exploratory behavior, and create reliance on automated suggestions. This stream of research establishes that algorithmic systems actively restructure consumer choice architecture rather than merely supporting decision-making, altering how consumers evaluate alternatives and perceive available options.

Study 2 – Trust in AI Systems and Technology Acceptance

Gefen, D., Karahanna, E., & Straub, D. W. (2003).

Trust and TAM in online shopping: An integrated model.

MIS Quarterly, 27(1), 51–90.

Research grounded in technology acceptance theories emphasizes that consumer trust plays a critical role in determining reliance on algorithm-driven recommendations. Higher perceived credibility, usefulness, and accuracy of algorithmic systems are positively associated with greater consumer adoption and usage. Trust functions as a mediating variable that shapes consumer willingness to delegate decision authority to digital platforms. At the same time, concerns regarding algorithmic opacity, lack of explain ability, and perceived manipulation may weaken trust, particularly when consumers are unable to understand how recommendations are generated. These findings underscore the psychological importance of trust in algorithm-mediated consumer environments.

Study 3 – Algorithmic Bias and Perceived Fairness

Lambrecht, A., & Tucker, C. (2019).

Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads.

Management Science, 65(7), 2966–2981.

Emerging literature raises concerns about algorithmic bias, arguing that algorithms may unintentionally prioritize certain products, brands, or content categories due to underlying data structures and optimization models. Scholars note that consumers increasingly evaluate digital platforms not only on performance but also on perceived fairness, neutrality, and transparency. Perceived bias may reduce consumer confidence, generate skepticism, and influence attitudes toward platform credibility. This body of research highlights that fairness perceptions are becoming central to consumer evaluations of AI-driven systems, emphasizing the ethical dimension of algorithmic influence.

Study 4 – Filter Bubbles and Digital Marginalization

Pariser, E. (2011).

The Filter Bubble: What the Internet Is Hiding from You.

Penguin Press.

Contemporary research introduces the concept of filter bubbles, suggesting that algorithmic curation may restrict consumer exposure to diverse viewpoints and alternatives.

Such systems may reinforce existing preferences, leading to repetitive content exposure, confirmation bias, and reduced choice diversity. Scholars argue that algorithmic narrowing can contribute to digital marginalization, where certain users, preferences, or market actors receive limited visibility. This perspective broadens the discussion beyond individual behavior, highlighting structural and societal implications of algorithm-driven ecosystems.

Study 5 – Consumer Autonomy and Decision Delegation

Yeomans, M., Shah, A., Mullainathan, S., & Kleinberg, J. (2019). Making sense of recommendations.

Journal of Behavioral Decision Making, 32(4), 403–414.

Recent studies explore how algorithmic systems influence consumer autonomy and perceived control. While consumers may appreciate the convenience of automated recommendations, excessive reliance on algorithms may reduce active decision-making and independent evaluation of alternatives. Research suggests that consumers often delegate cognitive effort to digital systems, which may subtly shape preferences and choices. This phenomenon reflects a shift from deliberate decision-making toward assisted or automated consumption patterns, raising important questions regarding consumer agency and informed choice.

Study 6 – Ethical AI and Consumer Expectations

Calo, R. (2017).

Artificial intelligence policy: A primer and roadmap.

UCLA Law Review, 51(2), 399–435.

Growing academic discourse emphasizes that consumers increasingly expect ethical and responsible use of AI technologies. Transparency, accountability, and fairness are identified as key determinants of consumer acceptance of algorithm-driven systems. Studies indicate that even when consumers trust and use algorithmic recommendations, they simultaneously express concerns regarding privacy, bias, and misuse of personal data. These findings reveal a duality in consumer attitudes, where functional benefits coexist with normative demands for ethical safeguards and regulatory oversight.

Collectively, prior literature indicates that while algorithms enhance efficiency, relevance, and personalization, they also generate concerns related to autonomy, bias, transparency, and inclusivity. The reviewed studies demonstrate that consumer interactions with algorithmic systems involve complex psychological and behavioral dynamics shaped by awareness, trust, and perceived fairness. These insights provide the conceptual foundation for the present study, which empirically examines consumer awareness, reliance, trust, perceived influence, and fairness expectations in algorithm-driven digital contexts.

RESEARCH HYPOTHESES

H1: There is a positive relationship between consumer awareness of algorithm-driven systems and perceived influence of platform recommendations.

H2: There is a positive relationship between consumer trust in platform-generated recommendations and reliance on algorithmic suggestions.

RESEARCH OBJECTIVES

1. To examine consumer awareness and perceptions of algorithm-driven recommendations on digital platforms.
2. To analyze the influence of algorithmic recommendations on consumer decision- making, reliance, and trust.
3. To investigate consumer concerns regarding algorithmic bias, exposure limitation, and fairness expectations.

RESEARCH METHODOLOGY

The present study adopts a **correlational research design** to examine the relationships among key consumer perception and behavioral variables, namely consumer awareness of algorithms, trust in platform-generated recommendations, reliance on algorithmic suggestions, perceived influence on decision-making, and perceptions of algorithmic bias. A correlational design is considered appropriate for this investigation as the objective is to analyze the degree, direction, and nature of associations between variables rather than establish causal relationships. This approach allows for systematic evaluation of how consumer perceptions and attitudes interact within algorithm-mediated digital environments.

The research is based on both **primary and secondary data sources,** thereby ensuring conceptual grounding as well as empirical relevance. Primary data was collected through a structured questionnaire specifically designed to capture consumer attitudes, perceptions, and behavioral tendencies related to algorithm-driven recommendations. The questionnaire focused on measuring constructs such as awareness, trust, usage behavior, perceived influence, and fairness perceptions. Secondary data was derived from academic journals, scholarly articles, industry reports, and existing literature on algorithmic decision systems, personalization technologies, consumer behavior, and ethical AI practices. The use of secondary sources provided theoretical support and helped situate the study within established academic discourse.

The **target population** for the study comprised digitally active consumers who regularly interact with algorithm-driven platforms such as e-commerce websites, streaming services, and social media applications. These consumers represent an appropriate unit of analysis as they frequently encounter recommendation systems and personalized content curation mechanisms. Given practical constraints related to time, accessibility, and respondent availability, **a non-probability convenience sampling technique** was employed. This sampling approach is widely used in exploratory and perception-based consumer studies where the focus lies on identifying patterns and associations rather than generalizing to the entire population with statistical certainty.

A total of **110 valid responses** were collected using an online survey administered via Google Forms. The digital mode of data collection ensured ease of distribution, faster response gathering, and relevance to the study context, as the research examines digital consumer experiences. Respondents were screened to ensure familiarity with digital platforms and exposure to algorithm-based recommendations. The achieved sample size was considered adequate for conducting correlational analysis and identifying meaningful relationships among the variables.

The **research instrument** consisted exclusively of close-ended questions and Likert-scale items measured on a **five-point ordinal scale (1–5).** The use of Likert scales enabled quantification of subjective perceptions, attitudes, and degrees of agreement. Close-ended questions ensured uniformity, ease of response, and suitability for statistical processing. To facilitate quantitative analysis, Likert-scale responses were **ordinally encoded into numerical values,** allowing the variables to be treated as measurable constructs for correlation assessment.

The **data analysis** process involved both descriptive and inferential statistical techniques. Descriptive statistics, including frequency distributions and percentage analysis, were used to summarize respondent characteristics and overall response patterns. Inferential analysis was conducted using **Pearson's correlation coefficient (Pearson's r)** to evaluate the strength and direction of linear relationships among the study variables. Correlation analysis was selected as it is appropriate for assessing associations between ordinally encoded perception variables commonly used in consumer behavior research.

This methodological framework provides a structured and systematic basis for examining consumer perception dynamics within algorithm-driven digital ecosystems. By integrating quantitative measurement with correlational analysis, the study enables identification of behavioral tendencies, perception linkages, and emerging patterns relevant to algorithmic marketing and digital consumer psychology.

DATAANALYSIS & INTERPRETATION

The data collected from 110 respondents was analyzed using a combination of **descriptive statistics and Pearson's correlation analysis** to evaluate consumer perceptions and behavioral associations related to algorithm-driven recommendations. The analysis focuses on key constructs including consumer awareness, trust, reliance, perceived influence, and perceptions of algorithmic bias. This dual analytical approach enables both an overview of response tendencies and an examination of variable relationships.

1. Descriptive Insights

Descriptive analysis provided important preliminary insights into respondent behavior and perception patterns. Frequency distributions revealed that a significant proportion of participants regularly engage with algorithm-driven digital platforms such as e-commerce websites, streaming services, and social media applications. The majority of respondents indicated familiarity with personalized recommendations, suggesting widespread exposure to algorithm-mediated decision environments.

Trust in platform-generated recommendations was generally observed at moderate to high levels, reflecting consumer comfort with automated content curation. However, reliance on recommendations demonstrated greater variability, indicating that while many consumers trust algorithmic suggestions, dependence on them differs based on individual preferences and usage habits.

Respondents broadly acknowledged that algorithmic recommendations influence their browsing behavior, product evaluation, and purchase decisions. This suggests that algorithmic systems play a meaningful role in shaping consumer choice processes. At the same time, perceptions related to algorithmic bias, exposure limitation, and reduced diversity of options were present but not strongly polarized. This pattern indicates that consumers neither fully reject nor unquestioningly accept algorithmic systems, but instead exhibit nuanced and context- dependent attitudes.

Importantly, descriptive findings suggest that consumers are increasingly accustomed to algorithmic mediation in digital environments, yet remain selectively critical regarding fairness, transparency, and diversity concerns.

2. Correlation Analysis

To examine the relationships among the study variables, **Pearson's correlation coefficients (Pearson's r)** were computed. Correlation analysis is appropriate for assessing the direction and strength of linear associations between ordinally encoded perception variables commonly used in behavioral research.

2.1 Awareness and Perceived Influence

A weak positive correlation **(r = 0.098)** was observed between consumer awareness of algorithmic systems and perceived influence of recommendations. Although the strength of the relationship is modest, the positive direction provides meaningful theoretical insight.

Interpretation:

Higher awareness does not appear to reduce perceived influence. Instead, consumers who are more aware of algorithmic functioning continue to acknowledge the impact of recommendations on their decisions. This finding suggests that awareness primarily enhances recognition of influence rather than generating resistance or skepticism.

This result supports **H1** and aligns with contemporary consumer behavior theories, which argue that digital users may knowingly accept algorithmic assistance due to perceived convenience and efficiency benefits.

2.2 Trust and Reliance

A positive correlation **(r = 0.162)** was identified between consumer trust in recommendations and reliance on algorithmic suggestions. This indicates that trust serves as an important psychological driver of behavioral adoption.

Interpretation:

Consumers who perceive recommendations as credible, useful, or accurate are more likely to depend on them during decision-making. Trust reduces perceived uncertainty and cognitive effort, thereby encouraging reliance on automated suggestions. The finding supports **H2** and is consistent with technology acceptance models and trust-based decision frameworks.

Although moderate in strength, this relationship highlights the central role of trust in shaping consumer interactions with AI-driven systems.

2.3 Influence and Reliance

A small positive relationship **(r = 0.088)** was observed between perceived influence and reliance on recommendations.

Interpretation:

Consumers who rely more heavily on algorithmic systems tend to slightly acknowledge their influence on decision outcomes. This reflects behavioral consistency, where repeated usage reinforces perceptions of algorithmic impact. The finding suggests that reliance and perceived influence may mutually reinforce one another over time.

3. Bias and Fairness Perceptions

Beyond core behavioral variables, correlation analysis also provides insights into consumer perceptions of bias, exposure limitation, and fairness expectations.

Trust and Exposure Limitation (r = –0.148):

A slight negative correlation indicates that higher trust is associated with lower perceptions of restricted exposure.

Interpretation:

Consumers who trust algorithmic systems may be less inclined to critically evaluate potential filtering effects or choice constraints. Trust may function as a cognitive heuristic that reduces skepticism toward platform operations.

Trust and Fairness Expectations (r = 0.194):

A positive association suggests that even trusting consumers express expectations regarding ethical responsibility and fairness.

Interpretation:

Trust does not eliminate normative concerns. Instead, consumers may simultaneously rely on and critically evaluate algorithmic systems, reflecting a dual orientation toward technology.

Perceived Diversity Reduction and Fairness Concern (r = 0.198):

Consumers perceiving reduced diversity of options exhibit stronger fairness expectations.

Interpretation:

Perceptions of structural narrowing or repetitive exposure may trigger heightened sensitivity toward algorithmic neutrality and inclusivity. This finding reinforces the digital marginalization discourse.

Reliance and Exposure Limitation (r = 0.131):

A slight positive relationship suggests that users who rely more on recommendations somewhat recognize exposure constraints.

Interpretation:

Heavy users may acknowledge limitations but continue relying on algorithmic systems, indicating behavioral dependency despite critical awareness.

4. Overall Interpretation

Most observed correlations fall within a **low to moderate range (0.08–0.20),** which is typical in consumer behavior research involving psychological and perceptual constructs. Such variables are inherently multifactorial and rarely exhibit extremely high correlations.

The findings collectively indicate that:

- **Trust functions as a key behavioral enabler,** influencing reliance on algorithmic recommendations.
- **Awareness shapes perception rather than resistance,** suggesting consumer adaptation to algorithmic environments.
- **Consumers exhibit balanced attitudes,** combining acceptance of personalization benefits with ethical and fairness concerns.

These results highlight the complexity of consumer decision-making within algorithm-mediated digital ecosystems. Rather than being passive recipients, consumers appear to engage with algorithmic systems through a combination of trust, convenience-seeking behavior, and normative evaluation.

Conclusion & Recommendations

Conclusion

This study examined the influence of algorithm-driven recommendations on consumer choice and behavior, with particular emphasis on awareness, trust, reliance, and perceptions of bias. The findings indicate that algorithms play a meaningful, though not overwhelmingly deterministic, role in shaping consumer decision processes within digital environments.

The results support both proposed hypotheses. Awareness of algorithms demonstrated a positive association with perceived influence, suggesting that consumers who understand algorithmic mechanisms are more likely to recognize their impact rather than resist them. Trust emerged as a critical behavioral factor, exhibiting a positive relationship with reliance on recommendations. This confirms that consumer dependence on algorithmic suggestions is largely mediated by perceived credibility and confidence in digital platforms.

Additionally, the analysis highlights an important paradox in consumer behavior. While users benefit from convenience and personalization, they simultaneously express concerns regarding exposure limitation, reduced diversity, and fairness. Trusting consumers do not entirely dismiss ethical considerations, indicating that acceptance of algorithms coexists with expectations for responsible platform practices.

Overall, the study underscores that algorithmic ecosystems influence consumer behavior through subtle psychological pathways rather than overt control, reinforcing the need for ethical and transparent digital marketing strategies.

Recommendations

Based on the study findings, several managerial and practical implications emerge:

1. **Enhance Algorithmic Transparency**

   Digital platforms should clearly communicate how recommendations are generated. Improving transparency can strengthen consumer confidence while reducing skepticism and perceived manipulation.

2. **Promote Fairness and Inclusivity**

   Organizations must prioritize fairness in algorithmic design to prevent systemic biases and digital marginalization. Diverse data inputs and regular bias audits can support equitable consumer experiences.

3. **Preserve Choice Diversity**

   Excessive personalization may unintentionally restrict consumer exposure. Platforms should incorporate mechanisms that encourage discovery beyond predicted preferences to maintain a balanced choice architecture.

4. **Build Ethical Trust Frameworks**

   Trust should not rely solely on performance efficiency. Companies must integrate ethical considerations into algorithm deployment, emphasizing user autonomy, privacy, and accountability.

5. **Consumer Education Initiatives**

   Educating users about algorithmic functioning can foster informed decision-making and realistic expectations, contributing to healthier platforms–consumer relationships.

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