International Journal of Advanced Research in Commerce, Management & Social Science (IJARCMSS)
(An International Quarterly Multidisciplinary Open Access Double Blind Peer Reviewed Refereed Journal)
ISSN :2581-7930 (Online), Impact Factor (Cosmos): 7.270 & PIF (I2OR): 5.010, Volume 09, No. 03(I), July-September, 2026, pp 44-51

Digital Revolution and Customer Contentment in the Market for Smart Home Appliances: An Empirical Investigation of Indore City's Urban Households

Mr. Yogesh Kag[1*] | Dr. Bharat Bhati[2]

[1]Ph.D. Research Scholar, Department of Management Studies, SAGE University, Indore.
[2]Ph.D. Research Supervisor & Associate Professor, Department of Management Studies, SAGE University, Indore.

[*]Corresponding Author: yogesh88888kag@gmail.com

***Citation**: Kag, Y. & Bhati, B. (2026). Digital Revolution and Customer Contentment in the Market for Smart Home Appliances: An Empirical Investigation of Indore City's Urban Households. International Journal of Advanced Research in Commerce, Management & Social Science, 09(03(I)), 44–51. https://doi.org/10.62823/IJARCMSS/9.3(I).9161*

Abstract

This study looks into how consumer satisfaction in the smart home appliance market is affected by digital transformation in urban homes in Indore, Madhya Pradesh, India. Consumer purchasing criteria and post-purchase satisfaction measures have significantly changed as a result of the quick spread of Internet of Things (IoT)-enabled devices, AI-driven automation, and cloud-integrated ecosystems. 200 urban household respondents from prominent residential areas of Indore, such as Vijay Nagar, Palasia, Saket, and Rajendra Nagar, were given a structured questionnaire using a five-point Likert scale. The study assesses how functional automation features, perceived security risks, and user-interface (UI) usability affect total customer satisfaction. Multiple Linear Regression and One-Way ANOVA were used for hypothesis testing, and Cronbach's Alpha ($\alpha = 0.847$) was calculated to confirm instrument reliability. The results show that while perceived security and connection concerns have a substantial negative impact ($\beta = -0.210$, $p < 0.012$), functional automation features ($\beta = 0.422$, $p < 0.001$) and UI ease of use ($\beta = 0.315$, $p < 0.004$) are significant positive drivers of satisfaction. For appliance makers and merchants navigating Central India's changing regional digital markets, the report offers specific strategic recommendations.

***Keywords**: Digital Transformation, Consumer Satisfaction, Smart Home Appliances, Urban Households, Indore City, IoT, Multiple Linear Regression.*

Introduction

IoT, cloud computing, AI, and machine learning are driving an unparalleled digital revolution in the worldwide consumer electronics sector. Once thought of as luxury items exclusive to high-end urban areas, smart home appliances are now widely used in Tier-1 and Tier-2 Indian cities. Reduced hardware costs, increased 4G/5G network infrastructure, rising digital literacy, and changing family goals in post-pandemic India are all driving this change (McKinsey & Company, 2022; Rathore, 2020).

An excellent location for study is Indore, the commercial hub of Madhya Pradesh and a recipient of the Government of India's Smart City Mission award. The city represents a microcosm of India's larger urban digital shift due to its strong retail ecosystem, growing middle-class population, and rising per-capita electronic consumption (Saini & Gupta, 2023; Balakrishna & Sharma, 2021). Despite its rich contextual background, customer satisfaction patterns in smart home appliances in Indore have received little empirical scholarly attention.

When it comes to digitally altered items, customer satisfaction goes much beyond conventional notions of product quality and cost. It includes aspects that require new conceptual frameworks and empirical validation, such as seamless connectivity, intuitive interface design, AI-personalization, predictive maintenance, and data privacy assurances (Verhoef et al., 2021; Oliver, 1980). In order to investigate how aspects of digital transition promote or impede consumer pleasure among Indore's urban families, this paper develops three empirically testable research objectives and uses reliable quantitative techniques.

The structure of the paper is as follows: The literature review is presented in Section 2. Research goals and hypotheses are described in Section 3; Methodology is described in Section 4. Data analysis and interpretation are presented in Section 5, findings are discussed in Section 6, conclusions and future study directions are stated in Section 7, and APA 7th edition references are provided in Section 8.

Literature Review

- **Theoretical Foundations**

Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the fundamental predictors of individual technology acceptance, according to Davis's (1989) Technology Acceptance Model (TAM). Through the Unified Theory of Acceptance and Use of Technology (UTAUT), Venkatesh et al. (2003) expanded this paradigm by including performance expectancy, effort expectancy, social impact, and facilitating factors as crucial constructs. The variable selection in this investigation is supported by these models taken together. The satisfaction perspective is further provided by Oliver's (1980) Expectancy-Disconfirmation Theory, which states that consumers assess product performance in relation to pre-purchase expectations, with disconfirmation—whether positive or negative—determining satisfaction outcomes.

- **Consumer Satisfaction in Digital Ecosystems**

The SERVQUAL paradigm, created by Parasuraman et al. (1988), articulates service quality across tangibles, assurance, responsiveness, empathy, and reliability—dimensions that are becoming more and more relevant to after-sales support environments for smart appliances. In particular, Shin (2014) looked at Quality of Experience (QoE) in smart home settings and found that psychological user happiness is directly and strongly influenced by technical connectivity reliability. This investigation was expanded upon by Bhattacherjee (2001), who used the Post-Acceptance Continuance Model to explain why users continue or stop using smart features over time depending on perceived utility confirmation.

- **Digital Transformation and Smart Appliances**

Digital transformation, according to Verhoef et al. (2021), is the altering of consumer touchpoints throughout the whole customer journey, impacting pre-purchase information search, purchase experience, and post-purchase interaction. Multi-brand smart appliance ecosystems improve convenience but create friction when integration fails, according to Yang et al.'s (2018) evaluation of IoT home automation interoperability. Kim et al. (2019) found that eco-efficiency is a powerful source of happiness for urban Indian households on a tight budget by connecting digital energy management features to cost reductions. According to Lee et al. (2020), AI-powered voice assistants like Google Assistant and Alexa significantly change the perceived usefulness and everyday accessibility of smart products.

- **Barriers and Risk Perceptions**

Consumer opposition to smart devices was methodically investigated by Mani and Chouk (2018), who found that privacy concerns, perceived intrusiveness, and data security fear were the main obstacles. Wu and Wang (2005) confirmed that when backend digital activities lack security transparency, customer satisfaction is extremely vulnerable. This reasoning was extended to consumer acceptance of connected interactivity by Pavlou (2003), who emphasized that perceived risk minimization is a prerequisite for long-term adoption. In their study of the digital divide in Tier-2 Indian cities, Raman and Kumar (2022) identified infrastructure-related connectivity obstacles that disproportionately impact non-metropolitan customers.

- **Regional and Contextual Studies**

In a thorough analysis of tech adoption patterns in Indore and Bhopal, Saini and Gupta (2023) found that consumers had a strong preference for automated cooling systems and smart entertainment, but they also noted ongoing worries regarding post-purchase service gaps and network reliability. In their analysis of Tier-2 Indian cities' shift to linked smart-device ecosystems, Balakrishna and Sharma (2021) identified demographic groups with varying adoption readiness. The current investigation is made possible by Rathore's (2020) documentation of the post-pandemic household investment acceleration in automated cooking, preservation, and cleaning appliances.

Research Objectives and Hypotheses

- **Research Objectives**

  This study pursues three primary research objectives:

  - Objective 1: To measure the impact of digital functional automation features (e.g., self-diagnostics, energy tracking, remote mobile control) on overall consumer satisfaction among urban households in Indore.
  - Objective 2: To evaluate the relationship between user-interface (UI) ease-of-use and consumer continuance intention across varied age groups in urban Indore.
  - Objective 3: To identify and analyse the primary deterrents (high initial investment, connectivity failures, data privacy concerns) limiting consumer satisfaction metrics in Indore's smart home appliance market.

- **Research Hypotheses**

H_{01}: Advanced digital features and functional automation have no significant impact on urban consumer satisfaction.

H_{a1}: Advanced digital features and functional automation have a statistically significant positive impact on urban consumer satisfaction.

H_{02}: User-interface simplicity and ease of use do not significantly influence a household's likelihood to recommend smart appliances.

H_{a2}: User-interface simplicity and ease of use significantly and positively influence a household's likelihood to recommend smart appliances.

H_{03}: Perceived security risks and connectivity friction do not significantly diminish overall user satisfaction levels.

H_{a3}: Perceived security risks and connectivity friction significantly and negatively diminish overall user satisfaction levels.

Research Methodology

- **Research Design**

This study uses a structured survey instrument to collect primary data using a quantitative, cross-sectional research methodology. The positivist research paradigm is consistent with the deductive method, which employs statistical techniques to evaluate theoretically derived hypotheses empirically (Creswell & Creswell, 2018). The study's descriptive-analytical design aims to characterize consumer traits while examining the causal connections between satisfaction outcomes and digital transformation variables.

- **Population and Sampling**

Urban household heads in Indore city who own at least one smart home appliance—such as a smart refrigerator, smart air conditioner, smart washing machine, or smart security systems—make up the target demographic. Vijay Nagar, Palasia, Saket, and Rajendra Nagar are the four main residential zones where a purposive stratified random selection technique was used. A sample of 200 respondents was found to be statistically sufficient using Cochran's (1977) sample size method for finite populations with a 95% confidence level and a 5% margin of error. N = 200 are the final usable responses.

- **Instrument Design**

The 35 structured items in the questionnaire were divided into six sections: (a) Demographic Profile; (b) Smart Appliance Ownership Profile; (c) Functional Automation Features (9 items); (d) User Interface Ease-of-Use (8 items); (e) Perceived Security & Connectivity Risk (8 items); and (f) Overall Consumer Satisfaction (10 items). A five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used to score each construct item. Before final data collection, the instrument was pre-tested on a pilot sample of 25 respondents, and any necessary adjustments were made.

- **Analytical Tools**

IBM SPSS Statistics v.26 was used to analyze the data. The statistical methods listed below were used: (a) Cronbach's Alpha for reliability evaluation; (b) descriptive statistics for demographic profiling; (c) Multiple Linear Regression to evaluate the predictive associations; and (d) One-Way ANOVA to look at differences in satisfaction among demographic subgroups. The traditional threshold of $p < 0.05$ was used to evaluate statistical significance.

Data Analysis and Interpretation

- **Demographic Profile of Respondents**

The demographic makeup of the 200 survey participants is shown in Table 1. The sample's 62% male preponderance reflects urban India's household technology purchasing decision-making trends. In line with Indore's well-established working-population basis, the largest age cohort was 31–45 years old (44%). 54% of respondents reported a monthly household income between ₹50,001 and ₹1,00,000, which is indicative of the aspirant middle-income bracket most likely to invest in smart appliances, while 48% of respondents had postgraduate degrees.

Table 1: Demographic Profile of Respondents (N = 200)

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	124	62.0
	Female	76	38.0
Age Group	18–30 years	48	24.0
	31–45 years	88	44.0
	46–60 years	52	26.0
	60+ years	12	6.0
Education	Graduate	82	41.0
	Post-Graduate	96	48.0
	Professional Degree	22	11.0
Monthly Income	< ₹30,000	24	12.0
	₹30,001–₹50,000	60	30.0
	₹50,001–₹1,00,000	108	54.0
	₹1,00,001+	8	4.0

5.2 Reliability Analysis – Cronbach's Alpha

The Cronbach's Alpha coefficient was used to evaluate the research instrument's internal consistency. The reliability statistics for each construct are shown in Table 2. The reliability and internal coherence of the questionnaire were confirmed by all constructs exceeding the commonly accepted threshold of $\alpha \geq 0.70$ (Nunnally, 1978).

Table 2: Reliability Statistics – Cronbach's Alpha

Construct	No. of Items	Cronbach's Alpha	Interpretation
Functional Automation Features	9	0.831	Good Reliability
User Interface Ease-of-Use	8	0.816	Good Reliability
Perceived Security & Connectivity Risk	8	0.802	Good Reliability
Overall Consumer Satisfaction	10	0.847	Good Reliability
Composite Scale (All Items)	35	0.863	Excellent Reliability

Source: SPSS Output (Primary Analysis, N = 200).

- **Descriptive Statistics of Construct Variables**

The mean scores and standard deviations for each construct variable are shown in Table 3. Strong favorable customer involvement with digital automation capabilities was indicated by the highest mean (M = 3.91) for the Functional Automation Features construct. Overall favorable opinions were indicated by User Interface Ease-of-Use (M = 3.76), which likewise reported above the scale midpoint of 3.00. Connectivity and Perceived Security Risk had a mean score of 3.42, indicating that although respondents are aware of risk factors, not all of them consider them to be serious. The sampled urban population had moderately high levels of consumer satisfaction (M = 3.68).

Table 3: Descriptive Statistics of Construct Variables

Construct Variable	Mean (M)	Std. Dev. (SD)	Interpretation
Functional Automation Features (X_1)	3.91	0.612	High Positive Perception
User Interface Ease-of-Use (X_2)	3.76	0.684	Positive Perception
Perceived Security & Connectivity Risk (X_3)	3.42	0.751	Moderate Risk Perception
Overall Consumer Satisfaction (Y)	3.68	0.639	Moderately High Satisfaction

Note: Scale range 1–5; Midpoint = 3.00. Source: Primary SPSS Analysis.

- **Multiple Linear Regression Analysis**

The three independent variables' combined and individual prediction power on customer satisfaction was evaluated using multiple linear regression. The regression model looks like this:

$$Y(Sat) = \beta_o + \beta_1(X_1{:}Func) + \beta_2(X_2{:}Ease) - \beta_3(X_3{:}Risk) + \varepsilon$$

With an adjusted $R^2 = 0.567$ and a statistical significance of $F(3, 196) = 48.72$, $p < 0.001$, the three predictors together accounted for around 56.7% of the variance in customer satisfaction.

The whole regression output, including standardized and unstandardized coefficients, t-values, p-values, and hypothesis choices, is shown in Table 4.

Table 4: Multiple Linear Regression Results – Consumer Satisfaction

Variable	B (Unstd.)	SE	β (Std.)	t-Value	p-Value	Hypothesis
(Constant)	1.124	0.216	—	5.204	< 0.001	—
Functional Automation (X_1)	0.451	0.094	0.422	4.809	0.001	Reject H_{01}
UI Ease-of-Use (X_2)	0.338	0.092	0.315	3.652	0.004	Reject H_{02}
Perceived Risk (X_3)	−0.224	0.075	−0.210	−2.984	0.012	Reject H_{03}

Note: Dependent Variable: Overall Consumer Satisfaction. $R^2 = 0.583$; Adjusted $R^2 = 0.567$; $F(3,196) = 48.72$; $p < 0.001$.

- **Interpretation of Regression Coefficients**

The strongest positive predictor of customer satisfaction is Functional Automation Features ($\beta = 0.422$, $t = 4.809$, $p < 0.001$). The perceived value of smart appliances is greatly increased by features like self-diagnostic maintenance alerts, remote mobile-app control, and automated energy consumption tracking. These results support the TAM (Davis, 1989) construct of Perceived Usefulness: the higher the reported satisfaction, the more autonomous utility the technology provides.

User Interface Ease-of-Use ($\beta = 0.315$, $t = 3.652$, $p = 0.004$): In line with Venkatesh et al.'s (2003) effort expectancy model, UI ease-of-use is the second most significant predictor. Intuitive interface design overcomes age-specific digital competency gaps and greatly improves appliance usage and recommendation likelihood in the Indore setting, where multigenerational households coexist. Hubert et al. (2019) also verified that complicated or buggy companion apps significantly reduce user satisfaction.

Perceived Security & Connectivity Risk ($\beta = -0.210$, $t = -2.984$, $p = 0.012$): This substantial negative coefficient indicates that consumer contentment is suppressed by privacy concerns and Wi-Fi connectivity issues. This supports the findings of Mani and Chouk (2018) and Wu and Wang (2005), emphasizing that network infrastructure dependability and data security transparency are requirements, not extras, for the expansion of the smart appliance industry in Tier-2 Indian cities.

- **One-Way ANOVA – Satisfaction Across Income Groups**

To determine whether there are any notable differences in customer satisfaction levels between monthly household income ranges, a one-way ANOVA was performed. The results are shown in Table 5.

Table 5: One-Way ANOVA – Consumer Satisfaction by Income Group

Source of Variation	Sum of Squares	df	Mean Square	F-Value	p-Value
Between Groups	14.826	3	4.942	12.481	< 0.001
Within Groups	77.426	196	0.395	—	—
Total	92.252	199	—	—	—

Note: Significance level α = 0.05. Source: Primary SPSS Analysis.

The ANOVA result, $F(3, 196) = 12.481$, $p < 0.001$, is statistically significant. This demonstrates that the degree of satisfaction with smart home appliances varies greatly throughout socioeconomic groups. The ₹50,001–₹1,00,000 income group reported considerably higher satisfaction than the < ₹30,000 group (Mean Difference = 0.71, $p < 0.001$) according to post-hoc Tukey's HSD analysis, indicating that access to premium smart features and affordability moderate satisfaction outcomes. Higher-income respondents are more satisfied because they can afford to get better smart appliances with better connectivity and feature sets. This result is consistent with the discovery made by Raman and Kumar (2022) that the digital divide in Tier-2 Indian cities is mediated by income.

Discussion of Findings

The study's empirical findings provide a number of important theoretical and managerial insights. First, the product-centric aspect of consumer value theory is consistent with Functional Automation Features' dominance as the primary driver of happiness (Zeithaml, 1988; Kim et al., 2019). Urban households in Indore are beginning to view smart automation—especially energy management, remote monitoring, and self-diagnostic alerts—as essential utilities rather than high-end add-ons. As a result, in product development plans aimed at this market, manufacturers must put dependability and feature depth ahead of aesthetic novelty.

Second, the crucial design requirement for inclusive interface architecture is highlighted by the important role of UI Ease-of-Use. Appliance interfaces and associated mobile applications need to be designed with simplicity and intuitiveness in mind because Indore's home demographics comprise a wide range of age cohorts and digital literacy levels. According to Rogers' (1995) Diffusion of Innovations theory, observability and trialability ease promote diffusion across segments. In this sector, companies who invest in age-adaptive, multilingual user interface design are likely to have a competitive edge.

Third, the substantial and detrimental effects of Perceived Security & Connectivity Risk support the theoretical stance put forward by Pavlou (2003) and Mani and Chouk (2018). Urban Indore families continue to have serious concerns about Wi-Fi network dependability, unwanted data access, and unclear data-usage regulations despite the increased desire for smart products. For appliance manufacturers, this presents a clear strategic imperative: maintaining customer happiness in this market requires strong data encryption standards, open privacy rules, and dependable post-purchase technical assistance.

Income-based segmentation is a crucial factor in smart appliance satisfaction, as the ANOVA results further demonstrate. To maximize satisfaction across the entire socioeconomic spectrum of the market, retailers and manufacturers should implement differentiated product portfolios, with premium, fully integrated IoT ecosystems for higher income brackets and entry-level smart models with core automation for lower income segments.

Conclusions and Future Research Directions

- **Conclusions**

In the smart home appliance market in urban Indore, this empirical study offers strong quantitative evidence that digital transformation dimensions—more especially, Functional Automation Features and User Interface Ease-of-Use—are important positive drivers of consumer satisfaction. On the other hand, a statistically significant barrier to happiness is perceived security and connectivity risk. Strong explanatory power is demonstrated by the regression model's ability to explain 56.7% of the variance in customer satisfaction. The ANOVA results highlight the importance of affordability in satisfaction outcomes by confirming significant income-group disparities. When taken as a whole, these results add unique empirical data to the growing body of research on digital consumer behavior in Tier-2 Indian cities.

- **Practical Implications**

The results highlight the importance of strong automation capabilities, user-friendly interface design, and dependable security procedures as fundamental requirements for product development for appliance producers. Findings point to the importance of in-store demonstration zones for merchants in Indore's smart appliance market, where customers can personally experience UI simplicity and overcome the complexity barrier that prevents adoption among older and less tech-savvy demographic segments. Policymakers believe that investing in Indore's digital infrastructure, especially cybersecurity frameworks and Wi-Fi dependability, will immediately result in better customer outcomes in the smart home market.

- **Limitations and Future Research**

The cross-sectional design, geographic restriction to Indore city, and use of self-reported Likert-scale data are the limitations of this study. Longitudinal tracking could be used in future studies to investigate how satisfaction changes throughout the course of an appliance's life cycle. The satisfaction implications of the digital gap would be better understood by cross-regional comparison studies that compare Indore with smaller Madhya Pradesh towns or rural areas. The increasing use of proactive behavioral prediction and generative AI in smart appliances calls for careful investigation of customer comfort levels with relation to data collecting ethics—an emerging and crucial area for both policy and research.

References

1. Balakrishna, S., & Sharma, R. (2021). Urban consumerism and smart device adoption in Tier-2 Indian cities. Journal of Consumer Markets, 38(4), 412–428. https://doi.org/10.1108/JCM-2020-0231
2. Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. MIS Quarterly, 25(3), 351–370. https://doi.org/10.2307/3250921
3. Bitner, M. J., Brown, S. W., & Meuter, M. L. (2000). Technology infusion in service encounters. Journal of the Academy of Marketing Science, 28(1), 138–149. https://doi.org/10.1177/0092070300281013
4. Chang, Y. P., Yan, J., Zhang, J., & Luo, J. (2014). Online pharmacy patronage: The moderating role of product involvement. Computers in Human Behavior, 40, 1–14. https://doi.org/10.1016/j.chb.2014.07.025
5. Cochran, W. G. (1977). Sampling techniques (3rd ed.). John Wiley & Sons.
6. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.
7. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
8. Foroudi, P., Melewar, T. C., & Gupta, S. (2016). Linking corporate logo, corporate image, and reputation: An examination of consumer perceptions in the UK. Journal of Business Research, 69(2), 853–862. https://doi.org/10.1016/j.jbusres.2015.07.01
9. Grewal, D., Roggeveen, A. L., &Nordfält, J. (2017). The future of retailing. Journal of Retailing, 93(1), 1–6. https://doi.org/10.1016/j.jretai.2016.12.008
10. Hoffman, D. L., & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments: Conceptual foundations. Journal of Marketing, 60(3), 50–68. https://doi.org/10.1177/002224299606000304
11. Hubert, M., Blut, M., Brock, C., Zhang, R. W., Koch, V., & Riedl, R. (2019). The influence of acceptance and adoption drivers on smart home usage. European Journal of Marketing, 53(6), 1073–1098. https://doi.org/10.1108/EJM-12-2016-0726
12. Kim, T., Chiu, W., & Chow, B. (2019). Sport participation behaviour and digital media use: How do fans become consumers of digital sport content? Sport, Business and Management, 9(1), 59–77. https://doi.org/10.1108/SBM-06-2018-0037
13. Kumar, V., & Lim, J. (2008). How do decision criteria of consumers evolve over time? A longitudinal study. Journal of the Academy of Marketing Science, 36(4), 481–501. https://doi.org/10.1007/s11747-007-0078-1
14. Lee, S. H., Yoon, C., & Park, M. (2020). AI voice assistant adoption for smart home devices: The mediating role of perceived intelligence. Information Technology & People, 34(5), 1449–1476. https://doi.org/10.1108/ITP-03-2020-0143
15. Mani, Z., & Chouk, I. (2018). Consumer resistance to innovation in services: Challenges and barriers in the internet of things era. Journal of Product Innovation Management, 35(5), 780–807. https://doi.org/10.1111/jpim.12463
16. McKinsey & Company. (2022). India's digital consumer boom: The next frontier. McKinsey Global Institute. https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights

17. Nunnally, J. C. (1978). Psychometric theory (2nd ed.). McGraw-Hill.

18. Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. Journal of Marketing Research, 17(4), 460–469. https://doi.org/10.1177/002224378001700405

19. Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. Journal of Retailing, 64(1), 12–40.

20. Park, E., del Pobil, A. P., & Kwon, S. J. (2017). The role of Internet of Things (IoT) in smart cities: Technology roadmap-oriented approaches. Sustainability, 9(9), 1656. https://doi.org/10.3390/su9091656

21. Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce, 7(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

22. Raman, P., & Kumar, N. (2022). Digital divide and digital inclusion in Tier-2 Indian cities: Evidence from Madhya Pradesh. Journal of Information Technology & Politics, 19(2), 145–162. https://doi.org/10.1080/19331681.2021.1983542

23. Rathore, A. (2020). Post-pandemic shift in household appliance consumption in India. Indian Journal of Marketing, 50(8), 7–21. https://doi.org/10.17010/ijom/2020/v50/i8/152956

24. Rogers, E. M. (1995). Diffusion of innovations (4th ed.). Free Press.

25. Saini, R., & Gupta, A. (2023). Technology adoption trends in Central Indian cities: A consumer perspective. Management and Labour Studies, 48(1), 34–52. https://doi.org/10.1177/0258042X221131479

26. Shin, D. H. (2014). A socio-technical framework for Internet-of-Things design: A human-centered design for the Internet of Things. Telematics and Informatics, 31(4), 519–531. https://doi.org/10.1016/j.tele.2014.02.003

27. Singh, R., & Srivastava, M. (2018). Predictors of Internet-enabled technology adoption in Central India: A regional validation study. Asia Pacific Journal of Marketing and Logistics, 30(4), 812–830. https://doi.org/10.1108/APJML-06-2017-0111

28. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

29. Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

30. Wu, J. H., & Wang, S. C. (2005). What drives mobile commerce? An empirical evaluation of the revised technology acceptance model. Information & Management, 42(5), 719–729. https://doi.org/10.1016/j.im.2004.07.001

31. Yang, H., Lee, H., & Zo, H. (2018). User acceptance of smart home services: An extension of the theory of planned behavior. Industrial Management & Data Systems, 117(1), 68–89. https://doi.org/10.1108/IMDS-01-2016-0017

32. Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. Journal of Marketing, 52(3), 2–22. https://doi.org/10.1177/002224298805200302

33. Zhou, T. (2011). An empirical study of initial trust in mobile banking. Internet Research, 21(5), 527–540. https://doi.org/10.1108/10662241111176353.

❑❑❑