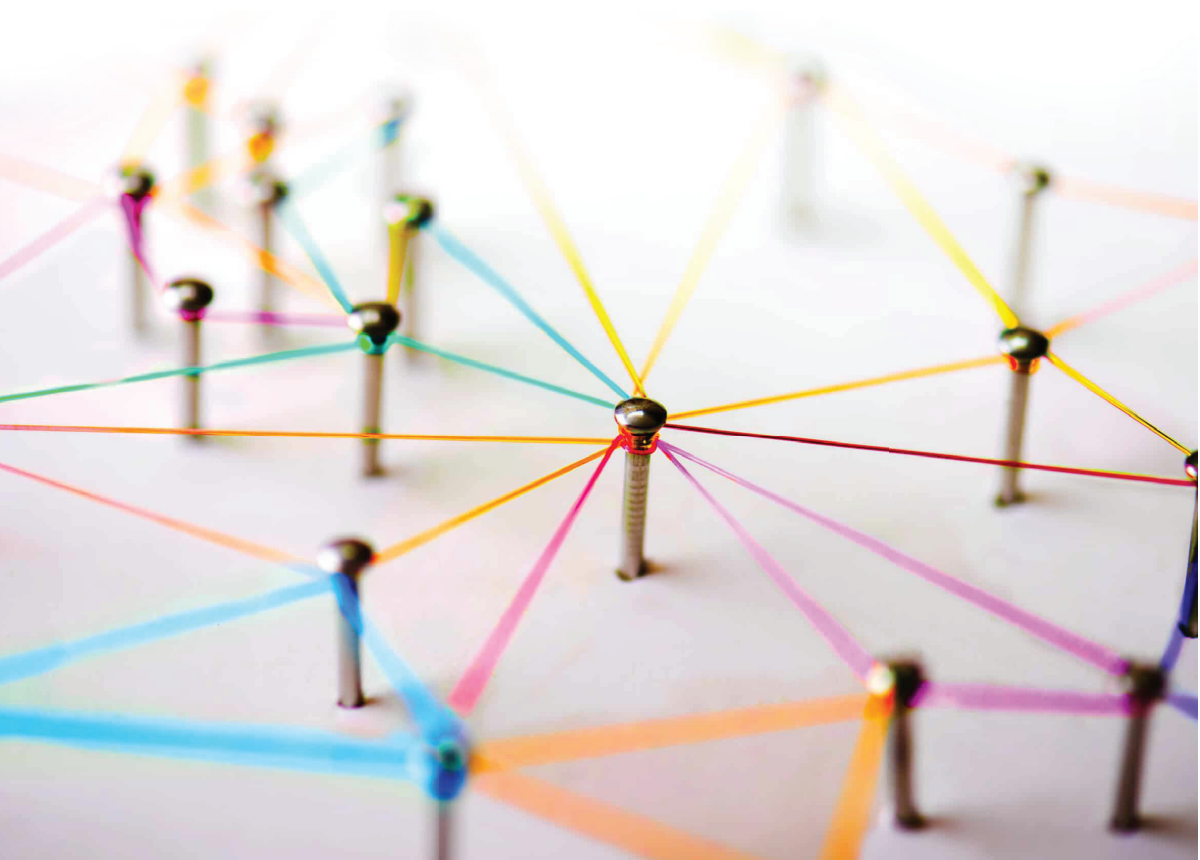


Volume 7 • Issue 2
December 2026



bsp.bimtech.ac.in
ISSN: 2581-9542
e-ISSN: 2582-3965

BIMTECH Business Perspectives



BIMTECH Business Perspectives is published biannually in June and December by Birla Institute of Management Technology (BIMTECH), Greater Noida, Uttar Pradesh.

BIMTECH Business Perspectives is hosted on our web-based online submission and peer review system. Please read the manuscript submission guidelines on the journal website, and then visit <https://peerreview.sagepub.com/bsp> to login and submit your article online. Manuscripts should be prepared in accordance with the 7th edition of the *Publication Manual of the American Psychological Association*.

Copyright © 2026 Birla Institute of Management Technology, Greater Noida, Uttar Pradesh. All rights reserved. The views expressed in the articles and other material published in *BIMTECH Business Perspectives* do not reflect the opinions of the Institute.

Annual Subscription: Individual rate (print only) ₹1,580; institutional rate (print only) ₹2,760. For orders from Pakistan, Bangladesh, Sri Lanka and Maldives, SAARC rates apply: individuals \$35; institutional rate \$50. Prices include postage. Print subscriptions are available for institutions at a discounted rate. For subscriptions, please write to: customerservicejournals@sagepub.in

Abstracting and Indexing: *BIMTECH Business Perspectives* is indexed in:

- UlrichWeb (Proquest)
- J-Gate
- India Citation Index
- Google Scholar

Change of Address: Four weeks' advance notice must be given when notifying change of address. Please send the old address label to ensure proper identification. Please specify the name of the journal and send change of address notification to customerservicejournals@sagepub.in

Printed and published by Registrar, BIMTECH, on behalf of Birla Institute of Management Technology (BIMTECH), Plot No. 5, Knowledge Park II, Institutional Area, Greater Noida (NCR), Uttar Pradesh 201 306, India. Printed at Sai Printo Pack Pvt Ltd, A 102/4 Phase II, Okhla Industrial Area, New Delhi, Delhi 110020.

Editor: Sugandh Ahuja

RNI No: UPENG/2018/76514

About the Journal

BIMTECH Business Perspectives is a scholarly Open Access journal of Birla Institute of Management Technology, India. The journal publishes original contribution in the functional areas of business management (see Aims and Scope). Furthermore, the journal is a platform for interdisciplinary studies that provide both empirical evidence and nuanced perspectives on business management in the national, regional, and global contexts. The contexts include, but not limited to, the contemporary economic, political, social, technological, and environmental challenges facing business stakeholders.

The journal brings out two issues per year, and it follows a double-anonymized peer-review process. All contributions should be well written in English. Submission to the journal should be relevant to one or more business and allied disciplines and backed by suitable methodology, sound analysis, practical perspectives, and managerial or policy implications.

To this end, *BIMTECH Business Perspectives* invites contributions from both the academic community and business practitioners. The journal publishes and disseminates original articles, review essays, perspectives, book reviews, interviews and invited pieces. Special theme-focused and/or guest-edited issues are also planned.

Aims and Scope

The objectives of *BIMTECH Business Perspectives*, the journal, are to encourage and publish research in the field of business management. The terms business and management are both broadly defined. While the former encompasses both discipline and business problem-based research, the latter includes the management of firms, groups, industries, regulatory bodies, government, and other institutions. The journal has a special focus on emerging and functional areas of business management. Consistent with the policy, the journal publishes peer-reviewed research in financial markets, emerging economies, entrepreneurship and start-ups, emerging technology and innovation in business functions, consumer behaviour, human behaviour in management decisions, risk management, supply chain management, business strategy, and other domains having a direct or indirect bearing on business management. The journal encourages both quantitative and qualitative research methods to unearth relevant findings. The journal aims to nurture a debate among individuals and groups, which have keen interest in business and managerial processes. The journal encourages inter-disciplinary studies that may lead to new understanding of business and management functions. The journal welcomes research papers examining dynamics of business management in the backdrop of changes in the global business environment. The journal serves as a platform that connects thought-leaders and researchers from diverse fields to address crucial business and management issues. Published twice a year (June and December), *BIMTECH Business Perspectives* is an official publication of Birla Institute of Management Technology (BIMTECH), Greater Noida, India. The journal has been publishing in its current form since 2019. Prior to 2019, the journal was known as *Business Perspectives*, which had a publication history of more than a decade.

If you wish to contact the editors of the journal *BIMTECH Business Perspectives*, please email at editor@bimtech.ac.in

Editorial Board

Editor

Sugandh Ahuja, *BIMTECH, Greater Noida, Uttar Pradesh, India*

Associate Editors

Dharen Kumar Pandey, *Indian Institute of Management Sambalpur, Sambalpur, Odisha, India*

Ngoc Cindy Pham, *City University of New York, Brooklyn College and the Graduate Center, New York, USA*

Rahul Sindhvani, *International Management Institute Delhi (IMI Delhi), India*

Saloni Sinha, *BIMTECH, Greater Noida, Uttar Pradesh, India*

Sugandh Ahuja, *BIMTECH, Greater Noida, Uttar Pradesh, India*

Neha Sharma, *BIMTECH, Greater Noida, Uttar Pradesh, India*

Shashi Kant Sharma, *BIMTECH, Greater Noida, Uttar Pradesh, India*

Editorial Advisory Board

Arindam Banerjee, *Shiv Nadar University Chennai, Rajiv Gandhi Salai (OMR), Kalavakkam, Chengalpattu (Dt), TN, India*

Nadia Doytch, *City University of New York, Brooklyn College, Koppelman School of Business, Department of Economics, Brooklyn, NY, USA*

Gulay Gunluk-Senesen, *Faculty of Political Sciences, Istanbul University, Beyazit-Fatih, Istanbul, Turkiye*

Pradeep Kautish, *Department of Marketing, Institute of Management, Nirma University, Ahmedabad, Gujarat, India*

Sunil Luthra, *All India Council for Technical Education, India*

D. K. Malhotra, *Director of MBA Program, School of Business, Thomas Jefferson University, Philadelphia, USA*

Shizhu Liu, *Department of Technology Management & Innovation Tandon School of Engineering, New York University, New York, USA*

Olawale Emmanuel Olayide, *University of Ibadan, Ibadan, Nigeria*

David R. Perkins, *Missouri State University, Springfield, MO, USA*

Shameem Shagirbasha, *Indian institute of management, Tiruchirappalli, India*

Gagan Deep Sharma, *University School of Management Studies, Guru Gobind Singh Indraprastha University, New Delhi, India*

Praveen Goyal, *Department of Management BITS, Pilani- Pilani Campus, India*

Anand Suryanarayana, *Director, Postgraduate Studies, Research and Innovation Department, College of Banking and Financial Studies, Muscat, Sultanate of Oman*

Thijs Ten Raaij, *Utrecht University, Amsterdam, The Netherlands*

Ankit Agarwal, *College of Business & Law, Adelaide University, Australia*

Naotoshi Umeno, *Osaka University of Commerce, Mikuriga Sakemachi, Higashi Osaka, Japan*

Volha Rudkouskaya, *Department of Economics Belarusian State Economic University, Minsk, Belarus*

Yanki Hartijasti, *Faculty of Economics & Business, Universitas Indonesia, Indonesia*

Contents

Articles

- Managing Digital Disruption: Strategies for Marketing and Management Transformation 135
Rajeev Kumar
- A Study on the Integration of ChatGPT in Management Accounting Practices 147
Shubham Singh Chandel, Jyotsna Dwivedi and Dawakit Lepcha
- Responsible Automation in E-business: A Framework for Agentic AI Integration and Governance 169
Mohammad Talha Siddiqui and Yusuf Kamal
- Antecedents of Environmentally Conscious Purchase Behavior: An Empirical Analysis 193
Hareesh Thummalapally, Anu Grover and Basil Khalid
- The Silent Saboteur: Unraveling the Impact of Smartphone Addiction on International Students' Academic Performance 212
Ayano Jenga and Meenu Gupta

Visit <https://www.bsp.bimtech.ac.in/>

Managing Digital Disruption: Strategies for Marketing and Management Transformation

BIMTECH Business Perspectives
7(2) 135–146, 2026
© The Author(s) 2026
DOI: 10.1177/25819542261449560
bsp.bimtech.ac.in



Rajeev Kumar¹ 

Abstract

The article provides a theoretical review of the impact of digital technologies on traditional business practices. The article suggests some of the important strategies for businesses to adapt, innovate, and thrive in a digitally disruptive landscape. The article emphasizes the importance of data-driven decision-making, customer-centric approaches, and agile management practices to excel in the competitive market. The present study provides pertinent and actionable insights to organizations, policymakers and researchers for maximizing resilience, agility and sustainable growth amid digital disruption.

Keywords

Digital disruption, marketing transformation, management strategy, business innovation, digital transformation, technology adaptation

Introduction

The rapid acceleration of digital technologies has transformed the global business landscape, forcing organizations to adapt or risk obsolescence. Digital disruption, characterized by the emergence of new technologies that challenge

¹ School of Management, Doon University, Dehradun, Uttarakhand, India

Corresponding author:

Rajeev Kumar, School of Management, Doon University, Dehradun, Uttarakhand 248001, India.
E-mail: ranjanrajeev87@gmail.com



Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 License (<http://www.creativecommons.org/licenses/by-nc/4.0/>) which permits non-Commercial use, reproduction and distribution of the work without further permission provided the original work is attributed.

traditional business models, has become a defining factor in modern marketing and management practices. Companies across industries must navigate this disruption effectively to maintain competitive advantages, drive innovation, and ensure sustainable growth. The integration of digital tools, data analytics, artificial intelligence (AI), and automation has revolutionized customer engagement, operational efficiency, and decision-making processes. As businesses face these profound changes, strategic transformation in marketing and management has become imperative (Bughin et al., 2018). Digital disruption refers to the transformation brought about by digital technologies that challenge the status quo, alter consumer behavior, and redefine industry dynamics. Unlike traditional market disruptions, which typically stem from new competitors or economic shifts, digital disruption is driven by technological advancements such as AI, machine learning, blockchain, big data, and cloud computing (Berman, 2012). Organizations that fail to foresee and embrace these changes face the risk of becoming obsolete, as seen in cases such as Kodak's inability to transition to digital photography and Blockbuster's failure to compete with streaming services like Netflix. Marketing, an important function for customer acquisition and retention, has been deeply impacted by digital advancements. Traditional marketing strategies that relied on television, print, and radio have been supplemented, and in some cases replaced, by digital marketing techniques such as search engine optimization (SEO), social media marketing, content marketing, and influencer collaborations (Chaffey & Ellis-Chadwick, 2019). These digital strategies allow businesses to reach target audiences more effectively, track consumer behavior through analytics, and personalize marketing campaigns for better engagement. The shift toward data-driven marketing necessitates an agile approach that prioritizes customer insights and real-time decision-making. AI-powered chatbots, recommendation engines, and programmatic advertising have enabled companies to deliver hyper-personalized experiences to consumers (Davenport et al., 2020). Businesses that adopt these technologies can create more dynamic, responsive, and effective marketing strategies, leading to improved customer satisfaction and brand loyalty. Beyond marketing, management practices also must evolve to stay abreast of digital disruption. Traditional hierarchical organizational structures are giving way to more agile, flexible, and collaborative models. Companies that adopt digital transformation strategies, such as lean management, remote workforce integration, and data-driven decision-making, gain a significant competitive edge (Westerman et al., 2014). Leaders must build a culture of innovation, where employees are encouraged to experiment, adapt, and leverage technology to enhance productivity. Furthermore, digital tools enable better supply chain management, predictive analytics, and automated workflow processes, which improve operational efficiency and cost-effectiveness (Bharadwaj et al., 2013). Companies leveraging cloud computing and enterprise resource planning (ERP) systems can streamline operations and enhance cross-functional collaboration. As digital transformation continues to evolve, organizations must prioritize continuous learning, upskilling, and reskilling to ensure that employees remain equipped with the necessary digital competencies.

Effective leadership is critical in guiding organizations through digital disruption. Leaders must possess a clear vision for digital transformation and be willing to invest in emerging technologies, workforce development, and innovative business models. Digital-savvy executives must champion change management initiatives and foster a culture of adaptability and resilience (Kane et al., 2015). Companies that successfully integrate digital strategies into their core operations position themselves for long-term success in an increasingly volatile market. Managing digital disruption requires a strategic and proactive approach to marketing and management transformation. Businesses that embrace digital innovations, leverage data-driven decision-making, and foster an adaptive organizational culture will thrive in the digital era. Marketing must evolve to be more personalized and analytics-driven, while management practices must prioritize agility, efficiency, and technological integration. Leadership plays a crucial role in ensuring that organizations remain competitive and responsive to emerging trends. As digital disruption continues to reshape industries, companies must remain vigilant, innovative, and committed to continuous transformation to secure their future success. The pace of digital disruption is reshaping marketing practices and managerial decision-making, creating both opportunities and strategic challenges for organizations. This study is motivated by the need to understand how firms can effectively realign marketing and management strategies to sustain competitiveness, agility, and value creation in an increasingly digital business environment.

Literature Review

The rapid increase in digital technologies has fundamentally reshaped industries, challenging traditional marketing and management practices as the opportunities and risks it poses shift over time (Evans & Forth, 2015). In the present scenario organizations face unprecedented disruption driven by innovations such as AI, big data analytics, and digital platforms. These changes demand a shift from conventional approaches to more customer-centric strategies to remain competitive. Therefore, organizations are forced to adapt, innovate, and reinvent to stay relevant and competitive (Wang, 2024). Proper understanding is therefore critical for businesses to encash on digital opportunities while minimizing risks. This study focuses on digital disruption, marketing evolution, and management adaptation, and provides a comprehensive framework to guide organizations through this transition. The increase in digital technologies has transformed the operations in the industries, thus challenging traditional marketing and management practices owing to the opportunities and risks it creates over time (Evans & Forth, 2015). The innovations in the areas of AI, business analytics, and digital platforms have completely disrupted the business landscape. These disruptions demand more customer-centric strategies to remain competitive. Digital disruptions should not be viewed as a threat, but as a catalyst for transformation, which requires changing the marketing strategies

that are future-focused, inclusive, and purpose-driven (Mogaji, 2025). To overcome digital disruptions smoothly, marketing simulations can be an efficient way to harness digital disruption. Marketing simulations define digital disruption as the change that takes place when new digital technologies change customer experiences, processes, and business models, thereby changing how value is co-created (Bolton et al., 2019). By focusing on techniques and tools such as online presence, customized marketing, social media engagement, content marketing, SEO, influencer collaborations, and performance monitoring, digital disruptions can be smoothly navigated, and marketing effectiveness can be enhanced to drive business growth in the digital landscape (Masliardi et al., 2023). The impact of digital transformation and disruptive technologies has impacted all industries globally. These disruptive technologies are related to AI, Robotics, Internet of Things (IoT), and Big Data. The main objective behind these technologies is to pace up the efficiency of the organizations. The use of AI can enhance the efficiency of the projects, making them less risky. Therefore, the use of AI ensures that the projects are less prone to risks and have a higher chance of success (El Khatib, 2024). Digital disruption often holds a negative connotation for businesses that view it as an attack on their existing business model, as it is thought of as a turmoil caused by digital innovation, which disturbs existing boundaries and reduces efficacy that had previously served to deliver customer value. However, digital disruption is negative only when businesses try to ignore the impending transformation within their industry. Rather than viewing it as negative, the visionary leaders embrace it to make their businesses competitive, which in turn leads to their continued success (Lee, 2024). Thus, the dynamic landscape of digital disruption and its impact on traditional marketing strategies is characterized by the introduction of innovative digital technologies and business models that have reshaped the marketing landscape for existing products and services. The role of social media in relationship marketing underlines its ability to foster a wide array of consumer-business interactions, ranging from short exchanges to in-depth exploration. Social media plays an indispensable role in contemporary relationship marketing strategies, meeting consumer needs, and building connections. Thus, a holistic understanding of the full impact of social media in this ever-evolving marketing landscape is important, and it can be taken up in future studies (Kabha et al., 2023). The literature review highlights the growing impact of digital disruption on marketing and managerial practices; however, limited research has specifically examined how organizations strategically respond to such disruptions to transform their marketing and management functions. This study addresses this gap by exploring integrated strategies that enable firms to adapt to digital transformation in dynamic market environments. By synthesizing insights from digital transformation and strategic management literature, the study advances theory by proposing a more comprehensive understanding of how digital capabilities influence organizational transformation and competitive advantage.

Objectives or Research Questions

Objectives:

1. To identify key challenges and opportunities posed by digital disruption in management.
2. To explore innovative strategies for organizations to thrive in a digitally transformed business environment.
3. To evaluate the role of technology and customer-centric approaches in driving sustainable growth during digital disruption.

Research questions:

1. What are the key challenges and opportunities created by digital disruption in contemporary management practices?
2. How are organizations adapting their strategies to effectively respond to and thrive in a digitally transformed business environment?
3. What innovative managerial and organizational strategies enable firms to gain a competitive advantage during periods of digital disruption?
4. How does the adoption of emerging digital technologies influence organizational performance and decision-making during digital transformation?
5. What role do customer-centric approaches play in leveraging digital technologies for sustainable organizational growth?
6. How can organizations integrate technology-driven innovation and customer-centricity to ensure long-term sustainability in a digitally disruptive environment?

Significance of the Study

The study addresses the urgent need for organizations to adapt to the rapidly evolving digital landscape. By providing insights, the study helps businesses to remain competitive and innovative amidst disruption. The study also contributes to the understanding of how digital tools and customer-centric approaches can drive sustainable growth, improve decision-making, and enhance organizational agility. Moreover, the study is useful in bridging the gap between traditional practices and modern demands, ensuring that businesses can effectively harness the opportunities presented by technological advancements and minimizing challenges.

Methodology

The study uses a qualitative approach to ensure a holistic understanding of the topic. Interviews provided valuable insights into best practices and challenges.

Interviews with technology experts, retail managers, and marketers provided diverse perspectives and emerging trends. The participants were purposively selected based on their substantial professional experience, direct involvement with digital transformation initiatives, and domain-specific expertise relevant to the research objectives. Each interview lasted approximately 30–45 minutes and was conducted through a virtual platform (e.g., Zoom/Google Meet) or in-person, depending on participant availability, and participants provided informed consent prior to participation. The study used unstructured, in-depth interviews guided by broad, open-ended questions aligned with the research objectives. By interviewing four key people from different domains, the study highlights the current status of technology and how it is being employed by different companies. Data were analyzed using manual thematic analysis. No qualitative analysis software was used; all coding was performed manually to retain closeness to the data. The study adopts an exploratory qualitative approach where in-depth interviews are used to generate rich insights rather than statistical generalization. The selection of four key informants was based on their extensive experience and strategic roles in their respective industries, enabling a detailed understanding of digital disruption strategies. Nevertheless, future research may expand the sample size across multiple firms and industries to enhance generalizability. Additionally, the review helped to validate findings and provide a framework for strategic recommendations.

Results

Participant 1: Technology Industry

Description: This short, unstructured interview was conducted with a technology firm executive who has experienced digital transformation. The discussion focused on marketing adaptation strategies in response to digital disruption.

Transcript Excerpt: *Interviewer: Can you describe how your organization has adapted its marketing strategies in response to digital disruption? Participant: Absolutely. Over the past five years, we have transitioned from traditional advertising to a digital-first approach. We rely heavily on data analytics to segment our audience and personalize content. AI-powered chatbots and automated customer engagement tools have enhanced our ability to interact with consumers in real-time. One of the biggest challenges has been ensuring our marketing teams are digitally fluent. We invested heavily in training and upskilling to bridge the knowledge gap.*

Participant 2: Retail Industry

Description: This interview was conducted with a retail company executive to explore how management strategies have evolved due to digital disruption.

Transcript Excerpt: *Interviewer: How has digital disruption changed your management approach? Participant: We had to rethink our entire operational*

strategy. Digital transformation meant integrating e-commerce, omnichannel supply chain solutions, and automation in warehouse management. **Interviewer:** What key strategies have been most effective. **Participant:** Agile management has been a game changer. We now work in shorter cycles, continuously iterating based on data insights. Employee resistance to change was an issue initially, but we addressed it through continuous communication and incentives for adopting digital tools.

Participant 3: Financial Services Industry

Description: A participant from a financial services company discussed leadership and strategic decision-making in navigating digital disruption.

Transcript Excerpt: Interviewer: As a leader, how do you approach digital transformation within your organization? **Participant:** Digital transformation is not just about technology it's about people and culture. We build a culture of innovation and encourage employees to embrace new digital tools. Our leadership team prioritizes investment in fintech solutions to remain competitive. **Interviewer:** Have you encountered any major roadblocks. **Participant:** Cybersecurity has been a primary concern. As we integrate more digital services, we must also strengthen our security frameworks to protect customer data.

Participant 4: Digital Strategist

Description: This expert provided insights on industry-wide trends in marketing and digital adaptation.

Transcript Excerpt: Interviewer: What are the biggest trends in digital marketing transformation? **Strategist:** Personalization and AI-driven automation are at the forefront. Brands are leveraging big data to deliver hyper-targeted campaigns. **Interviewer:** How should companies prepare for future disruptions? **Strategist:** Organizations should adopt a proactive learning mindset. Continuous investment in emerging technologies and data analytics will ensure long-term success.

Discussion

The study highlights the critical need for organizations to adapt to the rapidly evolving digital landscape. Digital disruption, fueled by advancements in technologies such as AI, big data analytics, cloud computing, and the IoT, has fundamentally altered consumer behavior and business operations. As a result, traditional marketing and management practices are no longer sufficient to maintain competitiveness in a dynamic market. One key aspect of navigating digital disruption is the adoption of customer-centric strategies. Today's consumers expect personalized, seamless experiences across multiple touchpoints. Businesses

must leverage data-driven insights to anticipate customer needs and deliver value through tailored products and services. Omnichannel marketing, which integrates online and offline platforms, has emerged as a vital tool for enhancing customer engagement and brand loyalty. Simultaneously, management practices must evolve to meet the demands of digital transformation. Agile methodologies, which emphasize flexibility, collaboration, and iterative progress, are essential for responding to fast-changing market conditions. Leaders must foster a culture of innovation and continuous learning to empower employees and encourage experimentation. Additionally, addressing skill gaps through training and development programs ensures the workforce is equipped to navigate technological advancements. However, the journey is not without challenges. Resistance to change, lack of digital expertise, and cybersecurity concerns often impede progress. Organizations must overcome these barriers by investing in strategic planning, robust infrastructure, and change management initiatives. Collaboration with technology partners and industry experts can further enhance the effectiveness of digital strategies. Ultimately, the ability to navigate digital disruption successfully lies in aligning technological capabilities with organizational goals. Companies that embrace transformation, prioritize customer needs, and cultivate a forward-thinking mindset are poised to achieve sustainable growth and resilience in the face of disruption. Companies like Netflix and Uber provide valuable insights into navigating digital transformation effectively (Thompson & Turner, 2023). Further discussion on digital transformation, highlighting strategic pathways that can be followed in order to navigate the demanding technological landscape (Κυρτσίδου, 2024).

The study integrates the Resource-Based View (RBV), Technology Acceptance Model (TAM), and Dynamic Capabilities to provide a comprehensive understanding of digital transformation. RBV explains how firms leverage internal resources and capabilities for competitive advantage, TAM helps interpret managerial and organizational acceptance of digital technologies, and Dynamic Capabilities highlight how firms adapt and reconfigure resources in rapidly changing digital environments. These theoretical lenses emerged during the data analysis phase, where interview insights consistently reflected themes of technological adoption, capability development, and strategic resource utilization, thereby establishing a clear connection between the empirical findings and the theoretical framework. Figure 1 provides a theoretical framework summary for navigating digital disruptions.

Managerial Implications

Digital disruption has significant managerial implications, requiring managers to rethink traditional management approaches and adopt agile, technology-driven strategies. Managers must invest in digital capabilities and emerging technologies while developing strong change leadership to manage resistance and foster a culture of innovation and continuous learning. A customer-centric mindset becomes essential, with digital tools enabling deeper customer insights, personalized

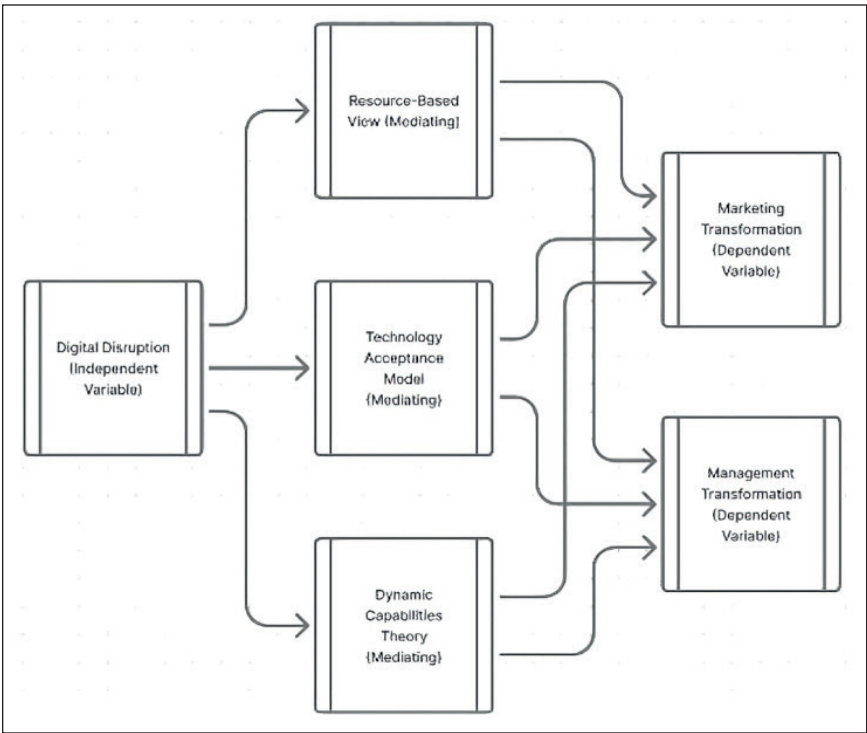


Figure 1. Theoretical Framework Summary for Navigating Digital Disruptions.

offerings, and improved experiences that drive competitive advantage. At the same time, managers must ensure cross-functional collaboration, strengthen cybersecurity and risk governance, and align digital initiatives with sustainability objectives to achieve long-term growth. Effective performance measurement and continuous adaptation are critical for ensuring organizational resilience and sustained success in a digitally transformed business environment.

Directions for Future Research

Future research could examine the long-term effects of digital transformation on marketing and management, analyzing the sustainability of strategies and organizational changes over time. Investigating the role of emerging technologies like blockchain, augmented reality (AR), and the IoT in shaping marketing and management strategies could provide deeper insights into their potential for disruption. Further investigating the ethical concerns associated with digital disruption, such as data privacy, algorithmic bias, and the impact on employment, would add a valuable perspective to the ongoing discourse. By addressing these research gaps, scholars and practitioners can better understand the full scope of

digital disruption and develop more effective strategies for the future of marketing and management.

Conclusion

Digital disruption has completely transformed the way organizations approach marketing and management practices. The advent of new and advanced technologies such as AI, IoT, machine learning, data analytics, and automation has opened new vistas for improving efficiency, enhancing customer experience, and innovative business models. However, these digital disruptions also present significant challenges for organizations, including the need for agile strategies, adapting to fast-paced technological shifts over time, flexible systems, managing change and managing a more complex, digitally-savvy workforce. This study highlights that the successful management of digital disruption requires a balanced approach, combining traditional management practices with modern technological innovations. Strategies suggested by the participants in interviews are concerned with customer-centric marketing, real-time data analysis, and digital collaboration tools, which have proven essential for driving transformation. Organizations must focus on skill upgradation of employees by providing opportunities for continuous learning, adapting to their culture, and ensuring that leadership is proactive in embracing change. The study suggests that companies that foster innovation and agility are better positioned competitively in the digital age. Moreover, adopting a holistic cross-functional approach to digital transformation enhances the likelihood of long-term success. These interviews highlight the varied approaches and challenges businesses face in navigating digital disruption. Marketing professionals emphasize data-driven strategies, operations leaders focus on agile management, CEOs prioritize culture and security, and digital strategists advocate for continuous learning. Together, these insights provide an understanding of effective strategies for marketing and management transformation in the digital age. The expected results of the study include a comprehensive framework of strategies that organizations can adopt to thrive in a digitally disrupted environment. The study's findings converge into four interrelated themes. First, digital disruption emerged as a strategic imperative, reshaping business models and competitive dynamics across sectors. Second, organizational capabilities and leadership readiness were identified as critical enablers in responding effectively to digital change. Third, technology adoption and customer-centric innovation played a pivotal role in enhancing agility and value creation. Finally, challenges related to skills gaps, cultural resistance, and infrastructural constraints moderated the pace and success of digital transformation. Collectively, these themes provide an integrated understanding of how organizations navigate digital disruption while highlighting areas for future research and managerial action. The findings aim to provide actionable insights to enhance organizational resilience, foster innovation, and drive sustainable growth in a competitive digital marketplace.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethical Approval

Not applicable.

Funding

The author received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Rajeev Kumar  <https://orcid.org/0000-0003-2217-1145>

References

- Berman, S. J. (2012). Digital transformation: Opportunities to create new business models. *Strategy & Leadership*, 40(2), 16–24.
- Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next-generation conceptual framework. *MIS Quarterly*, 37(2), 471–482.
- Bolton, R. N., Chapman, R. G., & Mills, A. J. (2019). Harnessing digital disruption with marketing simulations. *Journal of Marketing Education*, 41(1), 15–31.
- Bughin, J., Catlin, T., Hirt, M., & Willmott, P. (2018). *Why digital strategies fail*. McKinsey & Company.
- Chaffey, D., & Ellis-Chadwick, F. (2019). *Digital marketing: Strategy, implementation, and practice*. Pearson.
- Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24–42.
- El Khatib, M. (2024). Digital transformation and digital disruption technologies: The effect of AI and machine learning on managing projects. In H. M. Alzoubi, M. T. Alshurideh, & S. Vasudevan (Eds.), *Technology innovation for business intelligence and analytics (TIBIA)* (Vol. 147). Springer. https://doi.org/10.1007/978-3-031-55221-2_4
- Evans, P., & Forth, P. (2015). Navigating a world of digital disruption. *IEEE Engineering Management Review*, 43(3), 89–97.
- Kabha, R., Kelkar, A. S., & Kamel, A. M. (2023). Digital disruptions and its impact on traditional marketing practices. *International Journal of Multidisciplinary Research in Commerce and Economics*, 5(5), 128–137.
- Kane, G. C., Palmer, D., Phillips, A. N., Kiron, D., & Buckley, N. (2015). Strategy, not technology, drives digital transformation. *MIT Sloan Management Review*, 14(1), 1–25.
- Κυρτσίδου, Α. Χ. (2024). *Navigating the digital disruption: Agile strategies for regulated global industries in the era of rapid technological changes in international business*. <https://dspace.lib.uom.gr/handle/2159/31421>
- Lee, M. T. (2024). Digital disruption and transformation. In Yew Haur Lee (Ed.), *Leading in a digitally disruptive world* (pp. 33–50). World Scientific Connect.

- Masliardi, A., Effendi, M., Ningrum, P. A., Hasnidar, H., & Mala, I. K. (2023). Digital disruption: Exploring the dynamics of marketing in the digital age. *SEIKO: Journal of Management & Business*, 6(2.1), 421–430.
- Mogaji, E. (2025). Digital disruption. In *Strategic marketing management*. Palgrave Macmillan. https://doi.org/10.1007/978-3-031-99367-1_11
- Thompson, E. M., & Turner, E. (2023). Navigating digital transformation: How businesses adapt and thrive in the age of disruption. *Research Studies of Business*, 1(01), 1–9.
- Wang, Z. (2024, May). Navigating the digital future: Strategies for corporate digital transformation. In *Proceedings of the 2024 International Conference on Applied Economics, Management Science and Social Development (AEMSS 2024)* (pp. 375–381). Atlantis Press.
- Westerman, G., Bonnet, D., & McAfee, A. (2014). *Leading digital: Turning technology into business transformation*. Harvard Business Press.

A Study on the Integration of ChatGPT in Management Accounting Practices

BIMTECH Business Perspectives
7(2) 147–168, 2026
© The Author(s) 2026
DOI: 10.1177/25819542261465208
bsp.bimtech.ac.in



Shubham Singh Chandel¹ , Jyotsna Dwivedi¹ and Dawakit Lepcha¹

Abstract

The present study aims at investigating the effect of implementing artificial intelligence through chatbots in the management accounting practices of accounting professionals and accounting students. This study intends to explore determinants of ChatGPT usage that involve PU of behavioural accounting, the effect of trust (TR) on accounting professionals and accounting students, and the potential moderating role of age and gender in ChatGPT usage. This study advances our understanding of the adoption of ChatGPT in more detail. The study applied the extended unified theory of acceptance and use of technology model paradigm, incorporating factors like social value (SV), monetary value (MV), emotional value (EV), quality value (QV) and TR. Data was collected as primary data involving 435 accounting professionals and students via online/offline closed-ended structured questionnaire surveys using a convenience sampling technique. This research was carried out between 23rd January and 23rd August. Hypotheses were tested, and empirical validation of the conceptual model was done using the Statistical Package for the Social Sciences and moderation analysis was done using Smart PLS 4. It was found out that factors such as effort expectancy, MV, EV, QV and TR had a great influence on the management intent behavioural intention. However, there were no statistically

¹ Faculty of Commerce and Management, Kalinga University, Nava Raipur, Chhattisgarh, India

Corresponding author:

Shubham Singh Chandel, Faculty of Commerce and Management, Kalinga University, Nava Raipur, Chhattisgarh 492101, India.

E-mail: shubhamschandel1999@gmail.com



Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 License (<http://www.creativecommons.org/licenses/by-nc/4.0/>) which permits non-Commercial use, reproduction and distribution of the work without further permission provided the original work is attributed.

significant implications for factors like performance expectancy and SV. This is how accounting professionals and accounting students can take advantage of the findings of this research. The reason for this is to effectively integrate ChatGPT into the domain of accounting and manage the implementation to enhance performance in management accounting practices. These aspects are essential when it comes to the implementation of artificial intelligence. The study is relevant to business, educational institutions and government sectors since it focuses on ChatGPT adoption.

Keywords

Technology adoption, artificial intelligence, managerial accounting, UTAUT2 model, behavioural intention

Introduction

The emergence of the concept of management accounting occurred in the 1960s as accountants started adding managerial sciences into the conceptual foundations of the new school of business accounting philosophy (Caplan, 1989). Behavioural accounting can be defined as a certain branch of accounting science devoted to understanding the psychological and managerial aspects and characteristics influencing the process of decision-making and its further transformation into accounting practices. The difference between managerial and conventional accounting lies in the fact that it takes into account not only accounting practices but also the results of research in such fields as psychology, sociology and others, which can be related to the concept of managerial sciences. The goal of managerial accounting is to study and predict the process of financial decision-making at the organisational level. The field of managerial accounting covers a wide range of topics, such as internal data structure related to managerial accounting, sociological aspects of accounting, the relationship between accounting and the environment (e.g., intergroup conflict), as well as others like accounting methodology and income taxation (Birnberg, 1973). The concept of managerial accounting represents the attempt of economists and other researchers to unite economic theories and practical financial practices through analysis of factors that deviate from the expectations regarding behaviour of individuals and organisations. The analysis covers many cognitive, emotional, social and psychological aspects that may affect the process of financial decision-making. The concept of behavioural accounting refers to the application of social science theories to some branches of accounting research, such as budgeting, decision-making, control and financial reporting (Balachandran, 1985). The notion of behavioural considerations has always played a significant role in accounting because the core objective of an accountant's report is to influence readers' behaviour. One of the core underlying assumptions in modern accounting is that the primary motive of external financial reports' readers is income.

Management and accountants have identical goals since the work of both specialists is measured based on this criterion (Elliott, 1971). In the context of an

organisation, there are numerous spheres that can affect different aspects of managerial accounting practices. They include the detection of facts requiring registration, evaluation of workers' reaction to standards and budgetary issues, analysis of the motivation of financial report readers, comprehension of the behaviour of owners, as well as the analysis of participation of taxing and regulatory authorities (Elliott, 1971). Modern researchers started paying increased attention to the problem facing managers, resulting in the establishment of various methodologies and a subsequent growth of definitions in the sphere of management accounting research (Birnberg, 2011). It is clear that the introduction of artificial intelligence into the process of management accounting marks a milestone in the development of comprehension of the complex relationship between the aspects related to human behaviour and financial decision-making. The addition of various factors makes it easier and more accurate to analyse the behaviour during financial decision-making and provide customised suggestions, detect the signs of fraud, as well as explore psychological aspects affecting the financial behaviour of individuals and groups. The inclusion of artificial intelligence (ChatGPT) into the process of business decision-making becomes crucial and lasting in terms of applications of ChatGPT (Cao et al., 2021). According to Jovanovic et al. (2022), the application of ChatGPT in decision-making allows for the hidden information from data to be processed faster than before. On the other hand, according to Brock and Von Wangenheim (2019), the use of this technology helps improve decision-making and knowledge management, as well as optimise customers' interaction with the company. Thus, it makes sense to note that the introduction of ChatGPT improves the decision-making and analytical skills of employees and increases the level of creativity.

As a result of implementation, the effectiveness, accuracy and flexibility of decision-making will increase, which was proven in studies conducted by Agrawal et al. (2017) and Metcalf et al. (2019). However, the realisation of the potential of ChatGPT-human symbiosis in corporate decision-making depends on whether people will accept the usage of ChatGPT. There is a lack of research examining human motivations for using ChatGPT from a human-centred point of view. Thus, it is still difficult to establish under which circumstances people are ready to collaborate with robots (Haesevoets et al., 2021). However, it makes sense to underline that the improvement of acceptance of information technologies (IT) has always been one of the key factors in the analysis of IT progress (Verdegem & De Marez, 2011). Moreover, the use of artificial intelligence continues to be a point of discussion in both companies and communities (Duan et al., 2019). In addition, Davenport et al. (2019) and Weld and Bansal (2019) have expressed serious doubts concerning ChatGPT. In particular, Johnson and Verdicchio (2017) stress the risk of uncontrollability of ChatGPT and its potential for catastrophe both for people and the whole society. Nowadays, organisations experience the growing concerns related to potential negative implications of using ChatGPT, such as problems with faulty decision-making, discrimination, hidden biases and so on (Dwivedi et al., 2021; Weld & Bansal, 2019). In addition, the European Commission (2020) and Shrestha et al. (2019) state that ChatGPT poses a threat to the confidentiality of the information, security of the system and overall

stability. At the personal level, in addition to optimistic expectations, there are growing concerns among managers and workers about job opportunities. Consequently, it is expected that the perspectives and motivations of managers and accountants towards using ChatGPT will depend on the benefits and disadvantages of introducing ChatGPT into accounting.

For analysing the tendency and readiness of accountants and professionals to introduce artificial intelligence into the sphere of management accounting, the enhanced unified theory of acceptance and use of technology (UTAUT) model was used. This model includes eight constructs: performance expectancy (PE), effort expectancy, habit (HT), social value (SV), monetary value (MV), emotional value (EV), quality value (QV) and trust (TR). For conducting the analysis, 399 valid responses were analysed. The sample included students and professionals working in the sphere of accounting. The present research adds the academic perspective to the continuously growing body of research in the field of ChatGPT applied to the sphere of management accounting. This research specifically aims at gaining the profound understanding of factors that may influence the perspectives and tendencies of professionals and students to use ChatGPT during decision-making. The further parts of this article are organised in the following way: Section Review of Literature gives a brief overview of the cooperation of humans with ChatGPT and explains why the UTAUT models help in explaining the adoption of ChatGPT. The section 'Research Model and Hypotheses' introduces the research hypothesis. The research methodology is discussed in the section 'Research Methodology'. The section 'Result' and 'Analysis' explains the analysis carried out and gives the outcomes obtained as a result. The sections 'Conclusion' and 'Implications' discuss the analysis of the results, potential consequences of our findings, as well as the limitations experienced during this research.

Review of Literature

Artificial Intelligence in Behavioural Accounting

The term 'Artificial Intelligence' was coined by John McCarthy (Yadav et al., 2017). Organisation for Economic Cooperation and Development (OECD) describes ChatGPT as a system operating on a machine, capable of making predictions, recommendations or decisions that have an impact on the physical or virtual environment according to the particular objectives specified by the human beings (ChatGPT). As the technology evolves, people can take advantage of ChatGPT in different activities involving a significant amount of knowledge (Seeber et al., 2020). According to Malone (2018), ChatGPT improves cognitive processes and enhances problem-solving capabilities of enterprises through greater effectiveness. The integration helps overcome limitations related to logical reasoning and achieve impartial judgement, enhanced decision-making skills and creativity (Burton et al., 2019). Integration of ChatGPT and human inputs allows for making decisions exceeding the capacities of any individual (Wang et al., 2016). Behavioural accounting is an area in accounting focusing on psychological and managerial

factors influencing decisions on accounting techniques. The concept of managerial accounting has been discussed extensively in the accounting literature for several decades (Birnberg & Shields, 1989). The notion of 'managerial sciences of accounting' implies examination of patterns and diversity in the perception and reaction of individuals to certain data. The concept has gradually evolved as an important area of accounting research. Several researchers have attempted to explain the evolution of the management accounting paradigm over time. Management control systems constitute an important aspect of managerial accounting research. Neuro accounting has emerged as a developing research area within management accounting. It focuses on understanding the cognitive processes underlying accounting-related decision-making. It suggests studying the brain activity to obtain greater insight into the decision-making process, moving beyond mere observation of behavioural patterns. The evolution of accounting software and advances in artificial intelligence have greatly transformed the accounting practice. The studies show incorporation of internet-enabled computers, software/expert systems, and improvements in artificial intelligence could increase the efficiency and effectiveness of accounting operations. The accounting industry has extensive experience in the application of ChatGPT in financial reporting and auditing for more than 25 years. The studies demonstrate a limited use of ChatGPT by managerial staff due to low comprehension of the human-to-ChatGPT interaction process. For obtaining the greatest benefits from human-ChatGPT collaboration, it is crucial to ensure sufficient understanding, acceptance and implementation of technology for performing work-related activities (Caputo et al., 2019; Chowdhury et al., 2022; Wamba-Taguimdje et al., 2020). There are two main problems arising from ChatGPT integration: first, adverse consequences related to bias, prejudice and irrational decision-making (Davenport et al., 2019); and second, employment risks (Rampersad, 2020). Automation of many accounting activities allows to introduce artificial intelligence quite efficiently. Additionally, ChatGPT can improve the precision of calculations and support managerial decision-making by providing timely analytical insights. ChatGPT, an artificial intelligence system, has enormous potential to improve the efficiency and innovation of accountants. Thus, for the improvement of professional performance, it is important for accounting students to be encouraged in adopting artificial intelligence. This research aims to analyse the extent of interconnectivity of different departments and control approaches within organisation. Like any other scientific field, behavioural accounting has distinctive features. Psychological research frequently examines internal mental processes to understand human behaviour and decision-making. Creating a connection between psychological bias and economic element proves to be difficult in the field of management accounting.

The Extended Unified Theory of Acceptance and Use of Technology Model

The UTAUT has been developed through a combination of testing of several components of the theory of reasoned action (TRA) and the technology acceptance model (TAM) models (Venkatesh et al., 2003). Four of the seven main

components had a noticeable effect on behavioural intention (BI). They include effort expectancy (EE), social influence (SI), PE and facilitating conditions (FC). The UTAUT model includes the concepts of perceived usefulness (PU) in the form of PE and perceived ease of use (PEOU) in the form of EE. This model strives to explain technology adoption and behaviour when participation in using technology is voluntary (Venkatesh et al., 2003). In the study by Dwivedi et al. (2017), the UTAUT model is investigated as extended with four external factors representing characteristics of technology (PE and EE) and environment (SI and enabling conditions). Numerous studies proved the extreme effectiveness of the UTAUT model in explanation of variability in the tendency to adopt technology (about 70%). But the traditional UTAUT model is found to be inappropriate for investigating ChatGPT due to its limited focus on technical procedures and inability to explain the complexity of the ChatGPT adoption process (Gursoy et al., 2019).

The UTAUT2 model is an elaborated version of the UTAUT model, incorporating three internal variables—price value (PV), HT and hedonic motivation (HM) (Venkatesh et al., 2012). Awareness that benefits of technology exceed costs means that it positively influences the use of technology (Venkatesh et al., 2012). Shen and Chuang (2010) found that when applying extended TAM with interactivity and self-efficacy to examine students' attitude and intentions towards management, they noticed that interactivity, self-efficacy, usability and PU had an impact on attitude and managerial intention. Researchers have done experimental studies on the UTAUT2 model, the basic technology adoption model, applied to consumer usage over the last 30 years after development of TAM. According to the study by Alkhwalidi and Abdulmuhsin (2021), PE, enabling conditions, technology readiness and attitude towards technology were the crucial factors which help predicting acceptance of distant learning by both samples. Upadhyay et al. (2022) found that PE, openness, SI, hedonic incentives and generativity positively influenced an entrepreneur's acceptance of ChatGPT. Affordance showed no significant relation to propensity to adopt ChatGPT, yet it impacted adoption tendency due to attitude.

Research Model and Hypotheses

Performance Expectancy

PE refers to the degree to which individuals believe that using a system can enhance their job performance (Venkatesh et al., 2003). It is closely related to the PU of technology (Zhou et al., 2022). Venkatesh et al. (2003) identified PE as one of the strongest predictors of BI to adopt new technologies. It also shapes users' attitudes towards technology adoption. In the case of ChatGPT, attitude reflects a person's willingness and inclination to use the technology (Chatterjee et al., 2021). PE also captures how useful, efficient and convenient users perceive a system to be when carrying out tasks (Venkatesh et al., 2012). Previous studies

have consistently reported a significant relationship between PE and BI (Deb & Lomo-David, 2014; Gupta et al., 2019; Oliveira et al., 2014).

H_1 : PE significantly influences the BI of accounting professionals and students to adopt ChatGPT in managerial accounting.

Effort Expectancy

EE refers to the ease associated with using a technology (Venkatesh et al., 2003). This concept is similar to PEOU in the Diffusion of Innovation (DoI) theory. EE reflects how easy or difficult users perceive the use of artificial intelligence within an organisation. Technology adoption is also shaped by individual characteristics and managerial attributes (Alhwaiti, 2023; Chatterjee et al., 2021).

H_2 : EE significantly influences the BI of accounting professionals and students to adopt ChatGPT in managerial accounting.

Habit

HT refers to the extent to which behaviours are performed automatically through repeated practice and day-to-day routine work (Casey & Wilson-Evered, 2012). Moorthy et al. (2019) describe HT as the tendency to use a system in such a way to have little conscious thought about the process. In simple terms, it reflects routine and automatic use of any task that develops over time. Earlier studies have shown that HT plays a significant role in influencing users' intentions to adopt the technology and continue using it (Gharrah & Aljaafreh, 2021; Huang & Kao, 2015; Nguyen et al., 2014).

H_3 : HT significantly influences the BI of accounting professionals and students to adopt ChatGPT in managerial accounting.

Social Value

SV refers to the benefits individuals gain from a product's ability to enhance their social image and self-concept (Sweeney & Soutar, 2001). While UTAUT uses the concept of SI, both ideas reflect the impact of other people's opinions and expectations on technology adoption. Similar concepts can be found in the subjective norm constructs of the TRA and the theory of planned behaviour (TPB). Therefore, SV reflects the extent to which family, friends, colleagues and peers influence an individual's decision to use technology (Alalwan et al., 2017; Gupta et al., 2019; Venkatesh et al., 2003; Zhou et al., 2010).

H_4 : SV significantly influences the BI of accounting professionals and students to adopt ChatGPT in managerial accounting.

Monetary Value

MV refers to the benefits that users perceive from reducing both the short-term and long-term costs which are associated with a product or service (Sweeney & Soutar, 2001). Within the UTAUT2 framework, this concept is represented by PV. PV reflects the balance between perceived benefits and costs (Venkatesh et al., 2012). In this study, MV represents users' evaluation of whether ChatGPT delivers sufficient value and cost savings. It also studies the improved outcomes relative to the resources invested (Kwateng et al., 2019; Sankaran & Chakraborty, 2020, 2022; Venkatesh et al., 2012).

H_5 : MV significantly influences the BI of accounting professionals and students to adopt ChatGPT in managerial accounting.

Emotional Value or Hedonic Motivation

EV refers to the positive feelings and emotional benefits generated through the use of any kind of products or services (Sweeney & Soutar, 2001). In this study, EV explains the intensity to which accountants and managers enjoy using ChatGPT. It also reveals the perceived emotional benefits from its use in their professional and personal work. HM refers to the enjoyment and pleasure derived from using technology (Venkatesh et al., 2012). Prior research has again and again found that enjoyment positively influences users' intentions to adopt new technologies (Gharrah & Aljaafreh, 2021; Nikolopoulou et al., 2020; Venkatesh et al., 2012).

H_6 : EV significantly influences the BI of accounting professionals and students to adopt ChatGPT in managerial accounting.

Quality Value

QV refers to the utility that users derive from a product's perceived quality and expected performance (Sweeney & Soutar, 2001). Previous studies have highlighted the importance of quality in creating perceptions of the value associated with it and influencing outcomes (Parasuraman et al., 1988). Service quality is commonly assessed by the comparison of expected performance with actual performance. This process is known as the disconfirmation paradigm (Oliver, 1980). According to this perspective, higher perceived quality leads to greater perceived value. In this study, QV reflects accountants' and managers' expectations regarding the quality, reliability and effectiveness of ChatGPT.

H_7 : QV significantly influences the BI of accounting professionals and students to adopt ChatGPT in managerial accounting.

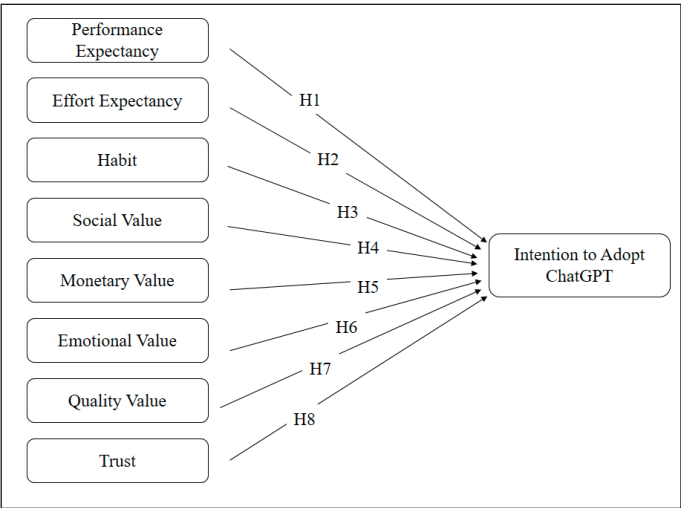


Figure 1. Proposed Research Model.

Source: Adapted from Venkatesh et al. (2012) and Sweeney and Soutar (2001).

Trust

TR is widely recognised as a key factor in technology adoption research and is frequently incorporated into TAM studies (Wu et al., 2011). Numerous studies have reported that TR positively affects users’ willingness to adopt and use technology (Alalwan et al., 2017; Gefen et al., 2003; Giovanis et al., 2019). Although TR and security have been examined broadly, Dahlberg et al. (2015) argue that they remain essential foundations for technology acceptance and continued use of the same over a long period of time.

H₈: TR significantly influences the BI of accounting professionals and students to adopt ChatGPT in managerial accounting.

Research Model

The proposed conceptual framework used in the study is presented in Figure 1.

Research Methodology

Sampling Procedure

To achieve the objectives of the study, primary data were collected using both online and offline survey approaches, including intercept sampling. (if the participants use mobile banking services). In offline mode, a device or application

cannot access online material or execute online tasks. A survey collected data from participants, including non-emailers. Accounting students, accountants and academics participated in the online poll. The volunteers were recruited by email (non-probabilistic convenience sampling). A convincing decision. Convenience sampling was employed to obtain respondents from diverse regions and backgrounds.

Instrument Development

Online and offline approaches, including intercept sampling, were used to collect the key data to meet the requirements. (if the participants use mobile banking services). A device or application in offline mode cannot access online material or execute online activities. A survey was utilised to collect data from participants, including non-emailers. Internet survey participants included accounting students, accountants and academics. Voluntary email non-probabilistic convenience sampling was used to recruit participants. This approach was considered appropriate for achieving the objectives of the study. Convenience: The sampling approach was used to obtain a representative sample from diverse cultures and areas. Participants were recruited from multiple sources to improve the diversity of the sample. Cities in northern and central India are sampled.

Face Validity and Content Validity

Validity was assessed to ensure simple, straightforward questions that responders may readily understand. The research was verified using a pilot study before data collection.

Data Collection

Data was primarily obtained from 420 participants through a combination of online and offline methodologies. The use of digital mechanisms, such as computers and mobile phones, is a common strategy in online surveys, offering benefits (Evans & Mathur, 2018). The constructs used in this study and their corresponding sources are presented in Table 1.

Data validation checks ensured data consistency, including integrity, validity and completeness checks on columns such as gender, age, education level and Likert scale items.

Useful sample: 21 respondents were eliminated owing to unengaged replies, missing data and non-use of ChatGPT, leaving 399 valid responses. Data adequacy demands a sample size of 5–10 times the number of elements (Hair et al., 2010). About 399 respondents satisfy the necessary sample size ($n > 150$) for datasets with several high factor loading scores ($> .8$) (Guadagnoli & Velicer, 1988).

Table 1. Variables with References.

Constructs	Cited Sources
Performance expectancy	Venkatesh et al. (2012)
Effort expectancy	Venkatesh et al. (2012)
Habit	Venkatesh et al. (2012)
Social value	Sweeney and Soutar (2001)
Emotional value	Sweeney and Soutar (2001)
Quality value	Sweeney and Soutar (2001)
Monetary value	Sweeney and Soutar (2001)
Trust	Doney and Cannon (1997), Gefen et al. (2003)
Behavioural intent	Venkatesh et al. (2012)

Source: Compiled from Venkatesh et al. (2012), Sweeney and Soutar (2001) and Gefen et al. (2003).

Result and Analysis

The demographic profile of the respondents is presented in Table 2.

Table 2. Demographic Profile of Respondents.

Respondents	No	%
Gender		
Male	186	47
Female	213	53
Age		
18–25	175	44
26–35	84	21
36–45	118	30
46–55	22	5
Profession		
Students	205	51
Accountants	80	20
Academicians	114	29
Total	399	100

Descriptive Statistics

Out of 399 respondents, females represent 53% of the total respondents, whereas males represent 47%. Most of the respondents are in the age group of 18–25 years, represent 51% as students, followed by the academicians.

The statistical software Smart PLS 4 is used to analyse the measurement model and test hypotheses. The use of PLS-SEM has two fundamental components: the measurement model, which is used to evaluate the reliability and validity of the measurements, and the structural model, which is employed to examine the hypothesised correlations between the study constructs.

Measurement Model

PLS-SEM begins with measurement model reliability and validity validation. The evaluation comprises item loadings, indicator reliability, composite reliability (CR), average variance extracted (AVE) and concept discriminant validity according to Hair et al. (2014). For convergent validity, factor loadings, CR and AVE are used; Table 3 shows the findings. Most scale items had factor loadings over 0.70 for their latent constructs, indicating substantial correlations.

PLS analysis showed that all constructs' CR and AVE values were above 0.5, confirming convergent validity. The scale has good internal consistency and reliability, since all constructs have Cronbach's α values over 0.80.

Fornell and Larcker's (1981) criteria are used to evaluate discriminant validity. According to this criterion, the square root of AVE for a concept should be bigger than its correlations with other constructs. Table 3 shows that none of the squared correlations with other items surpasses the AVE of any construct, confirming discriminant validity.

The results of reliability and convergent validity analysis are presented in Table 3.

Table 4 presents the discriminant validity analysis using the Fornell–Larcker criterion.

The Structural Model and Hypothesis Testing

Figure 2 illustrates the structural model obtained through PLS-SEM analysis, including the coefficients for each association. The results suggest that the changes in PE, EE, HT, SV, MVs, EVs, QV and TR account for 35%, 24.5%, 23%, 22%, 6.7%, 20% and 16.3%, respectively variance of the differences seen in intent to adopt ChatGPT in managerial accounting.

Additional information on the outcomes of PLS path analysis may be found in Table 5. The findings of the PLS-SEM analysis indicate that PE, EE, MV, EV, SV and TR significantly influence the BI of respondents to adopt ChatGPT in management accounting practices. These findings suggest that respondents perceive

Table 3. Reliability and Convergent Validity.

	Cronbach's α	Composite Reliability	Average Variance Extracted (AVE)
Effort expectancy	0.916	0.941	0.799
Emotional value	0.932	0.956	0.88
Habit	0.918	0.942	0.802
Intention to adopt ChatGPT	0.941	0.958	0.849
Monetary value	0.924	0.946	0.815
Performance expectancy	0.906	0.934	0.78
Quality value	0.909	0.936	0.787
Social value	0.911	0.938	0.791
Trust	0.961	0.972	0.895

Table 4. Discriminant Validity Using Fornell–Larcker Criterion.

	Effort Expectancy	Emotional Value	Habit	Intention to Adopt ChatGPT	Monetary Value	Performance Expectancy	Quality Value	Social Value	Trust
Effort expectancy	0.894								
Emotional value	0.744	0.938							
Habit	0.803	0.744	0.895						
Intention to adopt ChatGPT	0.699	0.862	0.739	0.922					
Monetary value	0.759	0.834	0.801	0.839	0.903				
Performance expectancy	0.742	0.636	0.709	0.698	0.758	0.883			
Quality value	0.744	0.82	0.708	0.799	0.834	0.67	0.887		
Social value	0.806	0.791	0.824	0.778	0.818	0.71	0.788	0.889	
Trust	0.732	0.804	0.74	0.841	0.807	0.625	0.839	0.784	0.946

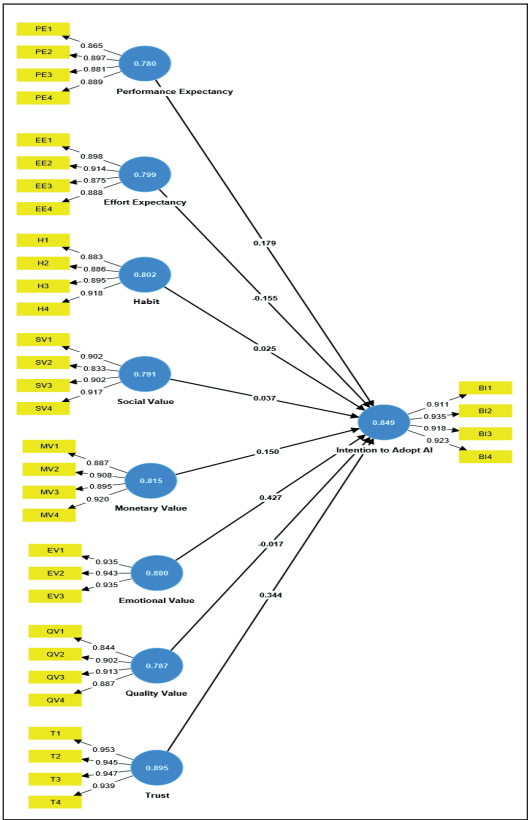


Figure 2. Structural Model and Path Coefficients.

Table 5. Hypothesis Testing Results.

Hypothesis	Path	Beta	T	p Values	Result
1	Performance expectancy $\geq$ intention to adopt ChatGPT	0.043	4.158	***	Accepted
2	Effort expectancy $\geq$ intention to adopt ChatGPT	0.057	2.679	**	Accepted
3	Habit $\geq$ intention to adopt ChatGPT	0.042	0.596	.551	Not accepted
4	social value $\geq$ intention to adopt ChatGPT	0.053	0.694	***	Accepted
5	Monetary value $\geq$ intention to adopt ChatGPT	0.049	3.053	**	Accepted
6	Emotional value $\geq$ intention to adopt ChatGPT	0.041	0.305	**	Accepted
7	Quality value $\geq$ Intention to adopt ChatGPT	0.051	0.318	.75	Not accepted
8	Trust $\geq$ intention to adopt ChatGPT	0.043	7.911	***	Accepted

Note: *** $p < .01$, ** $p < .05$, * $p < .10$.

ChatGPT as a useful, reliable and value-enhancing technological tool for improving accounting-related decision-making and efficiency. However, HT and QV were not found to have a statistically significant influence on BI. This implies that routine usage behaviour and perceived quality alone are insufficient to motivate the adoption of ChatGPT in management accounting.

Conclusion

The results obtained as part of this study prove that such factors as PE, EE, MV, EV, SV and TR are important when discussing BIs among both accounting professionals and students to use ChatGPT within management accounting. At the same time, it should be noted that the TR factor and EV showed greater influence compared to other variables. On the contrary, the relationship between HT and BI, as well as QV and BI are not statistically significant. These facts indicate that even though ChatGPT proves to be helpful, valuable and useful for management accountants to make decisions, habitual adoption and quality are not enough for this technology. Overall, the study proves that artificial intelligence in management accounting is increasingly popular, and the value of technology in this sphere is crucial for its adoption.

The coefficients related to the relationship between quality value and behavioural intention were not statistically significant, which is consistent with findings reported in several previous studies. This suggests that management accountants tend to apply manual or other technologies for data analysis. The only exception is Oliveria et al. (2014), who showed a significant effect of QV, but apparently, it is less influential than other aspects covered by UTAUT. According to Venkatesh et al. (2012), EE can be interpreted as expectations regarding ease of use, learning and necessity, which is important when it comes to ChatGPT adoption.

It has been confirmed by this study that TR is the second most influential aspect in terms of adoption of ChatGPT among management accountants, supporting results obtained by Alalwan et al. (2017), Giovanis et al. (2019), and Kwateng et al. (2019). In addition, ChatGPT software is highly popular, meaning that it is reliable and easy to use. ChatGPT developers should ensure secure operations for management accountants, and the introduction of TR mechanisms in this sphere could enhance ChatGPT adoption rates, and different security measures would boost their safety (Gefen et al., 2003).

ChatGPT adoption within management accounting appears to be based on its MV, which positively correlates with professionals' BI. It means that Indian management accountants view intrinsic motivation as an important reason for adopting this technology. The results support Venkatesh et al.'s finding of a great effect of social norm (technological popularity and recommendations of peers) on professionals' adoption of ChatGPT in management accounting (2003, 2012). The findings agree with Alalwan et al. (2017); Baabdullah et al. (2019); Baptista and Oliveira (2015); Boonsiritomachai and Pitchayadejanant (2017); Kwateng et al. (2019).

On the other hand, it has been discovered that SV elements, such as the influence of colleagues, friends and relatives, can influence managerial accounting professionals' adoption of ChatGPT. On the basis of Oliver's 1980 disconfirmation paradigm, Baptista and Oliveira (2015) and Shareef et al. (2018) suggested that the view of professionals can be formed with the help of experience in terms of ChatGPT-driven services. The expectation of better service results in increased EV. Second, one research suggests that the importance of customer satisfaction can increase ChatGPT application quality and consistency (Sweeney & Soutar, 2001).

Management accountants can save time and money by using applications driven by ChatGPT for non-financial management accounting responsibilities, such as accessing digital passbooks or paying utility bills. These results agree with previous findings (Alalwan et al., 2017; Baptista & Oliveira, 2015; Kwateng et al., 2019; Venkatesh et al., 2012). Signals related to MV also demonstrate that professionals tend to adopt ChatGPT in management accounting if they consider it as a tool that allows them to reduce expenses.

Implications

First, it promotes the adoption and use hypotheses of ChatGPT in management accounting. Adoption and use hypotheses of ChatGPT will add value to the literature on this topic, and future research work can build upon these insights (Webster & Watson, 2002).

Also, this study analyses various components of PERVAL and provides valuable results related to the adoption of ChatGPT in management accounting. The current model includes novel social, emotional, monetary and qualitative PERVAL components. Also, moderating factors influencing the interaction between components under analysis are taken into consideration. The methodology described above helps understand the complexities of ChatGPT adoption and implementation in the field of management accounting.

Management Implications

The study makes a number of recommendations for educational institutions and accounting firms striving to increase their effectiveness in adopting and implementing ChatGPT in managing accounting. This insight could be utilised in recruiting, engaging and retaining ChatGPT adopters among students, accountants and academics because it allows automating usual processes in accounting and managing accounting with ChatGPT. Businesses and educational institutions could take advantage of changing market conditions in terms of financial services and the disruptive nature of ChatGPT in accounting for boosting effectiveness, creating money and maintaining relationships with stakeholders through novel approaches. ChatGPT innovations, together with advancements in machine learning, would enable educational institutions and accounting firms to meet the

needs of students and customers. In this regard, TR plays a critical role from both academic and professional viewpoints as stated above. Establishing and maintaining TR implies analysing actions, not just words.

From the findings provided above concerning the components of PERVAL, it follows that stakeholders are interested in receiving MV from utilising ChatGPT in management accounting. This important information might be helpful to educational institutions and accounting firms in providing high-level ChatGPT-based financial and non-financial services. It is important to focus on building TR when considering PERVAL components because this factor is vital from an academic and professional viewpoint, according to this study. Thus, the establishment of TR requires studying deeds. In light of the fact that only a small percentage of academic and professional accounting stakeholders used ChatGPT in the context of financial and non-financial transactions based on World Bank statistics (Demirguc-Kunt et al., 2018), this finding is particularly valuable. Such information would help educational institutions and accounting firms in obtaining the necessary insights for the effective implementation and usage of ChatGPT in their management accounting services.

In today's era of falling bank branches and ATMs usage, the current study becomes important for governments, educational institutions and accounting firms seeking ways to persuade stakeholders to use ChatGPT for financial and non-financial accounting transactions. ChatGPT saves time and effort for manual accounting among students, accountants and academics. The above findings could be of great importance to educational institutions, accounting firms and accounting departments within educational institutions, considering ChatGPT as a low-cost technology for reducing costs, minimising expenses and time; popularising ChatGPT-enabled accounting services; expanding accounting practices regardless of physical location and adaptability.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Shubham Singh Chandel  <https://orcid.org/0009-0005-9771-3211>

References

- Agrawal, A., Gans, J., & Goldfarb, A. (2017). *How ChatGPT will change the way we make decisions*. Harvard Business Review. <https://hbr.org/2017/07/how-ai-will-change-the-way-we-make-decisions>
- Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust.

- International Journal of Information Management*, 37(3), 99–110. <https://doi.org/10.1016/j.ijinfomgt.2017.01.002>
- Alhwaiti, M. (2023). Acceptance of artificial intelligence application in the post-COvid era and its impact on faculty members' occupational well-being and teaching self efficacy: A path analysis using the UTAUT 2 model. *Applied Artificial Intelligence*, 37(1). <https://doi.org/10.1080/08839514.2023.2175110>
- Alkhwaldi, A. F., & Abdulmuhsin, A. A. (2021). Crisis-centric distance learning model in Jordanian higher education sector: Factors influencing the continuous use of distance learning platforms during COVID-19 pandemic. *Journal of International Education in Business*, 15(2), 250–272. <https://doi.org/10.1108/jieb-01-2021-0001>
- Baabdullah A. M., Alalwan A. A., Rana N. P., Kizgin H., & Patil P. (2019). Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model. *International Journal of Information Management*, 44, 38–52.
- Baptista G., & Oliveira T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior*, 50, 418–430.
- Balachandran, M. (1985). Behavioral accounting. *Behavioral & Social Sciences Librarian*, 4(2–3), 21–27. https://doi.org/10.1300/j103v04n02_03
- Birner, J. G. (1973). Empirical research in behavioral accounting. *Management International Review*, 13(2/3), 71–77. <http://www.jstor.org/stable/40226230>
- Birner, J. G. (2011). A proposed framework for behavioral accounting research. *Behavioral Research in Accounting*, 23(1), 1–43.
- Birner, J. G., & Shields, J. F. (1989). Three decades of behavioral accounting research: A search for order. *Behavioral Research in Accounting*, 1, 23–74.
- Boonsiritomachai, W., & Pitchayadejanant, K. (2017). Determinants affecting mobile banking adoption by generation Y based on the unified theory of acceptance and use of technology model modified by the technology acceptance model concept. *Kasetsart Journal of Social Sciences*. <https://doi.org/10.1016/j.kjss.2017.10.005>
- Brock, J. K., & Von Wangenheim, F. (2019). Demystifying ChatGPT: What digital transformation leaders can teach you about realistic artificial intelligence. *California Management Review*, 61(4), 110–134. <https://doi.org/10.1177/1536504219865226>
- Burton, J. W., Stein, M. K., & Jensen, T. B. (2019). A systematic review of algorithm aversion in augmented decision-making. *Journal of Behavioral Decision-Making*, 33(2), 220–239. <https://doi.org/10.1002/bdm.2155>
- Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and managerial intentions towards using artificial intelligence for organizational decision-making. *Technovation*, 106, 102312. <https://doi.org/10.1016/j.technovation.2021.102312>
- Caplan, E. H. (1989). Behavioral accounting—A personal view. *Behavioral Research in Accounting*, 1, 109.
- Caputo, F., Cillo, V., Candelò, E., & Liu, Y. (2019). Innovating through digital revolution. *Management Decision*, 57(8), 2032–2051. <https://doi.org/10.1108/md-07-2018-0833>
- Casey, T., & Wilson-Evered, E. (2012). Predicting uptake of technology innovations in online family dispute resolution services: An application and extension of the UTAUT. *Computers in Human Behavior*, 28(6), 2034–2045. <https://doi.org/10.1016/j.chb.2012.05.022>
- Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2021). Assessing organizational users' intentions and behavior to ChatGPT integrated CRM systems: A meta-UTAUT approach. *Information Systems Frontiers*. <https://doi.org/10.1007/s10796-021-10181-1>

- Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). ChatGPT-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of Business Research*, 144, 31–49. <https://doi.org/10.1016/j.jbusres.2022.01.069>
- Dahlberg, T., Guo, J., & Ondrus, J. (2015). A critical review of mobile payment research. *Electronic Commerce Research and Applications*, 14(5), 265–284. <https://doi.org/10.1016/j.elerap.2015.07.006>
- Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2019). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24–42. <https://doi.org/10.1007/s11747-019-00696-0>
- Deb, M., & Lomo-David, E. (2014). An empirical examination of customers' adoption of m-banking in India. *Marketing Intelligence & Planning*, 32(4), 475–494. <https://doi.org/10.1108/mip-07-2013-0119>
- Doney, P. M., & Cannon, J. P. (1997). An examination of the nature of trust in buyer–seller relationships. *Journal of Marketing*, 61(2), 35–51. <https://doi.org/10.1177/002224299706100203>
- Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision-making in the era of Big Data—Evolution, challenges and research agenda. *International Journal of Information Management*, 48, 63–71. <https://doi.org/10.1016/j.ijinfomgt.2019.01.021>
- Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2017). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, 21(3), 719–734. <https://doi.org/10.1007/s10796-017-9774-y>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J. S., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., . . . Williams, M. D. (2021). Artificial intelligence (ChatGPT): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Elliott, R. K. (1971). Aspects of behavioral accounting. *Journal of Accountancy (Pre-1986)*, 131, 63.
- European Commission. (2020). White paper on artificial intelligence: A European approach to excellence and trust. In *European Commission*. https://commission.europa.eu/publications/white-paper-artificial-intelligence-european-approach-excellence-and-trust_en
- Evans, J. R., & Mathur, A. (2018). The value of online surveys. *Internet Research*, 28(4), 854–887.
- Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *Management Information Systems Quarterly*, 27(1), 51. <https://doi.org/10.2307/30036519>
- Gharrah, A. S. A., & Aljaafreh, A. (2021). Why students use social networks for education: Extension of UTAUT2. *Journal of Technology and Science Education*, 11(1), 53. <https://doi.org/10.3926/jotse.1081>
- Giovanis, A., Assimakopoulos, C., & Sarmaniotis, C. (2019). Adoption of mobile self-service retail banking technologies. *International Journal of Retail & Distribution Management*, 47(9), 894–914. <https://doi.org/10.1108/ijrdm-05-2018-0089>
- Guadagnoli, E., & Velicer, W. F. (1988). Relation of sample size to the stability of component patterns. *Psychological Bulletin*, 103(2), 265–275.

- Gupta, K. P., Manrai, R., & Goel, U. (2019). Factors influencing adoption of payments banks by Indian customers: Extending UTAUT with perceived credibility. *Journal of Asia Business Studies*, 13(2), 173–195. <https://doi.org/10.1108/jabs-07-2017-0111>
- Gursoy, D., Hengxuan, O., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (ChatGPT) device use in service delivery. *International Journal of Information Management*, 49, 157–169. <https://doi.org/10.1016/j.ijinfomgt.2019.03.008>
- Haesevoets, T., De Cremer, D., Dierckx, K., & Van Hiel, A. (2021). Human-machine collaboration in managerial decision-making. *Computers in Human Behavior*, 119, 106730. <https://doi.org/10.1016/j.chb.2021.106730>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.
- Huang, C. Y., & Kao, Y. S. (2015). UTAUT2 based predictions of factors influencing the technology acceptance of phablets by DNP. *Mathematical Problems in Engineering*, 2015, 1–23. <https://doi.org/10.1155/2015/603747>
- Johnson, D. G., & Verdicchio, M. (2017). ChatGPT anxiety. *Journal of the Association for Information Science and Technology*, 68(9), 2267–2270. <https://doi.org/10.1002/asi.23867>
- Jovanovic, M., Sjödin, D., & Parida, V. (2022). Co-evolution of platform architecture, platform services, and platform governance: Expanding the platform value of industrial digital platforms. *Technovation*, 118, 102218. <https://doi.org/10.1016/j.technovation.2020.102218>
- Kwateng, K. O., Atiemo, K. a. O., & Appiah, C. (2019). Acceptance and use of mobile banking: An application of UTAUT2. *Journal of Enterprise Information Management*, 32(1), 118–151. <https://doi.org/10.1108/jeim-03-2018-0055>
- Malone, T. W. (2018). How human-computer ‘Superminds’ are redefining the future of work. *MIT Sloan Management Review*. <https://sloanreview.mit.edu/article/how-human-computer-superminds-are-redefining-the-future-of-work/#:~:text=All%20superminds%20have%20a%20kind,physical%2C%20activities%20of%20these%20groups>
- Metcalf, L. E., Askay, D. A., & Rosenberg, L. (2019). Keeping humans in the loop: Pooling knowledge through artificial swarm intelligence to improve business decision-making. *California Management Review*, 61(4), 84–109. <https://doi.org/10.1177/0008125619862256>
- Moorthy, K., Yee, T. T., T'ing, L. C., & Kumaran, V. V. (2019). Habit and hedonic motivation are the strongest influences in mobile learning behaviours among higher education students in Malaysia. *Australasian Journal of Educational Technology*, 35(4). <https://doi.org/10.14742/ajet.4432>
- Nguyen, T., Nguyen, T. M., Pham, Q. T., & Misra, S. (2014). *Acceptance and use of E-learning based on cloud computing: The role of consumer innovativeness* (pp. 159–174). Springer eBooks. https://doi.org/10.1007/978-3-319-09156-3_12
- Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2020). Acceptance of mobile phone by university students for their studies: An investigation applying UTAUT2 model. *Education and Information Technologies*, 25(5), 4139–4155. <https://doi.org/10.1007/s10639-020-10157-9>
- Oliveira, T., Faria, M., Thomas, M. A., & Popović, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, 34(5), 689–703. <https://doi.org/10.1016/j.ijinfomgt.2014.06.004>

- Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, 17(4), 460. <https://doi.org/10.2307/3150499>
- 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.
- Rampersad, G. (2020). Robot will take your job: Innovation for an era of artificial intelligence. *Journal of Business Research*, 116, 68–74. <https://doi.org/10.1016/j.jbusres.2020.05.019>
- Sankaran, R., & Chakraborty, S. (2020). Why customers make mobile payments? Applying a means-end chain approach. *Marketing Intelligence & Planning*, 39(1), 109–124. <https://doi.org/10.1108/mip-12-2019-0622>
- Sankaran, R., & Chakraborty, S. (2022). Factors impacting mobile banking in India: Empirical approach extending UTAUT2 with perceived value and trust. *IIM Kozhikode Society & Management Review*, 11(1), 7–24. <https://doi.org/10.1177/2277975220975219>
- Seeber, I., Waizenegger, L., Seidel, S., Morana, S., Benbasat, I., & Lowry, P. B. (2020). Collaborating with technology-based autonomous agents. *Internet Research*, 30(1), 1–18. <https://doi.org/10.1108/intr-12-2019-0503>
- Shen, C.-C., & Chuang, H.-M. (2010). Exploring users' attitudes and intentions toward the interactive whiteboard technology environment. *International Review on Computers and Software*, 5, 200–208.
- Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, 61(4), 66–83. <https://doi.org/10.1177/0008125619862257>
- Sweeney, J., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing*, 77(2), 203–220. [https://doi.org/10.1016/s0022-4359\(01\)00041-0](https://doi.org/10.1016/s0022-4359(01)00041-0)
- Upadhyay, N., Upadhyay, S., & Dwivedi, Y. K. (2022). Theorizing artificial intelligence acceptance and digital entrepreneurship model. *International Journal of Entrepreneurial Behaviour & Research*, 28(5), 1138–1166. <https://doi.org/10.1108/ijeb-01-2021-0052>
- Venkatesh, V., Morris, M., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, 27(3), 425. <https://doi.org/10.2307/30036540>
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *Management Information Systems Quarterly*, 36(1), 157. <https://doi.org/10.2307/41410412>
- Verdegem, P., & De Marez, L. (2011). Rethinking determinants of ICT acceptance: Towards an integrated and comprehensive overview. *Technovation*, 31(8), 411–423. <https://doi.org/10.1016/j.technovation.2011.02.004>
- Wamba-Taguimdje, S., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Influence of artificial intelligence (ChatGPT) on firm performance: The business value of ChatGPT-based transformation projects. *Business Process Management Journal*, 26(7), 1893–1924. <https://doi.org/10.1108/bpmj-10-2019-0411>
- Wang, N., Pynadath, D. V., & Hill, S. C. (2016). Trust calibration within a human-robot team: Comparing automatically generated explanations. 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI). <https://doi.org/10.1109/hri.2016.7451741>

- Weld, D. S., & Bansal, G. (2019). The challenge of crafting intelligible intelligence. *Communications of the ACM*, 62(6), 70–79. <https://doi.org/10.1145/3282486>
- Wu, K., Zhao, Y., Zhu, Q., Tan, X., & Zheng, H. (2011). A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type. *International Journal of Information Management*, 31(6), 572–581. <https://doi.org/10.1016/j.ijinfomgt.2011.03.004>
- Yadav, A., Gupta, V., Sahu, H., & Shrimal, S. (2017). Artificial intelligence—New era. *International Journal of New Technology and Research (IJNTR)*, 3(3), 30–33.
- Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, 26(4), 760–767. <https://doi.org/10.1016/j.chb.2010.01.013>
- Zhou, M., Dzingirai, C., Hove, K., Chitata, T., & Mugandani, R. (2022). Adoption, use and enhancement of virtual learning during COVID-19. *Education and Information Technologies*, 27(7), 8939–8959. <https://doi.org/10.1007/s10639-022-10985-x>

Responsible Automation in E-business: A Framework for Agentic AI Integration and Governance

BIMTECH Business Perspectives
7(2) 169–192, 2026
© The Author(s) 2026
DOI: 10.1177/25819542261479531
bsp.bimtech.ac.in



Mohammad Talha Siddiqui¹  and Yusuf Kamal¹ 

Abstract

This study proposes the Responsible Autonomy Framework (RAF), a layered governance architecture for agentic artificial intelligence (AI) in e-business. The RAF integrates operational efficiency, strategic adaptability, and responsible oversight into a single layered model. Using a conceptual research design grounded in an integrative literature review, agency theory, and sociotechnical systems thinking, the study develops a three-layer model comprising operational autonomy, strategic autonomy, and responsible autonomy. In which responsibility acts as the governing layer rather than an afterthought. The review finds that existing governance frameworks address transparency, accountability, or fairness largely in isolation, with none spanning the full path from operational automation to embedded governance, while the RAF addresses this by treating responsible design as a condition for sustainable autonomy rather than a competing value to be balanced against it. The framework offers managers actionable guidance for deploying agentic AI responsibly and offers regulators a structured basis for balancing innovation with oversight, while extending agency theory and sociotechnical systems theory through a reconceptualisation of agentic AI as a sociotechnical principal-cum-agent.

Keywords

Responsible autonomy framework (RAF), agentic artificial intelligence (AI), e-business, operational autonomy, strategic autonomy, explainable AI (XAI)

¹ University of Lucknow, Uttar Pradesh, India

Corresponding author:

Mohammad Talha Siddiqui, University of Lucknow, Lucknow, Uttar Pradesh 226003, India.
E-mail: siddiqui_talha@lkouniv.ac.in



Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 License (<http://www.creativecommons.org/licenses/by-nc/4.0/>) which permits non-Commercial use, reproduction and distribution of the work without further permission provided the original work is attributed.

Introduction

The digital transformation of organisations has evolved through several distinct phases from the early computerisation and process automation to the current integration of intelligent, adaptive and autonomous systems. Within this evolution, e-businesses have been at the forefront of adopting automation technologies across domains such as customer service, supply chain management, marketing and regulatory compliance. Automation through chatbots, robotic process automation (RPA) and large language models (LLMs) has enabled faster query handling, reduced costs and improved personalisation in customer engagement (Duesterwald et al., 2024; Hughes et al., 2025; Van et al., 2025). In the supply chain and logistics, predictive maintenance, dynamic route optimisation and AI-driven demand forecasting have redefined the efficiency benchmarks (Gong, 2025; Nicoletti & Appolloni, 2025). The marketing functions have increasingly used artificial intelligence (AI) recommendation systems to create personalised consumer experiences, while compliance activities such as auditing, fraud detection and transaction verification have become progressively automated (Hnatyshyn et al., 2025; Sallem et al., 2024).

Despite these developments, most automation has stayed focused on deterministic and rule-based systems designed primarily for efficiency, speed and accuracy. The emergence of agentic AI represents a marked shift in this pattern, moving attention from pre-programmed automation to autonomous and goal-directed decision-making. The agentic systems combine perception, reasoning and adaptive learning, allowing them to operate as semi-independent entities capable of handling the complex interactions within both the digital and physical contexts (Duesterwald et al., 2024; Hughes et al., 2025). This shift carries major implications for the electronic business. The AI agents now contribute to strategic decision-making, manage the coordination across the supply chains, personalise the customer experiences in real time and handle the compliance requirements with limited human involvement (Gong, 2025; Van et al., 2025).

The integration of autonomy into business operations introduces new challenges related to governance and accountability. In traditional automated systems, the decision-making stays under human supervision, but the autonomous AI agents make the boundaries of responsibility less clear when mistakes, ethical issues or unintended outcomes occur. The questions of transparency, interpretability and trust become central, particularly in areas such as finance, healthcare and international electronic commerce (Biswas & Talukdar, 2025; Hughes et al., 2025). Regulatory frameworks such as the European Union Artificial Intelligence Act and the General Data Protection Regulation (GDPR) highlight the importance of strong accountability and compliance structures, reinforcing that autonomy must develop alongside responsibility (Manda et al., 2024; Vatankhah et al., 2024).

Thus, while the e-businesses benefit from the efficiency and innovation through the agentic AI, the rapid evolution of autonomy necessitates a framework that integrates operational automation, strategic adaptability and responsible governance. The Responsible Autonomy Framework (RAF), introduced below,

positions responsibility not as an afterthought but as the structural layer of autonomy, ensuring that the digital transformation of the e-businesses evolves in alignment with societal expectations and regulatory norms.

Research Problem

The rise of agentic AI in e-business introduces new and significant opportunities and risks, necessitating critical reflection on its governance and accountability. The traditional automation frameworks stressed efficiency, consistency and cost reduction, with human supervision ensuring responsibility for the outcomes (Bohnsack & De Wet, 2025; Thapliyal & Thapliyal, 2024). The growing autonomy of the AI agents capable of independently interpreting the environments, adapting to the feedback and making strategic decisions raises significant challenges regarding transparency, explainability and liability (Biswas & Talukdar, 2025; Hughes et al., 2025). Unlike deterministic systems, agentic AI operates with degrees of unpredictability, creating the ‘black box’ effect that obscures the decision processes and complicates both managerial oversight and regulatory compliance (Alshaketheep et al., 2024; Vannostrand et al., 2024).

The challenge becomes more serious in the fields where the AI decisions have financial, legal or ethical consequences. In financial services, autonomous agents now assist with credit evaluation, fraud detection and investment planning. The mistakes or bias in these settings can cause reputational harm, financial loss or legal liability (Munoko et al., 2020; Sallem et al., 2024). Within the supply chain networks, agentic AI improves procurement and logistics efficiency, yet its independent actions can expose weaknesses in the coordination and accountability between the organisations (Duesterwald et al., 2024; Gong, 2025). In marketing, agentic systems such as recommendation tools strengthen personalisation but may also reinforce bias, compromise data privacy or weaken consumer trust (Biswas & Talukdar, 2025; Van et al., 2025). The autonomy without governance erodes confidence across these domains.

The current governance and ethical frameworks stay fragmented. The frameworks stressing risk management (Wirtz et al., 2022), digital ethics (Ashok et al., 2022) or holistic responsibility (Kottur, 2024) each provide valuable insights, yet they primarily address either compliance, trust or ethics in isolation. None sufficiently reconcile the tension between empowering the AI agents with autonomy and embedding accountability throughout their decision lifecycles. The policy developments such as the GDPR and the EU AI Act highlight the growing regulatory concern, but the operationalisation in the fast-evolving agentic AI environments remains unclear (Manda et al., 2024; Vatankhah et al., 2024).

The research problem can therefore be summarised as the governance gap in transitioning from automation to autonomy in e-business. The AI agents promise adaptability, scalability and innovation, but the absence of integrated frameworks risks creating opaque, unaccountable and potentially harmful systems. This article responds to this gap by proposing the RAF, which positions responsibility as the embedded structural element of autonomy rather than the external corrective

measure. In doing so, it aims to bridge the divide between technological advancement and ethical governance, ensuring that the agentic AI strengthens rather than undermines the foundations of trust in digital business ecosystems.

Objectives and Research Questions

The primary objective of this study is to conceptualise and develop the RAF, which is a layered model that integrates operational efficiency, strategic adaptability and responsible governance into a unified approach for e-business autonomy. Unlike the prior frameworks, the RAF positions responsibility as the structural component of autonomy itself. The aim is to advance the theory, provide managerial guidance and inform regulatory practice by ensuring that autonomy in the digital business ecosystems evolves in tandem with accountability and trust.

To achieve this objective, the study addresses the following research questions:

- RQ1: How can the existing approaches to automation, governance and digital ethics be synthesised to conceptualise the unified framework for responsible autonomy in e-business?
- RQ2: In what ways does the RAF contribute to advancing the theory, managerial practice and policy in the governance of agentic AI for e-business?

Literature Review

The academic study of automation in electronic commerce has developed across the three largely separate streams: the operational adoption of information technologies for the efficiency and process standardisation; the governance frameworks designed to manage the risks associated with the digital systems; and the emerging body of work on responsible AI. While each stream has produced valuable insights, they have evolved with limited cross-pollination, leaving the gap at precisely the intersection that the agentic AI now occupies. This review traces the development of each stream and identifies the specific limitations that the RAF is designed to address.

Evolution of E-business Automation

The early research on electronic commerce automation focused primarily on aligning the information technology governance with organisational performance. Liu et al. (2010) proposed the holistic governance framework for e-business success, arguing that the effective management of risk, performance and compliance was central to realising the strategic potential of the digital systems. Their framework was grounded in the assumption that human oversight remained primary and that automation served a supporting role in standardising the routine

processes. Similar themes appeared in the work on enterprise resource planning and supply chain coordination, where the efficiency gains of the automated data pipelines were offset by the concerns about the system rigidity and the limited capacity of the rule-based models to handle the contextual variation (Hnatyshyn et al., 2025; Murphy et al., 2024).

The scope of the automation expanded substantially with the emergence of AI-driven customer engagement tools. Adam et al. (2021) demonstrated that AI-based chatbots in customer service could improve response consistency and reduce handling time, though their study also identified the tension between scalability and the quality of the complex, context-sensitive interactions. The deployment of LLMs extended these capabilities, enabling the conversational agents to engage with a broader range of queries and to support personalisation at scale (Duesterwald et al., 2024; Van et al., 2025). In logistics and supply chain management, predictive maintenance systems and dynamic routing algorithms began to demonstrate measurable reductions in disruption exposure and operational cost (Gong, 2025; Nicoletti & Appolloni, 2025). In accounting and compliance, the automated auditing tools improved the accuracy and speed of anomaly detection while reducing the workload associated with the manual review (Ramon-Poma et al., 2024; Sallem et al., 2024).

Despite these advances, a persistent limitation ran through the automation literature: the systems described remained fundamentally reactive and rule-bound. They could execute the predefined workflows efficiently but struggled to adapt to unfamiliar conditions, exercise contextual judgement or act strategically in dynamic environments. Hughes et al. (2025) characterise this as the distinction between task automation and genuine intelligence, arguing that the former improves efficiency within the known parameters while the latter requires the capacity for reasoning, adaptation and goal-directed behaviour. The transition from one to the other is the defining challenge that agentic AI addresses and that the existing governance frameworks have been slow to catch up with.

Rise of Agentic AI in E-business

The limitations of conventional automation have driven the growing interest in agentic AI systems that combine autonomy, adaptability and continuous learning. Unlike the rule-based predecessors, the agentic systems can decompose the goals, interpret the feedback and improve their performance over time, acting as semi-independent participants within digital ecosystems rather than as passive execution engines (Biswas & Talukdar, 2025; Hughes et al., 2025). The implications for the e-business are substantial. In e-commerce, recommendation systems have moved beyond the fixed association rules to employ reinforcement learning, generating personalised suggestions in real-time based on the evolving customer behaviour (Biswas & Talukdar, 2025; Van et al., 2025). In supply chain management, the adaptive agents now simulate disruption scenarios and autonomously reconfigure the logistics networks to maintain operational continuity (Gong, 2025; Nicoletti & Appolloni, 2025). In financial services, agentic systems support credit

assessment, fraud detection and portfolio optimisation using continuous learning to balance risk and responsiveness (Vannostrand et al., 2024).

The integration of natural language processing and multimodal reasoning has expanded the role of agentic systems beyond background data processing into active organisational participation. The conversational agents now contribute to decision-making in the customer support and strategic management contexts, not merely retrieving the information but synthesising it into recommendations and adapting their approach based on conversational cues (Duesterwald et al., 2024; Hughes et al., 2025). The use of reinforcement learning from human feedback has further aligned the agentic behaviour with the ethical principles and the contextual priorities, enabling the organisations to embed the value-based constraints into the learning process itself (Biswas & Talukdar, 2025; Huang, 2025).

These developments represent the qualitative shift in the relationship between AI and organisational decision-making. The systems now in use are no longer the adjuncts to human judgement but the active co-participants whose decisions carry the real operational and ethical weight. As Bohnsack and De Wet (2025) argue, AI is increasingly becoming the strategy itself rather than the tool for executing the strategies defined by humans. This shift demands governance approaches that extend beyond risk mitigation to address accountability, transparency and the distribution of responsibility in the systems where human agency and AI agency are increasingly intertwined.

Challenges in Responsible AI Deployment

The governance challenges associated with the agentic AI deployment centre on the four interrelated dimensions: transparency, accountability, fairness and regulatory compliance. Each has received substantial attention in the literature, though typically in isolation from the others.

Transparency, which is the capacity of the AI systems to render their decision processes interpretable to the users, managers and regulators, is widely recognised as foundational to trust. Explainable AI (XAI) methods such as LIME and SHAP have demonstrated the technical feasibility of generating post-hoc explanations for the complex model outputs, showing which variables drove the specific recommendation or classification (Jahan et al., 2025; Sanjammagari et al., 2026). In fraud detection, the transparent decision trails have been shown to improve both the detection of false positives and the maintenance of consumer confidence (Ansari et al., 2023). However, the interpretability of the individual decisions becomes progressively harder to guarantee as the models grow more complex and as the agentic systems engage in the multi-step reasoning processes that resist simple post-hoc explanation (Petrenko, 2025).

Accountability, which is the attribution of responsibility for the AI-generated decisions, raises distinct challenges in the agentic contexts where the decisions emerge from the interaction of multiple agents rather than from a single identifiable system. Franklin et al. (2022) propose a causal framework for attributing responsibility to artificial autonomous agents, incorporating elements such as

intent, autonomy and foreseeability. Triantafyllou and Radanovic (2023) extend this to the decentralised multi-agent settings, proposing computational methods for approximating the degrees of responsibility using Monte Carlo Tree Search. These contributions are technically sophisticated, but their integration into the operational governance practices in the e-business remains largely unexplored.

Fairness concerns the risk that the AI systems replicate or amplify the structural inequities embedded in the training data. The research has documented how the hiring tools, credit scoring models and customer segmentation systems can reproduce the discriminatory patterns that undermine both the ethical legitimacy and the regulatory compliance (Sallem et al., 2024; Shankar, 2024). The challenge is not merely technical; it is also organisational, requiring that fairness be treated as the design criterion rather than the post-deployment audit item. In e-business, fairness lapses carry the reputational, legal and ethical consequences that extend beyond the immediate transaction to affect long-term consumer trust.

Regulatory compliance is becoming an increasingly structured requirement. The GDPR mandates data minimisation, purpose limitation and the right to explanation for the automated decisions affecting individuals (Hughes et al., 2025; Vatankhah et al., 2024). The European Union Artificial Intelligence Act introduces the risk-based categorisation framework that classifies the AI systems according to their potential for harm, imposing higher transparency and oversight requirements on the high-risk applications in sectors such as financial services, healthcare and employment. The organisations operating agentic AI systems in these sectors must demonstrate not only regulatory compliance at a point in time but the ongoing adaptability to the regulatory environment that continues to evolve. The pace of regulatory development often outstrips the capacity of the organisations to adjust their governance structures, creating what Manda et al. (2024) describe as the persistent compliance lag.

Taken together, these challenges indicate that responsible AI deployment in e-business requires more than the sum of its parts. Addressing transparency in isolation does not resolve accountability; achieving regulatory compliance does not guarantee fairness. What is needed is an integrated framework that treats these dimensions as the structurally connected requirements rather than the discrete risk categories to be managed separately.

Existing Governance Frameworks and Their Limitations

This subsection examines five representative governance frameworks individually, building on the dimensions introduced above, to identify precisely where each falls short for agentic AI environments.

Liu et al. (2010) established one of the earliest structured approaches to IT governance in e-business, integrating risk management, performance monitoring and organisational alignment within the unified framework. While foundational, their model was designed for human-supervised automation and does not address the governance challenges that arise when AI systems act with the degrees of independent agency.

Al-Mushayt (2019) extended the governance thinking into the AI-augmented e-government contexts, identifying privacy, transparency and citizen trust as the central concerns in the automation of public services. The framework represented the important early recognition that AI deployment requires trust-building mechanisms beyond technical performance, but its scope remained limited to supervised automation rather than autonomous decision-making.

Wirtz et al. (2022) proposed a more comprehensive risk-based governance model organising the AI risks into the six categories: technological, data-related, ethical, legal, organisational and societal. Their integrative approach brought a useful structure to the governance field and provided the basis for the systematic risk assessment. However, its primary orientation is towards risk control rather than the responsible enablement of autonomy. It offers limited guidance on how organisations can use the adaptive and strategic capabilities of the agentic AI while maintaining accountability.

Ashok et al. (2022) addressed the ethical dimension more directly, proposing an ontological framework for digital ethics that translates values such as intelligibility, accountability, fairness, autonomy and privacy into operational guidelines. This contribution provided the principled moral basis for responsible AI, but the framework's applicability to the genuinely autonomous systems where the AI agents make the complex decisions without the direct human involvement remains limited. The challenge of governing the emergent agent behaviour that was not explicitly anticipated at the design time is not fully resolved.

Kottur (2024) offered the most holistic of the existing models integrating fairness, transparency, accountability, privacy and robustness within the framework that emphasises multi-stakeholder cooperation. Like its predecessors, however, the framework is primarily designed for the contexts in which human oversight is readily available. It does not provide the specific mechanisms for governing the agents that operate with significant independence, particularly in the contexts where the speed and complexity of the agentic decision-making exceed the capacity for real-time human review.

The cumulative limitation of these frameworks is their failure to conceptually integrate the operational capabilities of the agentic AI with the governance mechanisms required to ensure responsible deployment. As Table 1 illustrates, each framework addresses a subset of the relevant dimensions, but none provides the end-to-end model that spans from the operational automation through the strategic agentic capabilities to the embedded responsible governance.

Columns represent: IT Governance: alignment of AI with the organisational performance; Trustworthy Automation: trust and transparency in the AI-assisted processes; Risk Management: structured identification and mitigation of the AI-related risks; Ethical Operationalisation: translating the ethical principles into the actionable guidelines; Holistic Responsibility: integration of the multiple responsibility dimensions; Agentic Autonomy: governance of the semi-independent AI agents.

Table 1. Comparison of Existing Governance Frameworks with the Proposed RAF.

Framework	IT Governance	Trustworthy Automation	Risk Management	Ethical Operational	Holistic Responsibility	Agentic Autonomy
Liu et al. (2010)	✓	Partial	✗	✗	✗	✗
Al-Mushayt (2019)	✓	✓	✓	Partial	Partial	✗
Wirtz et al. (2022)	✓	✓	✓	Partial	Partial	✗
Ashok et al. (2022)	Partial	✓	Partial	✓	Partial	✗
Kottur (2024)	✓	✓	✓	✓	✓	✗
RAF (This Study)	✓	✓	✓	✓	✓	✓

Notes: ✓: addressed; Partial: partially addressed; ✗: not addressed.

Research Gap and Positioning of This Study

The review of the existing frameworks shows the consistent pattern: the governance approaches in e-business have developed in response to the challenges of the automated and AI-assisted systems operating under meaningful human oversight but have not kept pace with the shift toward agentic AI that operates with degrees of independence that fundamentally alter the governance requirements. Three specific gaps are identifiable.

First, no existing framework provides the integrated model that connects the operational automation, strategic agentic capabilities and the responsible governance within a single, coherent architecture. The governance literature and the agentic AI literature have developed largely in parallel with limited cross-referencing. The RAF addresses this by treating the responsibility not as the external control layer but as the structural component of the autonomy model itself.

Second, the existing frameworks address the governance primarily as a matter of risk management, compliance or ethical principles. They do not account for the possibility that responsibility and autonomy can be designed to reinforce each other; that building explainability, accountability and privacy-by-design into the agentic systems from the outset may enhance rather than constrain their operational and strategic effectiveness. The RAF makes this argument explicitly and provides the framework through which it can be operationalised.

Third, none of the reviewed frameworks provides actionable guidance for the managers deploying the agentic AI in the e-business contexts. The transition from the theoretical principles to the operational decisions about the system design, human oversight structures and the regulatory alignment requires a prescriptive model oriented toward design and action, which the RAF provides in line with the Gregor (2006) Type V theory classification.

Research Methodology

The conceptual research design is adopted with the primary aim of developing the RAF for e-business autonomy. The conceptual research does not rely on empirical data collection but advances the knowledge by synthesising, extending and reconfiguring the existing theoretical perspectives into the new contribution (MacInnis, 2011). In line with Gregor's (2006) typology of theory contributions, the RAF constitutes the Type V theory 'theory for design and action' in that it prescribes how agentic AI systems can be structured and governed responsibly in e-business contexts.

Conceptual Theory-building Approach

The conceptual approach is particularly appropriate given the evolving and unsettled nature of AI autonomy in e-business where the empirical consensus is still limited. Following MacInnis (2011), the contributions are made through the integration and extension: the integration by drawing together the multiple strands of literature—automation, agentic AI and responsible governance—that have largely developed in isolation; and the extension by reconfiguring these literatures into the unified framework that positions the responsibility not as an add-on but as the structural layer of autonomy.

Rather than describing the agentic AI merely as the technical evolution of automation, the RAF positions the AI agents as semi-autonomous actors situated within sociotechnical systems. This conceptualisation aligns with agency theory, which examines accountability and decision delegation and with sociotechnical systems theory, which emphasises the interdependence of technological artefacts and organisational structures. By drawing on these perspectives, the RAF advances beyond the descriptive accounts of the AI applications to propose a prescriptive model for responsible autonomy in e-business.

Literature-informed Conceptual Synthesis and Mechanism Extraction

The RAF was constructed through the literature-informed synthesis process rather than the systematic coding exercise. The prior governance and automation frameworks (e.g., Al-Mushayt, 2019; Ashok et al., 2022; Kottur, 2024; Liu et al., 2010; Wirtz et al., 2022) were critically examined to identify the mechanisms they emphasised, such as efficiency, risk management, accountability and ethical safeguards.

From this analysis and the rigorous literature review, the mechanisms relevant to e-business autonomy were extracted and clustered abductively into the three interlinked domains:

The operational autonomy: mechanisms that automate and optimise the routine processes for efficiency and scalability.

The strategic autonomy: mechanisms that support adaptive decision-making, coordination and foresight in the changing markets.

The responsible autonomy: mechanisms that embed governance, accountability and trust as the cross-cutting requirements.

This mechanism extraction process ensured that each element of the RAF is grounded in the prior studies while being reorganised into the layered model that integrates efficiency, adaptability and responsibility. The abductive reasoning approach, moving iteratively between the theoretical insights and the observed organisational challenges, enabled the framework to reconcile the fragmented literatures and highlight the underexplored connections.

Design and Action Orientation

Although conceptual in nature, the RAF is oriented towards design and action. Following Gregor (2006), such theories do not merely explain or predict the phenomena but offer guidance for practice. Accordingly, the RAF is presented as the prescriptive artefact that operates across the three domains:

For the theory, it extends the sociotechnical and agency theory by embedding responsibility into autonomy.

For the practice, it provides the managers with a structured roadmap for deploying the agentic AI responsibly in digital commerce.

For the policy, it offers the regulators insights into balancing innovation with governance in the e-business ecosystems.

Conceptual Framework

The RAF: Overview and Logic

The RAF is built on the single governing argument: that the responsible deployment of agentic AI in e-business is not achieved by adding governance as an afterthought to the autonomous systems but by treating the responsibility as the structural layer of the autonomy model from the outset. This argument distinguishes the RAF from the prior frameworks which have tended to address efficiency, risk and ethics as the separate concerns to be balanced against one another. In the RAF, the three layers—operational autonomy, strategic autonomy and responsible autonomy are logically ordered and functionally interdependent. The operational autonomy provides the efficiency substrate; the strategic autonomy enables the adaptive, goal-directed behaviour; and the responsible autonomy supplies the governance architecture that gives the first two layers their legitimacy, accountability and societal acceptability.

The framework draws on the two theoretical traditions. The agency theory originating with Jensen and Meckling (1976) provides the conceptual vocabulary for understanding the delegation of the decision-making authority from the principals to the agents and the governance mechanisms required to align the agent behaviour with the principal interests. In the context of agentic AI, the principal-agent relationship is no longer exclusively human: the AI agents act on behalf of the organisational principals and the governance challenges associated with this delegation the information asymmetry, moral hazard, and misaligned incentives

take on new technical and ethical dimensions. The RAF addresses these by embedding the accountability and transparency mechanisms directly into the agent architecture rather than relying solely on post-hoc monitoring.

The sociotechnical systems theory, which emphasises the mutual constitution of the social structures and the technological artefacts (Orlikowski, 1992; Trist & Bamforth, 1951), provides the second theoretical foundation. From this perspective, the AI agents are not merely technical tools but sociotechnical entities whose behaviour is shaped by and shapes the organisational and social contexts in which they operate. The responsible autonomy layer of the RAF instantiates this perspective by requiring that human oversight, ethical alignment and regulatory compliance be embedded within the system design rather than imposed externally after deployment. The three layers of the RAF thus represent not the technical stack but the sociotechnical architecture in which the capacity for autonomous action and the structures of accountability are co-designed.

Structure of the Framework

The RAF is organised as a three-layer model in which each layer represents the distinct domain of the AI capability and the governance responsibility. The layers are cumulative rather than sequential: the operational autonomy operates continuously as the foundation; the strategic autonomy is built upon and extends the operational layer; and the responsible autonomy functions as the governing super-structure that shapes and constrains the activities of both. Figure 1 illustrates the structure and the relationships between the layers.

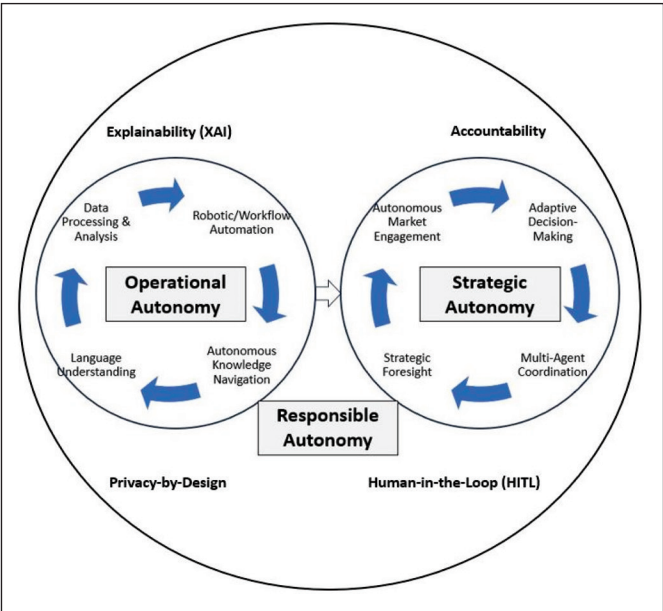


Figure 1. Proposed Responsible Autonomy Framework for E-business.

The relationships between the layers operate in both directions. The outputs of the operational autonomy the data processing, language understanding, knowledge navigation and workflow execution provide the informational and technical substrate upon which the strategic autonomy depends. The strategic decisions about the pricing, procurement, market engagement and the multi-agent coordination in turn generate the conditions that the responsible autonomy layer must govern: the higher the degree of strategic autonomy exercised by the AI agents, the more critical it becomes that explainability, accountability, privacy and human oversight are properly instantiated. At the same time, the governance mechanisms of the responsible autonomy layer actively shape how the operational and strategic functions are designed and constrained. The explainability requirements, for example, influence which AI architectures are appropriate for the high-stakes operational tasks; the accountability frameworks determine how the autonomous procurement decisions must be logged and auditable; and the human-in-the-loop structures define the thresholds at which the strategic decisions require human review before the execution.

Operational Autonomy

The operational autonomy encompasses the AI capabilities that enable the e-businesses to automate the routine, high-volume processes with minimal human intervention. Four mechanisms constitute this layer: data processing and analysis, language understanding, autonomous knowledge navigation and robotic and workflow automation. Together, these mechanisms provide the efficiency and scalability substrate upon which the more complex agentic capabilities depend.

The data processing and analysis involves the automated extraction, organisation and interpretation of the large and varied data sets, converting the raw information into actionable insights for tasks including financial reporting, demand forecasting and compliance monitoring (Hnatyshyn et al., 2025; Sallem et al., 2024).

Language understanding enables the AI systems to interpret and generate natural language supporting customer engagement, internal communication and document processing through conversational agents and NLP-based tools (Adam et al., 2021; Hughes et al., 2025).

Autonomous knowledge navigation extends the informational reach of the AI agents by enabling them to retrieve and synthesise information from distributed sources, such as external databases, regulatory repositories and competitor intelligence platforms, without requiring manual query formulation (Petrenko, 2025; Sifakis et al., 2025).

Robotic and workflow automation translates the AI capabilities into the physical and digital operational execution, encompassing RPA in the back-office functions and the physical robotics in the fulfilment and logistics (Mahler et al., 2019; Nicoletti & Appolloni, 2025).

Strategic Autonomy

Strategic autonomy represents the capacity of the AI agents to engage in goal-directed, adaptive and forward-looking behaviour that goes beyond the execution of predefined processes. This layer encompasses adaptive decision-making, multi-agent coordination, strategic foresight and autonomous market

engagement, and it is at this level that the potential of agentic AI to act as a genuine strategic partner rather than merely an operational tool is most fully realised.

The adaptive decision-making involves the continuous modification of strategies, processes and resource allocations in response to real-time data, enabling e-businesses to respond dynamically to market changes, customer behaviour shifts and competitive pressures (Shili & Anwar, 2025; Wang et al., 2025).

The multi-agent coordination enables the distributed AI systems, with specialised agents managing the supply chains, customer service, financial transactions and analytics, to collaborate through shared protocols, producing the collective intelligence that exceeds the capabilities of any individual system (Pal et al., 2018; Xu et al., 2023).

Strategic foresight equips the AI systems to anticipate future risks and opportunities through predictive analytics and scenario simulation, supporting proactive planning rather than reactive adjustment (Carayannis et al., 2025).

Autonomous market engagement describes the capacity of the AI agents to interact directly with external parties, the customers, suppliers and competitors, negotiating, forming relationships and shaping the market dynamics without requiring human initiation of each interaction (Kwon et al., 2024; Minarsch et al., 2022).

Responsible Autonomy

Responsible autonomy is the governing layer of the RAF. It does not add new AI capabilities to the operational and strategic layers but instead provides the governance architecture that ensures both layers operate in alignment with the organisational values, regulatory requirements and societal expectations. Four mechanisms constitute this layer: explainability, accountability, privacy-by-design and human-in-the-loop governance.

Explainability (XAI) requires that the AI systems be capable of rendering their decision processes interpretable to the relevant stakeholders. In the e-business contexts, this means providing both the users and the managers with transparent accounts of why the product was recommended, the credit decision was reached, or the pricing adjustment was made (Chernyaeva et al., 2025; Sanjammagari et al., 2026).

Accountability establishes the mechanisms through which the responsibility for the AI-generated decisions can be attributed, traced and reviewed, including the audit trails, digital signature systems and the blockchain-based records that provide the permanent, tamper-evident logs of the agent actions (Franklin et al., 2022; Mashatan et al., 2021).

The privacy-by-design embeds the data protection principles into the technical architecture of the AI systems from the outset rather than treating compliance as a post-deployment concern, consistent with the requirements of the GDPR and aligned with the risk-based classification approach of the EU AI Act (Danatzis et al., 2024; Vatankhah et al., 2024).

The human-in-the-loop governance ensures that human judgement remains integral to the high-stakes decisions, providing the oversight thresholds at which the autonomous action is paused and the human review is triggered, thereby preserving the meaningful human agency within the AI-augmented decision processes (Holzinger et al., 2025; Hughes et al., 2025).

Integrated Use Case: Agentic AI Deployment in a Mid-scale E-commerce Firm

To illustrate how the three layers of the RAF operate in practice and how the governance mechanisms of the responsible autonomy layer shape the behaviour of the operational and strategic AI functions, this section presents the integrated use case based on the hypothetical mid-scale e-commerce firm operating across multiple national markets. The scenario is designed to be representative of the deployment challenges faced by organisations in this sector, drawing on the patterns documented in the empirical literature reviewed above. The firm in question deploys the suite of AI agents across its customer engagement, pricing, procurement and compliance functions.

The scenario proceeds through the five stages, each activating the different RAF mechanisms and illustrating the interdependencies between the layers. Table 2 summarises the full scenario; the narrative below provides the analytical context.

Table 2. RAF Use Case: Agentic AI Deployment in an E-commerce Firm.

RAF Layer	Mechanism Activated	System Action	Governance Safeguard	Outcome
Operational autonomy	Data processing and analysis	AI pipeline detects the anomalous drop in the checkout conversions; RPA flags it for review	Audit log generated; data access governed by the Privacy-by-Design protocols	Rapid identification of the suspected fraudulent promotion code
Operational autonomy	Language understanding	NLP-enabled customer service agent handles the surge in complaint messages with personalised responses	HITL override available; escalation threshold triggers the human agent review for the complex cases	Customer queries resolved without the human bottleneck; escalations logged
Strategic autonomy	Adaptive decision-making	AI dynamically adjusts the pricing and inventory allocation based on the real-time demand signals	XAI module generates the explanation of the pricing decision for the compliance review	Revenue optimised; pricing decisions traceable and auditable
Strategic autonomy	Multi-agent coordination	Procurement agent renegotiates the supplier contracts autonomously as the supply chain disruption is detected	Accountability framework assigns the decision responsibility; blockchain records the contract modifications	Supply continuity maintained; agent actions documented and reversible
Responsible autonomy	Explainability (XAI) + HITL	Senior manager reviews the AI-generated explanation of the high-value credit decision and exercises override	Human override exercised; decision rationale stored for the regulatory submission	Regulatory compliance maintained; customer trust preserved

In Stage 1, the operational anomaly detection system drawing on the data processing and analysis mechanism identifies the statistically unusual decline in the checkout conversions over the 4-hour window. The system flags the pattern consistent with the misuse of the promotional discount code and generates the incident report automatically logged to the audit trail governed by the privacy-by-design protocols to ensure that the customer data involved is handled in compliance with the GDPR data minimisation requirements. The efficiency gain here is clear: the anomaly is identified within minutes rather than the hours or days that manual monitoring would require.

Stage 2 illustrates the language understanding mechanism operating within the responsible autonomy guardrails. As the promotional anomaly generates customer complaints, the NLP-enabled customer service agent processes the incoming messages and provides personalised responses resolving the majority without human escalation. The responsible autonomy layer requires, however, that the human-in-the-loop threshold be set: any complaint involving the claimed financial loss above the specified value is automatically escalated to the human agent with the AI draft response presented alongside the relevant context. This design preserves operational efficiency while ensuring that the consequential decisions retain human oversight.

In Stage 3, the strategic autonomy layer is activated as the adaptive decision-making agent receives the anomaly report and recalibrates the firm's dynamic pricing model. Drawing on the real-time demand data and the identified fraud pattern, the agent adjusts the prices across the affected product categories and reallocates the inventory to mitigate the revenue impact. Critically, the explainability mechanism of the responsible autonomy layer requires the agent to generate a structured explanation of each pricing adjustment specifying the variables that drove the decision, the alternatives considered and the expected revenue impact for review by the compliance function. This explanatory output serves both internal governance purposes and satisfies the interpretability requirements that would apply under the EU AI Act's high-risk categorisation of the AI systems used in the commercial decision-making.

Stage 4 shows the multi-agent coordination under the accountability framework. As the anomaly investigation shows that the fraudulent promotional code originated with the compromised third-party affiliate, the procurement agent autonomously initiates the contract renegotiation with the affiliate management system, suspending the affiliate's access and triggering the review of the associated supplier agreements. Each autonomous action taken by the procurement agent is recorded on the blockchain-based audit ledger, providing the immutable record of the decision sequence that can be reviewed by the legal counsel, compliance officers or the regulators if required. The accountability framework thus transforms the potential governance failure of the autonomous agent taking the consequential commercial actions without the traceable decision trail into a fully auditable process.

Stage 5 captures the human-in-the-loop mechanism at the strategic level. The senior manager is presented with the AI's recommendation to permanently delist the compromised affiliate and adjust the firm's affiliate programme terms.

The responsible autonomy layer provides the manager with the structured decision support package: the AI's recommendation, the explanatory rationale, the relevant contractual and regulatory context and the summary of the potential financial and reputational consequences of each available option. The manager exercises the human override, modifying the AI's recommendation to include the monitored probationary period rather than the immediate permanent delisting, which is the careful judgement that the AI's optimisation logic had not fully anticipated. This decision is documented, and the AI's learning model is updated to incorporate the revised outcome weighting.

Taken as a whole, this use case shows the three properties of the RAF that distinguish it from the existing governance approaches. First, the responsible autonomy layer operates continuously across all stages, not as the discrete compliance checkpoint but as the embedded governance architecture that shapes how the operational and strategic AI agents are designed and constrained. Second, the governance mechanisms—explainability, accountability, privacy-by-design and the human-in-the-loop are not alternatives but complements: they address the different aspects of the governance challenge and collectively provide the coverage that no single mechanism could offer. Third, the framework does not restrict the AI agency in ways that compromise the operational efficiency or the strategic adaptability; it channels that agency into the forms that are transparent, traceable and amenable to human review at the appropriate thresholds. The RAF's central argument that responsibility and autonomy can reinforce rather than constrain each other is illustrated concretely by the scenario.

Theoretical and Practical Contribution

The RAF's central contribution lies not in introducing a new theoretical perspective but in integrating three previously disconnected streams of literature on operational automation, strategic AI capability, and responsible governance into a single coherent framework. At the theoretical level, this integration is achieved by reconceptualising agentic AI agents through the combined lens of agency theory and sociotechnical systems theory, as entities that exercise delegated authority on behalf of organisational principals while remaining embedded within, and shaped by, the social and institutional structures of the organisations they serve. This synthesis does not displace either theory; it shows how their combination addresses a gap that neither fully resolves alone.

At the framework level, the RAF's primary contribution is the integration. As Table 3 illustrates, no existing framework spans the full range from operational automation through the strategic agentic capabilities to responsible governance. The RAF fills this gap not by adding the fourth dimension to the existing frameworks but by reconceiving the relationship between autonomy and responsibility: rather than treating them as competing values to be balanced, the RAF treats responsible design as the condition of possibility for sustainable autonomy. The AI system that is not accountable, transparent and aligned with human oversight is not fully autonomous in any meaningful sense; it is merely uncontrolled.

Table 3. Mechanisms at Different Layers of the Proposed Responsible Autonomy Framework.

RAF Layer	Mechanism	Supporting Literature
Operational autonomy	Data processing & analysis	Gong, 2025; Hnatyshyn et al., 2025; Murphy et al., 2024; Sallem et al., 2024; Van et al., 2025; Zamain & Subramanian, 2024
	Language understanding	Adam et al., 2021; Duesterwald et al., 2024; Hughes et al., 2025; Van et al., 2025
	Autonomous knowledge navigation	Nicoletti & Appolloni, 2025; Petrenko, 2025; Sifakis et al., 2025
	Robotic/workflow automation	Hughes et al., 2025; Mahler et al., 2019; Nicoletti & Appolloni, 2025
Strategic autonomy	Adaptive decision-making	Kaur & Prashar, 2025; Puhakainen et al., 2003; Shili & Anwar, 2025; Wang et al., 2025
	Multi-agent coordination	Pal et al., 2018; Qiu & Yang, 2021; Xu et al., 2023
	Strategic foresight	Alhyasat et al., 2025; Carayannis et al., 2025; Goncalves et al., 2025; How & Cheah, 2024
	Autonomous market engagement	Kwon et al., 2024; Minarsch et al., 2022; Rosaci & Sarne, 2012; Sümer et al., 2025; Zhao et al., 2025
Responsible autonomy	Explainability (XAI)	Chernyaeva et al., 2025; Jahan et al., 2025; Oprea & Bâra, 2025; Sanjammagari et al., 2026
	Accountability	Chen, 2015; Franklin et al., 2022; Mashatan et al., 2021; Saha et al., 2014; Triantafyllou, 2023; Triantafyllou & Radanovic, 2023
	Privacy-by-design	Bussone et al., 2020; Cuzzocrea & Soufargi, 2025; Danatzis et al., 2024; Patel et al., 2020; Xu et al., 2012
	Human-in-the-loop (HITL)	Chen et al., 2025; Egbengwu et al., 2025; Holzinger et al., 2024, 2025; Mitsiaki et al., 2025; Syed et al., 2025

At the practical level, the RAF provides the managers and policymakers with a structured model for the responsible scaling of agentic AI in digital commerce. The use case presented in Section ‘Integrated Use Case: Agentic AI Deployment in a Mid-scale e-commerce Firm’ shows that the framework is not merely prescriptive in the abstract but actionable in the specific deployment contexts. By mapping the specific governance mechanisms to the specific operational and strategic functions, the RAF reduces the distance between the governance theory and the governance practice, the distance that, as the literature review shows, has been the persistent limitation of the existing approaches.

Conclusion

The RAF has been developed as an integrative conceptual framework advancing the integration of AI in e-business. The framework moves beyond the narrow efficiency-driven automation to articulate the layered progression of operational

autonomy, strategic autonomy and responsible autonomy. The operational autonomy captures the automation of the repetitive and efficiency-oriented processes such as transaction processing, logistics optimisation and conversational interfaces, thereby establishing the foundations of scalability and cost reduction (Duesterwald et al., 2024; Gong, 2025). The strategic autonomy builds on this base by highlighting the proactive, adaptive and collaborative functions of the AI agents, particularly through multi-agent systems (MAS), advanced scenario modelling and autonomous decision-making in fast-moving environments (Huang, 2025; Queiroz et al., 2024). The responsible autonomy layer embeds governance, transparency and ethics directly into the architecture of the autonomy, ensuring that the e-businesses achieve not only the agility and efficiency but also the accountability, fairness and societal trust (Dignum, 2019; Hughes et al., 2025).

By unifying these layers, the RAF contributes to understanding the shift from automation to autonomy in e-business. It shows how the AI agents are no longer passive tools but increasingly act as proactive strategic partners while staying embedded within the ethical and regulatory guardrails. This integration positions the RAF as a marked theoretical and practical advancement in the ongoing digital transformation of commerce. Responsibility is not a constraint on autonomy; it is what makes autonomy sustainable.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Declaration of Generative AI and AI-assisted Technologies in the Manuscript Preparation Process

During the preparation of this work, the authors used QuillBot and ChatGPT to improve the writing style and to correct grammatical errors. After using these tools, the authors thoroughly reviewed and edited the content as needed and take full responsibility for the content of the published article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iDs

Mohammad Talha Siddiqui  <https://orcid.org/0000-0001-7165-4317>
Yusuf Kamal  <https://orcid.org/0000-0002-1557-8775>

References

- Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, 31(2), 427–445. <https://doi.org/10.1007/s12525-020-00414-7>
- Alhyasat, W. B. A. K., Alhyasat-Al-Balqa, E. B., & Khattab, S. A. (2025). Technology trends in strategic management in the AI era: Systematic literature review. *Human Systems Management*, 44(5), 764–781. <https://doi.org/10.1177/01672533251322396>

- Al-Mushayt, O. S. (2019). Automating e-government services with artificial intelligence. *IEEE Access*, 7, 146821–146829. <https://doi.org/10.1109/ACCESS.2019.2946204>
- Alshaketheep, K., Mansour, A. M., Al-Ma'aitah, M. M. L., Dabaghia, M. N., & Dabaghie, Y. M. (2024). Leveraging AI predictive analytics for marketing strategy: The mediating role of management awareness. *Journal of System and Management Sciences*, 14(2), 71–89. <https://doi.org/10.33168/JSMS.2024.0205>
- Ansari, M., Ali, S. A., Alam, M., Chaudhary, K., & Rakshit, S. (2023). Unlocking the power of explainable AI to improve customer experiences in e-commerce. In *AI-based data analytics: Applications for business management* (pp. 31–48). CRC Press. <https://doi.org/10.1201/9781032614083-3>
- Ashok, M., Madan, R., Joha, A., & Sivarajah, U. (2022). Ethical framework for artificial intelligence and digital technologies. *International Journal of Information Management*, 62, Article 102433. <https://doi.org/10.1016/j.ijinfomgt.2021.102433>
- Biswas, A., & Talukdar, W. (2025). *Building agentic AI systems: Create intelligent, autonomous AI agents that can reason, plan, and adapt*. Packt Publishing.
- Bohnsack, R., & De Wet, M. (2025). *AI is the strategy: From agentic AI to autonomous business models onto strategy in the age of AI* (arXiv:2506.17339). arXiv. <https://arxiv.org/abs/2506.17339>
- Bussone, A., Kasadha, B., Stumpf, S. C., Durrant, A. C., Tariq, D. S., Gibbs, J. J., Lloyd, K. C., & Bird, J. (2020). Trust, identity, privacy, and security considerations for designing a peer data sharing platform between people living with HIV. In *Proceedings of the ACM on Human-Computer Interaction*, 4(CSCW2), Article 148. <https://doi.org/10.1145/3415244>
- Carayannis, E. G., Dumitrescu, R., Falkowski, T., Papamichail, G., & Zota, N. R. (2025). Enhancing SME resilience through artificial intelligence and strategic foresight: A framework for sustainable competitiveness. *Technology in Society*, 81, Article 102835. <https://doi.org/10.1016/j.techsoc.2025.102835>
- Chen, J., Lim, C. P., Tan, K. H., Govindan, K., & Kumar, A. (2025). Artificial intelligence-based human-centric decision support framework: An application to predictive maintenance in asset management under pandemic environments. *Annals of Operations Research*, 350(2), 493–516. <https://doi.org/10.1007/s10479-021-04373-w>
- Chen, R. (2015). Autonomous tracing system for backward design in food supply chain. *Food Control*, 51, 70–84. <https://doi.org/10.1016/j.foodcont.2014.11.004>
- Chernyaeva, O., Lee, O. K. D., & Hong, T. (2025). From fake to AI-generated: Leveraging information manipulation theory and explainable AI for robust detection of manipulated reviews. *Decision Support Systems*, 197, Article 114522. <https://doi.org/10.1016/j.dss.2025.114522>
- Cuzzocrea, A., & Soufargi, S. (2025). AB-DOM: An algorithmic framework for supporting privacy-preserving big data publishing in big data lakes. *IEEE Transactions on Big Data*. Advance online publication. <https://doi.org/10.1109/TBDATA.2025.3570081>
- Danatzi, I., Chandler, J. D., Akaka, M. A., & Ng, I. C. L. (2024). Designing digital platforms for social justice: Empowering end users through the Dataswyft platform. *MIS Quarterly*, 48(4), 1771–1802. <https://doi.org/10.25300/MISQ/2024/18334>
- Dignum, V. (2019). Ensuring responsible AI in practice. In *Responsible artificial intelligence: How to develop and use AI in a responsible way* (pp. 93–105). Springer. https://doi.org/10.1007/978-3-030-30371-6_6
- Duesterwald, E., Isahagian, V., Jayaram, K. R., Kumar, R., Muthusamy, V., Oum, P., Thomas, G., & Venkateswaran, P. (2024). A conversational assistant framework for automation. In *Proceedings of the Middleware Industrial Track 2024* (pp. 1–7). Association for Computing Machinery. <https://doi.org/10.1145/3700824.3701093>

- Egbengwu, V., Garn, W., & Turner, C. J. (2025). Metaverse for manufacturing: Leveraging extended reality technology for human-centric production systems. *Sustainability*, 17(1), Article 280. <https://doi.org/10.3390/su17010280>
- Franklin, M., Ashton, H., Awad, E., & Lagnado, D. A. (2022). Causal framework of artificial autonomous agent responsibility. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 276–284). Association for Computing Machinery. <https://doi.org/10.1145/3514094.3534140>
- Goncalves, R. P., Spaniol, M. J., Rowland, N. J., & Rytter, N. G. M. (2025). Reflections on building an artificial intelligence bot to prepare students to engage in strategic conversations during foresight fieldwork. *Futures and Foresight Science*, 7(1), Article e202. <https://doi.org/10.1002/ffo2.202>
- Gong, S. (2025). Digital transformation of supply chain management in retail and e-commerce. *International Journal of Retail & Distribution Management*, 53(2), 1–19. <https://doi.org/10.1108/IJRDM-02-2023-0076>
- Gregor, S. (2006). The nature of theory in information systems. *MIS Quarterly*, 30(3), 611–642. <https://doi.org/10.2307/25148742>
- Hnatyshyn, L., Prokopyshyn, O., Maletska, O., Keleberda, T., & Pylypenko, K. (2025). Digital innovations in accounting as economic growth factors of an enterprise. *Scientific Bulletin of Mukachevo State University. Series Economics*, 12(1), 75–89. <https://doi.org/10.52566/msu-econ1.2025.75>
- Holzinger, A., Fister, I., Fister, I., Kaul, H. P., & Asseng, S. (2024). Human-centered AI in smart farming: Toward Agriculture 5.0. *IEEE Access*, 12, 62199–62214. <https://doi.org/10.1109/ACCESS.2024.3395532>
- Holzinger, A., Zatloukal, K., & Muller, H. (2025). Is human oversight to AI systems still possible? *New Biotechnology*, 85, 59–62. <https://doi.org/10.1016/j.nbt.2024.12.003>
- How, M., & Cheah, S. M. (2024). Forging the future: Strategic approaches to quantum AI integration for industry transformation. *AI*, 5(1), 290–323. <https://doi.org/10.3390/ai5010015>
- Huang, K. (2025). AI agents and business workflow. In *Agentic AI: Theories and practices* (pp. 135–166). Springer. https://doi.org/10.1007/978-3-031-90026-6_5
- Hughes, L., Dwivedi, Y. K., Malik, T., Shawosh, M., Albashrawi, M. A., Jeon, I., Dutot, V., Appanderanda, M., Crick, T., De', R., Fenwick, M., Gunaratnege, S. M., Jurcys, P., Kar, A. K., Kshetri, N., Li, K., Mutasa, S., Samothrakis, S., Wade, M., & Walton, P. (2025). AI agents and agentic systems: A multi-expert analysis. *Journal of Computer Information Systems*, 65(4), 489–517. <https://doi.org/10.1080/08874417.2025.2483832>
- Jahan, N., Ahamed, J., & Nandi, D. (2025). Enhancing e-commerce sentiment analysis with advanced BERT techniques. *International Journal of Information Engineering and Electronic Business*, 17(3), 49–61. <https://doi.org/10.5815/ijieeb.2025.03.04>
- Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4), 305–360. [https://doi.org/10.1016/0304-405X\(76\)90026-X](https://doi.org/10.1016/0304-405X(76)90026-X)
- Kaur, A., & Prashar, D. (2025). Web scraping for product recommendations: A review of techniques and applications. *Journal of Computer Science*, 21(6), 1425–1439. <https://doi.org/10.3844/jcssp.2025.1425.1439>
- Kottur, R. (2024). Responsible AI development: A comprehensive framework for ethical implementation in contemporary technological systems. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 10(6), 1553–1561. <https://doi.org/10.32628/cseit241061197>

- Kwon, D., Weiss, E., Kulshrestha, T., Chawla, K., Lucas, G. M., & Gratch, J. (2024). Are LLMs effective negotiators? Systematic evaluation of the multifaceted capabilities of LLMs in negotiation dialogues. In *Findings of the Association for Computational Linguistics: EMNLP 2024* (pp. 5391–5413). Association for Computational Linguistics. <https://doi.org/10.18653/v1/2024.findings-emnlp.310>
- Liu, X., Wu, L., Yu, J., & Lei, X. (2010). A holistic governance framework for e-business success. In *Proceedings of the 2010 International Conference on Management of e-Commerce and e-Government* (pp. 142–146). IEEE. <https://doi.org/10.1109/ICMcCG.2010.36>
- MacInnis, D. J. (2011). A framework for conceptual contributions in marketing. *Journal of Marketing*, 75(4), 136–154. <https://doi.org/10.1509/jmkg.75.4.136>
- Mahler, J., Matl, M., Satish, V., Danielczuk, M., DeRose, B., McKinley, S., & Goldberg, K. (2019). Learning ambidextrous robot grasping policies. *Science Robotics*, 4(26), Article eaau4984. <https://doi.org/10.1126/scirobotics.aau4984>
- Manda, V. K., Christy, V., & Rao, J. M. (2024). Ethical AI and decision-making in management leadership. In *Ethical dimensions of AI development* (pp. 197–226). IGI Global. <https://doi.org/10.4018/979-8-3693-4147-6.ch009>
- Mashatan, A. A., Lemieux, V. L., Lee, S., Szufel, P., & Roberts, Z. (2021). Usurping double-ending fraud in real estate transactions via blockchain technology. *Journal of Database Management*, 32(1), 27–48. <https://doi.org/10.4018/JDM.2021010102>
- Minarsch, D., Favorito, M., Hosseini, S. A., Turchenkov, Y., & Ward, J. (2022). Autonomous economic agent framework. In *Engineering Multi-Agent Systems* (Lecture Notes in Computer Science, Vol. 13190, pp. 237–253). Springer. https://doi.org/10.1007/978-3-030-97457-2_14
- Mitsiaki, A., Tsita, C., Dimitriou, N., & Tzovaras, D. (2025). A human-centric decision support system for zero-defect manufacturing enabled by human-in-the-loop learning. *Communications in Computer and Information Science*, 2582, 3–16. https://doi.org/10.1007/978-3-031-96199-1_1
- Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. *Journal of Business Ethics*, 167(2), 209–234. <https://doi.org/10.1007/s10551-019-04407-1>
- Murphy, B., Feeney, O., Rosati, P., & Lynn, T. (2024). Exploring accounting and AI using topic modelling. *International Journal of Accounting Information Systems*, 55, Article 100709. <https://doi.org/10.1016/j.accinf.2024.100709>
- Nicoletti, B., & Appolloni, A. (2025). A digital twin framework for enhancing human-agent AI-machine collaboration. *Journal of Intelligent Manufacturing*. Advance online publication. <https://doi.org/10.1007/s10845-025-02637-x>
- Oprea, S. V., & Băra, A. (2025). Diverse counterfactual explanations (DiCE) role in improving sales and e-commerce strategies. *Journal of Theoretical and Applied Electronic Commerce Research*, 20(2), Article 96. <https://doi.org/10.3390/jtaer20020096>
- Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science*, 3(3), 398–427. <https://doi.org/10.1287/orsc.3.3.398>
- Pal, G., Li, G., & Atkinson, K. M. (2018). Multi-agent big-data lambda architecture model for e-commerce analytics. *Data*, 3(4), Article 58. <https://doi.org/10.3390/data3040058>
- Patel, F. B., Jain, N., Menon, R., & Kodeboyina, S. (2020). Comparative study of privacy preserving-contact tracing on digital platforms. In *Proceedings of the 2020*

- International Conference on Communication and Information Processing* (pp. 137–141). IEEE. <https://doi.org/10.1109/ICCIS1257.2020.9247782>
- Petrenko, A. I. (2025). Agent-based approach to implementing artificial intelligence (AI) in service-oriented architecture (SOA). *System Research and Information Technologies*, 2025(1), 104–123. <https://doi.org/10.20535/SRIT.2308-8893.2025.1.08>
- Puhakainen, P., Candolin, C., & Kari, H. H. (2003). Using adaptive decision making based on incomplete trust in electronic commerce. In *Proceedings of the IASTED International Conference on Communication, Network, and Information Security* (pp. 191–194). ACTA Press.
- Qiu, L., & Yang, L. (2021). The research of co-evolution mechanisms between cross-border e-commerce and manufacturing cluster: An agent-based model. *E3S Web of Conferences*, 235, Article 03048. <https://doi.org/10.1051/e3sconf/202123503048>
- Queiroz, M., Anand, A., & Baird, A. (2024). Manager appraisal of artificial intelligence investments. *Journal of Management Information Systems*, 41(3), 682–707. <https://doi.org/10.1080/07421222.2024.2376383>
- Ramon-Poma, G. M., Macias-Cabrera, A. G., Yamil, A. A. P., & Jacobo, A. P. D. (2024). Impact of artificial intelligence on the accounting profession. In *Development of scientific research in the social sciences: An approach from the Latin American university* (Vol. 238, pp. 360–386). <https://doi.org/10.53486/issc2023.29>
- Rosaci, D., & Sarnè, G. M. L. (2012). A multi-agent recommender system for supporting device adaptivity in e-commerce. *Journal of Intelligent Information Systems*, 38(2), 393–418. <https://doi.org/10.1007/s10844-011-0160-9>
- Saha, G. K., Desai, M., Ghosh, A., & Saha, N. (2014). Digital signature modeling in e-business. In *Proceedings of the 11th IEEE International Conference on e-Business Engineering* (pp. 350–354). IEEE. <https://doi.org/10.1109/ICEBE.2014.67>
- Sallem, N. R. M., Hussain, N. H. C., Muhmad, S. N., Adnan, N. S., & Halmi, S. A. H. (2024). Artificial intelligence (AI) revolution in accounting and auditing field: A bibliometric analysis. *Advances in Social Sciences Research Journal*, 11(9.2), 64–78. <https://doi.org/10.14738/assrj.119.2.17402>
- Sanjamagari, H. S. G., Sougandhika, G. S., & Srinivasa Desikan, K. E. (2026). Bridging the trust gap: Leveraging explainable AI for personalized e-commerce recommendations. In *Lecture Notes in Computer Science* (Vol. 15706, pp. 225–236). Springer. https://doi.org/10.1007/978-981-96-8889-0_19
- Shankar, V. (2024). Managing the twin faces of AI: A commentary on ‘Is AI changing the world for better or worse?’ *Journal of Macromarketing*, 44(4), 892–899. <https://doi.org/10.1177/02761467241286483>
- Shili, M., & Anwar, S. (2025). Real-time electrical energy optimization in e-commerce systems based on IoT and mobile agents. *Information*, 16(7), Article 551. <https://doi.org/10.3390/info16070551>
- Sifakis, J., Li, D., Huang, H., Zhang, Y., Dang, W., Huang, R., & Yu, Y. (2025). *A reference architecture for autonomous networks: An agent-based approach*. arXiv. <https://arxiv.org/abs/2503.12871>
- Sümer, M. S., Özsoy, T., Yildirim Okay, F., & Kok, I. (2025). Smart agents as customers: A semi-autonomous digital commerce model for Industry 5.0. In *Proceedings of the 2025 International Conference on Human-Oriented Robotics and Automation*. IEEE. <https://doi.org/10.1109/ICHORA65333.2025.11017052>
- Syed, D. A., Quadri, W., Rahmani Choubbeh, N., Pinzone, M., & Gusmeroli, S. (2025). Approaching interoperability and data-related processing issues in a human-centric industrial scenario. *Communications in Computer and Information Science*, 2328, 21–34. https://doi.org/10.1007/978-3-031-78572-6_2

- Thapliyal, K., & Thapliyal, M. (2024). Chatbot-XAI: The new age artificial intelligence communication tool for e-commerce. *Studies in Computational Intelligence*, 1094, 77–100. https://doi.org/10.1007/978-3-031-55615-9_6
- Triantafyllou, S. (2023). Forward-looking and backward-looking responsibility attribution in multi-agent sequential decision making. In *Proceedings of the 22nd International Conference on Autonomous Agents and Multiagent Systems: Doctoral Consortium* (pp. 2952–2954). International Foundation for Autonomous Agents and Multiagent Systems.
- Triantafyllou, S., & Radanovic, G. (2023). Towards computationally efficient responsibility attribution in decentralized partially observable MDPs. In *Proceedings of the 22nd International Conference on Autonomous Agents and Multiagent Systems* (pp. 131–139). International Foundation for Autonomous Agents and Multiagent Systems.
- Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the Longwall method of coal-getting: An examination of the psychological situation and defences of a work group at the coal face. *Human Relations*, 4(1), 3–38. <https://doi.org/10.1177/001872675100400101>
- Van, N. D., Hoang, C. C., & Khoa, B. T. (2025). Bibliometric examination of artificial intelligence within the framework of e-commerce technology from 1996 to 2024. *Journal of Logistics, Informatics and Service Science*, 12(2), 138–150. <https://doi.org/10.33168/JLISS.2025.0209>
- Vannostrand, P. M., Hofmann, D. M., Ma, L., & Rundensteiner, E. A. (2024). Actionable recourse for automated decisions: Examining the effects of counterfactual explanation type and presentation on lay user understanding. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1682–1700). Association for Computing Machinery. <https://doi.org/10.1145/3630106.3658997>
- Vatankhah, S., Bamshad, V., Arici, H. E., & Duan, Y. (2024). Ethical implementation of artificial intelligence in the service industries. *The Service Industries Journal*, 44(9–10), 661–685. <https://doi.org/10.1080/02642069.2024.2359077>
- Wang, T. C., Guo, R.-S. A., Chen, C., & Li, C. (2025). Multi-stage data-driven framework for customer journey optimization and operational resilience. *Mathematics*, 13(7), Article 1145. <https://doi.org/10.3390/math13071145>
- Wirtz, B. W., Weyerer, J. C., & Kehl, I. (2022). Governance of artificial intelligence: A risk and guideline-based integrative framework. *Government Information Quarterly*, 39(4), Article 101685. <https://doi.org/10.1016/j.giq.2022.101685>
- Xu, H., Crossler, R. E., & Belanger, F. (2012). A value sensitive design investigation of privacy enhancing tools in web browsers. *Decision Support Systems*, 54(1), 424–433. <https://doi.org/10.1016/j.dss.2012.06.003>
- Xu, L., Proselkov, Y., Schoepf, S., Minarsch, D., Minaricova, M., & Brintrup, A. (2023). Implementation of autonomous supply chains for digital twinning: A multi-agent approach. *IFAC-PapersOnLine*, 56(2), 11076–11081. <https://doi.org/10.1016/j.ifacol.2023.10.812>
- Zamain, N. S. A., & Subramanian, U. (2024). The impact of artificial intelligence in the accounting profession. *Procedia Computer Science*, 238, 849–856. <https://doi.org/10.1016/j.procs.2024.06.102>
- Zhao, L., Cai, L., & Wang, J. (2025). Federated learning-based autonomous economic agent for portfolio allocation. *Mathematics*, 13(4), Article 427. <https://doi.org/10.3390/math13040427>

Antecedents of Environmentally Conscious Purchase Behavior: An Empirical Analysis

BIMTECH Business Perspectives
7(2) 193–211, 2026
© The Author(s) 2026
DOI: 10.1177/25819542261481411
bsp.bimtech.ac.in



Hareesh Thummalapally¹ , Anu Grover¹  and Basil Khalid¹

Abstract

Gauging the extent of consumers' propensity to opt for green products over conventional products has gained significant traction. Based on the theory of planned behavior, the study has been endeavored to evaluate the influence of social media determinants on environmentally conscious purchase behavior for green products. Partial Least Squares Structural Equation Modeling was conducted to analyze the data, collected from 342 respondents. The findings indicate that green self-identity and perceived consumer effectiveness positively influence environmental attitudes (EAs), which, in turn, drive environmentally conscious purchase intentions and ultimately lead to environmentally conscious purchasing behavior. However, trust in social media was found to have an insignificant impact on EAs. The insights from the study can assist business professionals in developing targeted marketing strategies and offer valuable policy suggestions to government and regulatory agencies.

Keywords

Green products, theory of planned behavior, social media, green self-identity, perceived consumer effectiveness, purchase intention, purchase behavior

¹ Department of Financial Administration, School of Management, Central University of Punjab, Bathinda, Punjab, India

Corresponding author:

Anu Grover, Department of Financial Administration, School of Management, Central University of Punjab, Bathinda, Punjab 151401, India.
E-mail: groverannu10@gmail.com



Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 License (<http://www.creativecommons.org/licenses/by-nc/4.0/>) which permits non-Commercial use, reproduction and distribution of the work without further permission provided the original work is attributed.

Introduction

In recent decades, the rise in particulate matter, irregular weather patterns, resource depletion, and worldwide environmental challenges have heightened consumers' awareness regarding environmental issues (Capstick et al., 2015; Lavuri et al., 2023; Mishal et al., 2017). Previously, consumers mainly focused on eco-friendly initiatives, often overlooking the environmental impact of production and consumption activities, even though these processes contributed to pollution. However, this perspective has shifted in recent years (Kim & Lee, 2023). Individuals are now more aware of the broader environmental implications and actively challenge the production of polluting goods while demanding greater accountability from governments and industries to adopt sustainable practices (Kim, 2014). As a result, environmentalism has become a critical signal, driving the growth of green sustainability and pushing businesses to adopt eco-friendly practices (Arora et al., 2023; Kautish et al., 2019). The concept of environmentally responsible behavior has emerged as a critical focus in modern marketing strategies for researchers and marketers (Jaiswal & Singh, 2018; Tsai et al., 2020). As consumers become increasingly aware of eco-sustainability, their purchasing choices reflect a growing commitment to sustainable practices. This trend has opened up new avenues for research into sustainable consumer behavior, providing a fertile ground for exploring eco-conscious behaviors in emerging markets (Kumar et al., 2017; Lavuri et al., 2023; Prakash & Pathak, 2017).

Moreover, to meet the growing demands of the 21st century, particularly in addressing the climate crisis, marketers are swiftly developing effective environmentally sustainable marketing strategies (Han & Xu, 2020). Organizations increasingly leverage social networks like Facebook, Instagram, and Twitter to promote green product lines, aligning with the push for sustainability (Arora et al., 2023; Grilli & Curtis, 2021). This strategy is particularly effective as these social media platforms heavily influence consumer attitudes and purchasing intentions toward green products. As of 2024, digital social media platforms have attracted more than five billion users worldwide, showing the growing impact of these platforms on daily life and consumer behavior (Petrosyan, 2024).

Organizations have the potential to significantly increase the market reach of sustainable products by actively promoting them on social media (Bedard & Tolmie, 2018; Zhao et al., 2019). This is particularly relevant in markets like India, where consumers are strongly inclined toward eco-friendly products (Kautish et al., 2019; Yadav & Pathak, 2017). Previous studies consistently indicate that sustainable values are crucial in driving green procurement (Kautish, 2020; Kautish & Dash, 2017; Kautish & Sharma, 2018). Additionally, understanding how social media marketing influences consumer intentions to purchase sustainable products is essential for effectively leveraging these platforms to enhance the market penetration of eco-friendly offerings. Hamid et al. (2017) and Tlebere et al. (2016) have pointed out a significant research gap regarding the media's impact on various sustainable initiatives, indicating a lack of insights into how social media influences environmentally conscious behaviors. To conduct an effective campaign that promotes socially responsible behavior, it is crucial to understand the underlying dynamics that facilitate this process (Kaur & Chahal,

2018; Singh Kushwaha, 2015). Investigating the antecedents of environmentally conscious purchase behavior (EPB) is essential for bridging the intention-behavior gap—a crucial aspect that this study addresses.

Despite increased awareness of green products, there remains a significant gap between individuals' intentions and their actual behavior. Characteristics of individuals displaying a "green gap" include a lack of justification and social awareness, emphasizing the importance of connecting consumers with green products to bridge this disparity. Therefore, this study aims to bridge this gap by measuring the effect of the main determinants of EPB in the domain of the social media environment. The study considers three research questions (RQs).

RQ1: Do selected determinants (green self-identity [GSI], perceived consumer effectiveness [PCE], and trust in social media [TS]) influence environmental attitudes (EAs) toward green products?

RQ2: Does EA impact environmentally conscious purchase intention?

RQ3: Does environmentally conscious purchase intention influence EPB? The study utilizes the theory of planned behavior (TPB) to understand consumers' EPB by adding variables related to social media, that is, TS, PCE and GSI.

The present research is systematized in the respective orders: First, the theoretical background of the study is addressed. Next, the literature review and development of the proposed hypothesis are discussed. The methodology and outcome of the hypothesis were thoroughly explained in the subsequent sections. The final section of the article addresses the implications, limitations, and future research directions.

Theoretical Background and Conceptual Framework

The TPB has proven to be a pivotal model in understanding consumer behavior, particularly in relation to environmentally conscious actions. The model, originally proposed by Ajzen (1985), emphasizes the role of attitudes, subjective norms, and perceived behavioral control in shaping consumer intentions. Over the years, numerous studies have utilized TPB to explore green purchase intentions across various sectors. For example, Shalender and Sharma (2021) applied TPB to examine how EAs influence consumer adoption intentions for electric vehicles in India, extending the model to include environmental concern. Shukla (2019) also employed TPB to evaluate Indian millennials' intent to purchase eco-friendly products, highlighting the significant influence of the model's core predictors: attitudes, subjective norms, and perceived control on behavioral intentions. Further, in the Indian context, Yadav and Pathak (2017) demonstrated its applicability in understanding consumer behavior toward green products. These studies collectively affirm TPB's effectiveness in capturing the key drivers of green purchase intentions across different demographic groups and sectors.

This study focuses on evaluating the purchase behavior of green products, particularly within India. The conceptual framework integrates insights from TPB while adding variables that account for social media's influence on consumer

behavior, providing a robust model to understand how EPB are shaped by GSI, TS, and PCE. By identifying the significant impact of these factors, this study offers valuable insights for marketers and policymakers aiming to promote sustainable consumption through targeted social media strategies and enhanced consumer engagement.

Literature Review and Hypothesis Development

GSI and EA

GSI extends the concept of self-identity to encompass the consumption of sustainable products, shaping behavior through alignment with personal, role, and social identities toward green practices. Self-identity operates as a guiding force influenced by both internal standards and societal norms, where intrinsic motivations play a pivotal role in individual decision-making processes (Sharma et al., 2022; Stets & Burke, 2003; Udall et al., 2021). Likewise, self-identity exerts a profound impact on environmental protection intentions, offering novel perspectives for the development of green policies and initiatives aimed at enhancing sustainability efforts (Mancha & Yoder, 2015). The interplay between green self-concept and self-identity significantly shapes intentions to purchase eco-friendly products, with self-identity serving as a crucial mediator in this relationship (Sharma et al., 2020). This positive influence of GSI encourages consumers to prioritize purchasing environmentally friendly products, establishing it as a precursor to their intention to buy green (Palomino Rivera & Barcellos-Paula, 2024).

According to Hustvedt and Dickson (2009), self-identity as a “green consumer” or “organic consumer” strongly influences attitudes and behaviors toward environmentally friendly products, highlighting its critical role in predicting and shaping consumer environmental actions. The alignment between consumers’ self-identities and their attitudes toward green products is consistently documented in previous research (Bartels & Hoogendam, 2011; Michaelidou & Hassan, 2008). Additionally, several studies have shown that GSI affects purchase intentions both directly and indirectly through various context-specific factors (Barbarossa et al., 2015; Confente et al., 2020; Whitmarsh & O’Neill, 2010). Based on the above, the following hypothesis is proposed:

H_1 : GSI has a significant influence on EA toward green products.

PCE and EA

PCE reflects the individuals’ confidence in the efficacy of their actions in addressing environmental issues (Munir et al., 2023). This concept involves assessing the consumer’s ability to appreciate sustainable development outcomes and contribute to their achievement through specific behaviors (Hanss & Doran, 2020). Consumers who believe their actions substantially impact the environment are more likely to engage in and sustain environmentally friendly practices, translating their intentions into actual actions (Affecting et al., 2024).

PCE is positively correlated with EA (Heo & Muralidharan, 2019), serving as a building block for stronger and more stable attitudes toward environmentally conscious behaviors (Vermeir & Verbeke, 2006). PCE enhances consumers' internal focus, fostering their belief in the potential efficacy of their actions in safeguarding and contributing to environmental preservation (Kumar et al., 2022). With stronger PCE beliefs, favorable EAs are more likely to lead to pro-environmental actions (Berger & Corbin, 1992). Hence, this study assumes the following hypothesis:

H_2 : PCE has a significant influence on EA toward green products.

TS Media and EA

Mataram (2020) described the term social media trustworthiness as representing consumers' beliefs about the authenticity and credibility of advertising content or sources. When individuals have an intense perception of the integrity of social media platforms, they are more likely to engage in environmentally conscious content (Han & Xu, 2020). Likewise, Xie and Madni (2023) stated that social media plays a stimulating role in shaping the subjective norms and perceptions of green consumption among the younger generation. Additionally, the relationship between social media and sustainable attitudes is characterized by the potential for prolonged social media usage to positively influence users' EAs due to exposure to eco-friendly content and community engagement (Zafar et al., 2021).

As social media contributes to increased knowledge about product development or processes, consumers are more likely to change their purchasing intentions and attitudes toward green products (Nekmahmud et al., 2022). TS media boosts consumers' confidence in eco-friendly products, fostering sustainable purchasing behaviors by facilitating the exchange of information about environmental benefits. This shapes their EAs and leads them toward more sustainable practices (Han & Xu, 2020; Zafar et al., 2021). Considering this, the following hypothesis is proposed:

H_3 : TS media has a significant influence on EA toward green products.

EA and Environmentally Conscious Purchase Intention

Individuals' EAs are an integral component of the sustainable decision-making process. It pertains to cognitive evaluations, affective responses, as well as behavioral tendencies that guide pro-environmental behavior (Kaiser et al., 2017). Gifford and Sussman (2012) noted that these attitudes are distinct from related constructs like beliefs, values, and personal norms, yet they play a crucial role in guiding behaviors for environmental sustainability. This mindset is shaped by beliefs, affect, and behavioral intentions regarding environmentally related activities (Singh & Gupta, 2013). Kotchen and Reiling (2000) opined that positive EAs are strong predictors of environmentally conscious buying habits; similarly, Kaiser et al. (2007) found that these attitudes shape intentions toward actions aligned with environmental preservation beliefs and values.

Consumers with a positive attitude toward environmental behavior are motivated to purchase green products, as supported by several studies indicating that EAs directly influence the purchase intentions of youth (Yadav & Pathak, 2017). In light of these considerations, we advance the following hypothesis:

H_4 : EA has a significant influence on environmentally conscious purchase intention toward green products.

Environmentally Conscious Purchase Intention and EPB

Environmentally conscious consumer behavior, characterized by consumers' preference for environmentally benign products, plays a crucial role in addressing environmental challenges (Heo & Muralidharan, 2019). This behavior is closely linked to environmental purchase intention, which is well-documented in the literature as a predictor of actual behavior. According to Ajzen (1985), intention, influenced by attitudes and subjective norms, strongly predicts consumer behavior. This intention is further reinforced by great concern for environmental and social issues, motivating eco-friendly purchasing behavior.

Further, Lazaroiu et al. (2019) reported that environmentally conscious purchase intentions are shaped by pro-EAs, beliefs, and perceived green accountability, moderated by product value. Consumer preference for green products is bolstered by ecological knowledge, which enhances perception of product quality and company credibility, highlighting the crucial role of green purchase intention in promoting sustainability (Costa et al., 2021). Despite variations across contexts, numerous studies affirm the positive relationship between intention and behavior, especially in environmental contexts (Shabnam, 2013; Thøgersen & Ölander, 2006). These findings underscore the significant role of consumer intention and environmental consciousness in promoting environmentally sustainable behaviors. From the preceding analysis, the following hypothesis is suggested:

H_5 : Environmentally conscious purchase intention has a significant influence on EPB toward green products.

Research Methodology

Construct Operationalization

A closed-ended research questionnaire was designed to test the relationships proposed in the conceptual model (Figure 1). All the measures used in the study were adapted from previous literature, and some items have been revised to ensure their context aligns with the objectives of the study. To assess GSI, scales developed by Kumar et al. (2023) and Palomino Rivera and Barcellos-Paula (2024) were adapted. The PCE was measured using scales from Polisetty et al. (2024) and Sun and Wang (2020). TS media was gauged through scales adapted from Pop and Zsuzsa (2020) and Xie and Madni (2023). EA was assessed using scales from

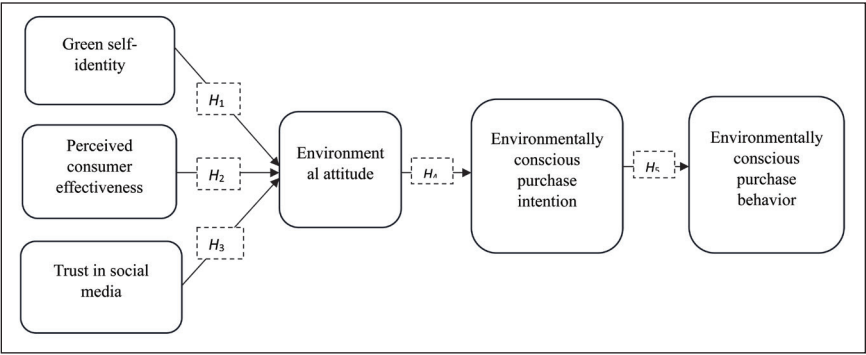


Figure 1. Depicts the Conceptual Model.

Kaur and Gupta (2022), Malik and Singhal (2017) and Uddin and Khan (2018). The scales for environmentally conscious purchase intention were adapted from Moslehpour et al. (2021), Sun and Xing (2022), and Yadav and Pathak (2017). Finally, EPB was measured using scales developed by Kumar and Pandey (2023) and Silintowe and Sukresna (2022).

Sampling Design and Data Collection

The present study adopted a purposive sampling approach, enabling selective targeting of participants with substantial knowledge and experience regarding green products, which aligns with the study’s emphasis on informed consumer behavior. This approach was selected to ensure the relevance of the data collected. The survey population comprised Indian green buyers, and data collection was conducted online via various social media platforms frequented by individuals who purchase green products. The study targeted a sample size of 342 respondents, including 187 males (54.68%) and 155 females (45.32%), consistent with Hair et al. (2014) who propose a sample size of 5 to 10 respondents per item for robust analysis.

SmartPLS software was utilized for data analysis, as it is particularly well-suited for complex models, small to medium sample sizes, and simultaneously examining multiple relationships among observed and latent variables. These capabilities make it an appropriate choice for investigating the multifaceted factors influencing consumers’ green product purchasing behavior.

Data Analysis and Results

Demographic Profile

The demographic profile analysis depicts that most respondents were male, with a number of 187 (54.68%), while females constituted 155 individuals (45.32%). The majority of the participants were between the ages of 21 and 30, indicating the young adult demographic profile. The respondents’ education qualifications

Table 1. Respondents' Demographic Analysis.

Demographic Variables	Frequency	Percentage
Gender		
Male	187	54.68%
Female	155	45.32%
Age		
18–20	66	19.3%
21–30	198	57.89%
31–40	58	16.96%
41–50	16	4.68%
Above 50	4	1.17%
Education Qualification		
Elementary School	4	1.17%
10th	12	3.51%
10th +2	37	10.82%
Diploma	3	0.88%
Graduation	195	57.02%
Post-graduation	89	26.02%
PhD	2	0.58%
Occupational Status		
Student	187	54.68%
Businessman	24	7.02%
Private employee	73	21.35%
Government employee	12	3.51%
Professional	18	5.26%
Housewife	25	7.31%
Others	3	0.88%
Living Area		
Rural	109	31.87%
Semi-urban	147	42.98%
Urban	86	25.14%

include 195 graduates (57.02%), 89 postgraduates (26.02%), 37 with 10+2 (10.82%), 12 with 10th grade, 4 with elementary school, 3 with diplomas, and 2 with PhDs. Most respondents were students (54.68%), followed by private employees (21.35%), housewives (7.31%), businessmen (7.02%), professionals (5.26%), government employees (3.51%), and others (0.88%). Most respondents lived in semi-urban areas (42.98%), followed by rural areas (31.87%) and urban areas (25.14%) (see Table 1).

Measurement Model

The measurement model was evaluated for reliability and validity following established guidelines (Diamantopoulos et al., 2012; Drolet & Morrison, 2001). Each indicator's factor loading was assessed and exceeded the recommended threshold of 0.70 (Hair et al., 2019), indicating that the items effectively measure their respective constructs. However, one item, EPB1, loaded slightly below the 0.70 threshold but was retained due to its theoretical relevance and contribution to the construct (Hair et al., 2017). Three measurement items, GSI3, PCE4, and

EA5, were excluded due to cross-loadings, which indicated issues with discriminant validity. Reliability and validity assessments were conducted to ensure that the measurement instruments consistently and accurately represent the underlying constructs. Furthermore, discriminant validity was evaluated using the criterion proposed by Fornell and Larcker (1981).

Reliability and Validity Analysis

Construct Reliability

Table 2 provides a construct reliability analysis, including Cronbach’s Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) for the constructs studied in this research. Initially, the study computed CA values ranging from 0.834 to 0.947, all exceeding the threshold of 0.70 (Hair et al., 2017). All constructs exhibit good to excellent internal consistency, with EA showing the highest consistency. Further, the CR values were measured, which ranged from 0.735 to 0.925, all greater than the threshold value of .70 established by Fornell and Larcker (1981) (see Table 2).

Table 2. Factor Loadings, Reliability and Convergent Validity.

Construct Items	Factor Loadings	Alpha	CR	AVE
GSI		0.929	0.944	0.738
GSI1	0.858			
GSI2	0.841			
GSI4	0.834			
GSI5	0.876			
GSI6	0.874			
GSI7	0.872			
PCE		0.897	0.929	0.765
PCE1	0.884			
PCE2	0.845			
PCE3	0.891			
PCE5	0.877			
TS		0.92	0.936	0.676
TS1	0.815			
TS2	0.811			
TS3	0.832			
TS4	0.842			
TS5	0.750			
TS6	0.846			
TS7	0.857			
EA		0.947	0.958	0.79
EA1	0.908			
EA2	0.911			
EA3	0.901			
EA4	0.906			

(Table 2 continued)

(Table 2 continued)

Construct Items	Factor Loadings	Alpha	CR	AVE
EA6	0.854	0.928	0.943	0.735
EA7	0.852			
EPI				
EPI1	0.869			
EPI2	0.873			
EPI3	0.877			
EPI4	0.864	0.834	0.883	0.603
EPI5	0.819			
EPI6	0.838			
EPB				
EPB1	0.661			
EPB2	0.827			
EPB3	0.852			
EPB4	0.797			
EPB5	0.729			

Table 3. Discriminant Validity.

	GSI	PCE	TS	EA	EPI	EPB
GSI	0.859					
PCE	0.855	0.874				
TS	0.725	0.76	0.822			
EA	0.846	0.864	0.686	0.889		
EPI	0.778	0.829	0.783	0.807	0.857	
EPB	0.716	0.721	0.724	0.707	0.758	0.776

Convergent Validity

To assess the convergent validity of scale items, the study employed the AVE. Each construct's AVE value is above the 0.50 threshold proposed by Fornell and Larcker (1981), indicating that the constructs explain more than 50% of the variance in their respective items. Thus, the constructs collectively exhibit robust convergent validity, as evidenced by their high AVE values and predominantly strong item loadings.

Discriminant Validity

Table 3 represents the discriminant validity assessment of the study constructs using the Fornell-Larcker criterion. According to Fornell and Larcker (1981), discriminant validity is confirmed when the square root of the AVE for each construct is greater than its correlations with all other constructs. The diagonal values represent the square roots of the AVE and are higher than the off-diagonal correlations in the corresponding rows and columns. Specifically, the values are as follows: GSI (0.859), PCE (0.874), TS (0.822), EA (0.889), EPI (0.857), and EPB (0.776). This indicates that each construct shares more variance with its indicators than with other constructs, thereby establishing discriminant validity.

Table 4. Structural Model Results.

Path	Beta Coefficient	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	p Values	Decision
GSI → EA	0.401	0.401	0.061	6.602	0	Supported
PCE → EA	0.522	0.521	0.056	9.377	0	Supported
TS → EA	−0.001	0.001	0.043	0.029	.977	Not supported
EA → EPI	0.807	0.807	0.025	32.742	0	Supported
EPI → EPB	0.758	0.76	0.029	26.34	0	Supported

Structural Model Analysis

The next step involved examining the structural model to validate the relationships among the constructs. The study assessed the impact of GSI, PCE, and TS media on EA, as well as the impact of attitude on purchase intention and the subsequent impact of intention on purchase behavior.

The structural model analysis reveals that GSI has a moderate positive relationship with EA (coefficient = 0.401, T-statistic = 6.602, $p = 0$). PCE shows a strong positive relationship with EA (coefficient = 0.522, T-statistic = 9.377, $p = 0$), indicating that individuals who believe their actions impact environmental conservation have stronger EAs. However, TS has a negligible relationship with EA (coefficient = −0.001, T-statistic = 0.029, $p = .977$). Additionally, EA strongly predicts environmentally conscious purchase intention (EPI) (coefficient = 0.807, T-statistic = 32.742, $p = 0$), and EPI significantly influences EPB (coefficient = 0.758, T-statistic = 26.34, $p = 0$), confirming the impact of intentions on actual behavior (see Table 4).

Discussion

The proliferation of sustainable practices has a profound effect on the perception of individuals toward green products. In recent years, there has been a significant shift in consumer attitudes and behaviors toward environmental protection (Zhuang et al., 2021). With growing concerns about the state of the natural environment, consumers are actively seeking out products that have minimal impact on the ecology. Additionally, social media serves a vital function in fostering environmental awareness and effecting positive behavioral change. This study was conducted to explore the influence of social media determinants on green products and their effect on consumers' EPB. Our conceptual framework is based on the TPB. Previous studies show a direct correlation between GSI and the intent to purchase eco-friendly products (Kumar et al., 2023). This suggests that people who see themselves as environmentally friendly are more likely to buy green products.

The findings of the study indicate that those who strongly associate themselves with environmentally friendly behaviors are more likely to hold a positive attitude

toward the environment. Similarly, the positive relationship between PCE and EA supports the idea that individuals who believe their actions can impact environmental conservation tend to have significantly stronger EAs. In addition to the findings described above, the study found that TS media exhibits an insignificant relation with EA, reflecting consumers' skepticism toward environmental messages and questioning the promises and commitment of companies. Research indicates that the widespread use of greenwashing can erode trust in environmental communication, impeding meaningful engagement and behavioral change among social media users concerned about environmental issues (Parguel et al., 2011).

The analysis further demonstrates that EA has a strong positive relationship with EPI, validating the strong influence of EAs on the intention to make environmentally friendly purchases. Consumer attitudes have a significant impact on green purchase intentions. Positive attitudes toward green products increase the likelihood of purchase (Moslehpour et al., 2023). Additionally, Cottrell (2003) and Choi and Kim (2021) underscore the influence of environmental consciousness on purchasing intentions, demonstrating that it consistently drives the propensity to purchase eco-friendly products. The results of this study reveal that purchase intention strongly translates into actual EPB, as evidenced by the path coefficient of 0.758 between EPI and EPB.

Theoretical Implications

The present study has significant theoretical implications. This study advances the understanding of consumers' EPB for green products by integrating social media determinants in the framework of TPB. Traditionally, the TPB accentuates the significance of attitudes, subjective norms, and perceived behavioral control in determining behavioral intentions and actual behaviors. The present study augments the theory by elucidating the impact of digital platforms, especially social media, on these core variables by incorporating GSI and PCE to better explain EPB.

Thus, this study represents a valuable addition to the exploration of environmentally conscious purchasing behavior and examination of the interrelations among peripheral social media elements to identify a new phenomenon.

Practical Implications

This research could furnish valuable insights into social media marketing and consumer behavior concerning environmentally sustainable products. These insights can assist business professionals in formulating effective marketing strategies and providing pertinent policy recommendations to governmental bodies. The findings of the study recommended that GSI and PCE were found to have a significant impact on EA, which may help marketers develop strategies aimed at fostering strong EPB. Because TS does not have a significant impact on EA, organizations are required to put their talents into perfecting the art of developing authentic and credible social media messages to win the trust of their customers. Lack of customers' TS media can become a bottleneck in shaping positive

attitudes toward green products. Furthermore, EA has a strong impact on EPI, and EPI is closely connected with the EPB; therefore, marketers must give active consideration to the variables proposed in the model while chalking out effective marketing policies.

The research indicates that marketing strategies focusing on enhancing personal impact awareness and providing credible and clear information are crucial for fostering a sustainable consumer culture. To develop effective sustainable strategies, businesses must understand the factors that motivate consumers to adopt environmentally conscious behavior. Educating customers about environmental threats can help cultivate a GSI, encouraging more sustainable consumer choices. These findings offer valuable guidance for brands and marketing practitioners in identifying effective strategies to promote green consumer behavior, optimizing marketing budgets, and developing robust relationships with consumers to support environmental sustainability initiatives.

Limitations and Future Research Directions

The study has a few constraints that limit the scope of potential research in the field of environmentally responsible consumption, which should be addressed in future studies. First, the data were collected at a single point in time, which may not capture the dynamic nature of consumer attitudes and behaviors. Longitudinal studies could offer valuable insights into how these factors evolve over time. Additionally, the study focused on specific variables like GSI, PCE, and EA, but did not consider other potentially influential factors such as cultural values, economic conditions, and political influences. Expanding the scope to include these factors could offer a more comprehensive understanding of what drives environmentally conscious behavior.

Future research should aim to include a more diverse sample in terms of age, gender, socioeconomic status, and geographic location to enhance the generalizability of the findings. Furthermore, comparing the effectiveness of different types of influencers (virtual vs. human) across various social media platforms can provide deeper insights into the most effective strategies for different demographics.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

ORCID iDs

Hareesh Thummalapally  <https://orcid.org/0000-0002-3072-5630>

Anu Grover  <https://orcid.org/0009-0009-9393-8973>

References

- Affecting, F., Intention, P., Green, O. F., Products, C., Generation, Y., Ho, I. N., & Minh, C. H. I. (2024). *Factors Affecting Purchase Intention of Green Cosmetics Products Toward*, 05(01), 6830–6836.
- Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckmann (Eds.), *Action control: From cognition to behavior* (pp. 11–39). Springer. https://doi.org/10.1007/978-3-642-69746-3_2
- Arora, N., Rana, M., & Prashar, S. (2023). How does social media impact consumers' sustainable purchase intention? *Review of Marketing Science*. <https://doi.org/10.1515/roms-2022-0072>
- Barbarossa, C., Beckmann, S. C., De Pelsmacker, P., Moons, I., & Gwozdz, W. (2015). A self-identity based model of electric car adoption intention: A cross-cultural comparative study. *Journal of Environmental Psychology*, 42, 149–160. <https://doi.org/10.1016/j.jenvp.2015.04.001>
- Bartels, J., & Hoogendam, K. (2011). The role of social identity and attitudes toward sustainability brands in buying behaviors for organic products. *Journal of Brand Management*, 18(9), 697–708. <https://doi.org/10.1057/bm.2011.3>
- Bedard, S. A. N., & Tolmie, C. R. (2018). Millennials' green consumption behaviour: Exploring the role of social media. *Corporate Social Responsibility and Environmental Management*, 25(6), 1388–1396. <https://doi.org/10.1002/csr.1654>
- Berger, I. E., & Corbin, R. M. (1992). Perceived consumer effectiveness and faith in others as moderators of environmentally responsible behaviors. *Journal of Public Policy & Marketing*, 11(2), 79–89. <https://doi.org/10.1177/074391569201100208>
- Capstick, S., Whitmarsh, L., Poortinga, W., Pidgeon, N., & Upham, P. (2015). International trends in public perceptions of climate change over the past quarter century. *Wiley Interdisciplinary Reviews: Climate Change*, 6(1), 35–61. <https://doi.org/10.1002/wcc.321>
- Choi, S., & Kim, I. (2021). Sustainability of nature walking trails: predicting walking tourists' engagement in pro-environmental behaviors. *Asia Pacific Journal of Tourism Research*, 26(7), 748–767. <https://doi.org/10.1080/10941665.2021.1908385>
- Confente, I., Scarpi, D., & Russo, I. (2020). Marketing a new generation of bio-plastics products for a circular economy: The role of green self-identity, self-congruity, and perceived value. *Journal of Business Research*, 112, 431–439. <https://doi.org/10.1016/j.jbusres.2019.10.030>
- Costa, C. S. R., Costa, M. F. da, Maciel, R. G., Aguiar, E. C., & Wanderley, L. O. (2021). Consumer antecedents towards green product purchase intentions. *Journal of Cleaner Production*, 313, Article 127964. <https://doi.org/10.1016/j.jclepro.2021.127964>
- Cottrell, S. P. (2003). Influence of sociodemographics and environmental attitudes on general responsible environmental behavior among recreational boaters. *Environment and Behavior*, 35(3), 347–375. <https://doi.org/10.1177/0013916503035003003>
- Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., & Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: A predictive validity perspective. *Journal of the Academy of Marketing Science*, 40(3), 434–449. <https://doi.org/10.1007/s11747-011-0300-3>
- Drolet, A. L., & Morrison, D. G. (2001). Do we really need multiple-item measures in service research? *Journal of Service Research*, 3(3), 196–204. <https://doi.org/10.1177/109467050133001>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>

- Gifford, R., & Sussman, R. (2012). Environmental attitudes. In S. D. Clayton (Ed.), *The Oxford handbook of environmental and conservation psychology* (pp. 65–80). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199733026.013.0004>
- Grilli, G., & Curtis, J. (2021). Encouraging pro-environmental behaviours: A review of methods and approaches. *Renewable and Sustainable Energy Reviews*, 135, Article 110039. <https://doi.org/10.1016/j.rser.2020.110039>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage.
- Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2), 107–123. <https://doi.org/10.1504/IJMDA.2017.087624>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hamid, S., Ijab, M. T., Sulaiman, H., Md. Anwar, R., & Norman, A. A. (2017). Social media for environmental sustainability awareness in higher education. *International Journal of Sustainability in Higher Education*, 18(4), 474–491. <https://doi.org/10.1108/IJSHE-01-2015-0010>
- Han, R., & Xu, J. (2020). A comparative study of the role of interpersonal communication, traditional media and social media in pro-environmental behavior: A China-based study. *International Journal of Environmental Research and Public Health*, 17(6), Article 1883. <https://doi.org/10.3390/ijerph17061883>
- Hanss, D., & Doran, R. (2020). Perceived consumer effectiveness. In W. Leal Filho, A. M. Azul, L. Brandli, P. G. Özuyar, & T. Wall (Eds.), *Responsible consumption and production* (pp. 535–544). Springer. https://doi.org/10.1007/978-3-319-95726-5_28
- Heo, J., & Muralidharan, S. (2019). What triggers young millennials to purchase eco-friendly products? The interrelationships among knowledge, perceived consumer effectiveness, and environmental concern. *Journal of Marketing Communications*, 25(4), 421–437. <https://doi.org/10.1080/13527266.2017.1303623>
- Hustvedt, G., & Dickson, M. A. (2009). Consumer likelihood of purchasing organic cotton apparel: Influence of attitudes and self-identity. *Journal of Fashion Marketing and Management*, 13(1), 49–65. <https://doi.org/10.1108/13612020910939879>
- Jaiswal, D., & Singh, B. (2018). Toward sustainable consumption: Investigating the determinants of green buying behaviour of Indian consumers. *Business Strategy and Development*, 1(1), 64–73. <https://doi.org/10.1002/bsd2.12>
- Kaiser, F. G., Oerke, B., & Bogner, F. X. (2007). Behavior-based environmental attitude: Development of an instrument for adolescents. *Journal of Environmental Psychology*, 27(3), 242–251. <https://doi.org/10.1016/j.jenvp.2007.06.004>
- Kaur, A., & Chahal, H. S. (2018). Role of social media in increasing environmental issue awareness. *Researchers World: Journal of Arts, Science and Commerce*, 9(1), 19–26. <https://doi.org/10.18843/rwjasc/v9i1/03>
- Kaur, J., & Gupta, M. (2022). Consumer buying behaviour toward green personal care products. In *2022 International Conference on Computational Modelling, Simulation and Optimization (ICCMO)* (pp. 407–411). IEEE. <https://doi.org/10.1109/ICCMO58359.2022.00084>
- Kautish, P. (2020). Values, sustainability consciousness and intentions for SDG endorsement. *Marketing Intelligence & Planning*. <https://doi.org/10.1108/MIP-09-2019-0490>
- Kautish, P., & Dash, G. (2017). Environmentally concerned consumer behavior: Evidence from consumers in Rajasthan. *Journal of Modelling in Management*, 12(4), 601–619. <https://doi.org/10.1108/JM2-05-2015-0021>

- Kautish, P., Paul, J., & Sharma, R. (2019). The moderating influence of environmental consciousness and recycling intentions on green purchase behavior. *Journal of Cleaner Production*, 228, 1425–1436. <https://doi.org/10.1016/j.jclepro.2019.04.389>
- Kautish, P., & Sharma, R. (2018). Study on relationships among terminal and instrumental values, environmental consciousness and behavioral intentions for green products. *Journal of Indian Business Research*, 13(1), 1–29. <https://doi.org/10.1108/JIBR-01-2018-0013>
- Kim, N., & Lee, K. (2023). *Environmental consciousness, purchase intention and actual purchase behavior of eco-friendly products: The moderating impact of situational context*. Multidisciplinary Digital Publishing Institute (MDPI).
- Kim, Y. (2014). *Antecedents of green purchase behavior: An examination of collectivism, environmental concern, and perceived consumer effectiveness*. (August).
- Kotchen, M. J., & Reiling, S. D. (2000). Environmental attitudes, motivations, and contingent valuation of nonuse values: A case study involving endangered species. *Ecological Economics*, 32(1), 93–107. [https://doi.org/10.1016/S0921-8009\(99\)00069-5](https://doi.org/10.1016/S0921-8009(99)00069-5)
- Kumar, A., & Pandey, M. (2023). Social media and impact of altruistic motivation, egoistic motivation, subjective norms, and eWOM toward green consumption behavior: An empirical investigation. *Sustainability*, 15(5), Article 4222. <https://doi.org/10.3390/su15054222>
- Kumar, B., Manrai, A. K., & Manrai, L. A. (2017). Purchasing behaviour for environmentally sustainable products: A conceptual framework and empirical study. *Journal of Retailing and Consumer Services*, 34, 1–9. <https://doi.org/10.1016/j.jretconser.2016.09.004>
- Kumar, N., Garg, P., & Singh, S. (2022). Pro-environmental purchase intention towards eco-friendly apparel: Augmenting the theory of planned behavior with perceived consumer effectiveness and environmental concern. *Journal of Global Fashion Marketing*, 13(2), 134–150. <https://doi.org/10.1080/20932685.2021.2016062>
- Kumar, R., Kumar, K., Singh, R., Sá, J. C., Carvalho, S., & Santos, G. (2023). Modeling environmentally conscious purchase behavior: Examining the role of ethical obligation and green self-identity. *Sustainability*, 15(8), Article 6426. <https://doi.org/10.3390/su15086426>
- Lavuri, R., Jindal, A., Akram, U., Naik, B. K. R., & Halibas, A. S. (2023). Exploring the antecedents of sustainable consumers' purchase intentions: Evidence from emerging countries. *Sustainable Development*, 31(1), 280–291. <https://doi.org/10.1002/sd.2389>
- Lazaroiu, G., Andronic, M., Uță, C., & Hurloiu, I. (2019). Trust management in organic agriculture: Sustainable consumption behavior, environmentally conscious purchase intention, and healthy food choices. *Frontiers in Public Health*, 7, Article 340. <https://doi.org/10.3389/fpubh.2019.00340>
- Malik, C., & Singhal, N. (2017). Consumer environmental attitude and willingness to purchase environmentally friendly products: An SEM approach. *Vision*, 21(2), 152–161. <https://doi.org/10.1177/0972262917700991>
- Mancha, R. M., & Yoder, C. Y. (2015). Cultural antecedents of green behavioral intent: An environmental theory of planned behavior. *Journal of Environmental Psychology*, 43, 145–154. <https://doi.org/10.1016/j.jenvp.2015.06.005>
- Mataram, U. (2020). *Dan Irritating Terhadap Attitude Toward Social Media Advertising Pada Masyarakat*, 9(2), 186–197.
- Michaelidou, N., & Hassan, L. M. (2008). The role of health consciousness, food safety concern and ethical identity on attitudes and intentions towards organic food.

- International Journal of Consumer Studies*, 32(2), 163–170. <https://doi.org/10.1111/j.1470-6431.2007.00619.x>
- Mishal, A., Dubey, R., Gupta, O. K., & Luo, Z. (2017). Dynamics of environmental consciousness and green purchase behaviour: An empirical study. *International Journal of Climate Change Strategies and Management*, 9(5), 682–706. <https://doi.org/10.1108/IJCCSM-11-2016-0168>
- Moslehpour, M., Chaipayruk, P., Faez, S., & Wong, W. K. (2021). Generation Y's sustainable purchasing intention of green personal care products. *Sustainability*, 13(23), Article 13385. <https://doi.org/10.3390/su132313385>
- Moslehpour, M., Chau, K. Y., Du, L., Qiu, R., Lin, C. Y., & Batbayar, B. (2023). Predictors of green purchase intention toward eco-innovation and green products: Evidence from Taiwan. *Economic Research-Ekonomska Istraživanja*, 36(2), Article 2121934. <https://doi.org/10.1080/1331677X.2022.2121934>
- Munir, A., Rehmat, M., & Nisar, A. (2023). Impact of perceived consumer effectiveness on green buying: A moderated mediation model. *Sukkur IBA Journal of Management and Business*, 10(1), 121–151. <https://doi.org/10.30537/sijmb.v10i1.1234>
- Nekmahmud, M., Naz, F., Ramkissoon, H., & Fekete-Farkas, M. (2022). Transforming consumers' intention to purchase green products: Role of social media. *Technological Forecasting and Social Change*, 185, Article 122067. <https://doi.org/10.1016/j.techfore.2022.122067>
- Palomino Rivera, H. J., & Barcellos-Paula, L. (2024). Personal variables in attitude toward green purchase intention of organic products. *Foods*, 13(2), Article 213. <https://doi.org/10.3390/foods13020213>
- Parguel, B., Benoît-Moreau, F., & Larceneux, F. (2011). How sustainability ratings might deter “greenwashing”: A closer look at ethical corporate communication. *Journal of Business Ethics*, 102(1), 15–28. <https://doi.org/10.1007/s10551-011-0901-2>
- Petrosyan, A. (2024). *Number of internet and social media users worldwide as of July 2024*. Statista. <https://www.statista.com/statistics/617136/digital-population-worldwide/>
- Polisetty, A., Chakraborty, D., Singu, H. B., & Behl, A. (2024). Examining the relationship between pro-environmental consumption behaviour and hedonic and eudaimonic motivation. *Journal of Environmental Management*, 359, Article 121095. <https://doi.org/10.1016/j.jenvman.2024.121095>
- Pop, R., & Zsuzsa, S. (2020). *Social media goes green: The impact of social media on green cosmetics purchase motivation and intention*. FIIB Business Review.
- Prakash, G., & Pathak, P. (2017). Intention to buy eco-friendly packaged products among young consumers of India: A study on developing nation. *Journal of Cleaner Production*, 141, 385–393. <https://doi.org/10.1016/j.jclepro.2016.09.116>
- Shabnam, S. (2013). Proposed model for predicting environmental purchase behavior of consumers. *European Academic Research*, 1(4), 444–466.
- Shalender, K., & Sharma, N. (2021). Using extended theory of planned behaviour (TPB) to predict adoption intention of electric vehicles in India. *Environment, Development and Sustainability*, 23(1), 665–681. <https://doi.org/10.1007/s10668-020-00602-7>
- Sharma, N., Lal, M., Goel, P., Sharma, A., & Rana, N. P. (2022). Being socially responsible: How green self-identity and locus of control impact green purchasing intentions? *Journal of Cleaner Production*, 357, Article 131895. <https://doi.org/10.1016/j.jclepro.2022.131895>

- Sharma, N., Saha, R., Sreedharan, V. R., & Paul, J. (2020). Relating the role of green self-concepts and identity on green purchasing behaviour: An empirical analysis. *Business Strategy and the Environment*, 29(8), 3203–3219. <https://doi.org/10.1002/bse.2567>
- Shukla, S. (2019). A study on millennial purchase intention of green products in India: Applying extended theory of planned behavior model. *Journal of Asia-Pacific Business*, 20(4), 322–350. <https://doi.org/10.1080/10599231.2019.1684171>
- Silintowe, Y. B. R., & Sukresna, I. M. (2022). Green self-identity as a mediating variable of green knowledge and green purchase behavior. *Jurnal Organisasi dan Manajemen*, 18(1), 74–87. <https://doi.org/10.33830/jom.v18i1.2564.2022>
- Singh, N., & Gupta, K. (2013). Environmental attitude and ecological behaviour of Indian consumers. *Social Responsibility Journal*, 9(1), 4–18. <https://doi.org/10.1108/17471111311307787>
- Singh Kushwaha, V. (2015). Mass media in disseminating environmental awareness. *International Journal of Research – GRANTHAALAYAH*, 3(9SE), 1–4. <https://doi.org/10.29121/granthaalayah.v3.i9se.2015.3185>
- Stets, J. E., & Burke, P. J. (2003). A sociological approach to self and identity. In M. R. Leary & J. P. Tangney (Eds.), *Handbook of self and identity* (pp. 128–152). Guilford Press.
- Sun, Y., & Wang, S. (2020). Understanding consumers' intentions to purchase green products in the social media marketing context. *Asia Pacific Journal of Marketing and Logistics*, 32(4), 860–878. <https://doi.org/10.1108/APJML-03-2019-0178>
- Sun, Y., & Xing, J. (2022). The impact of social media information sharing on the green purchase intention among Generation Z. *Sustainability*, 14(11), Article 6879. <https://doi.org/10.3390/su14116879>
- Thøgersen, J., & Ölander, F. (2006). The dynamic interaction of personal norms and environment-friendly buying behavior: A panel study1. *Journal of Applied Social Psychology*, 36(7), 1758–1780. <https://doi.org/10.1111/j.0021-9029.2006.00080>
- Tlebere, T., Scholtz, B., & Calitz, A. P. (2016). Using social media to improve environmental awareness in higher education institutions. In *Springer proceedings in business and economics* (pp. 101–111). Springer. https://doi.org/10.1007/978-3-319-25153-0_9
- Tsai, P. H., Lin, G. Y., Zheng, Y. L., Chen, Y. C., Chen, P. Z., & Su, Z. C. (2020). Exploring the effect of Starbucks' green marketing on consumers' purchase decisions from consumers' perspective. *Journal of Retailing and Consumer Services*, 56, Article 102162. <https://doi.org/10.1016/j.jretconser.2020.102162>
- Udall, A. M., de Groot, J. I. M., De Jong, S. B., & Shankar, A. (2021). How I see me—A meta-analysis investigating the association between identities and pro-environmental behaviour. *Frontiers in Psychology*, 12, Article 582421. <https://doi.org/10.3389/fpsyg.2021.582421>
- Uddin, S. M. F., & Khan, M. N. (2018). Young consumer's green purchasing behavior: Opportunities for green marketing. *Journal of Global Marketing*, 31(4), 270–281. <https://doi.org/10.1080/08911762.2017.1407982>
- Vermeir, I., & Verbeke, W. (2006). Sustainable food consumption: Exploring the consumer “attitude-behavioral intention” gap. *Journal of Agricultural and Environmental Ethics*, 19(2), 169–194. <https://doi.org/10.1007/s10806-005-5485-3>
- Whitmarsh, L., & O'Neill, S. (2010). Green identity, green living? The role of pro-environmental self-identity in determining consistency across diverse pro-environmental behaviours. *Journal of Environmental Psychology*, 30(3), 305–314. <https://doi.org/10.1016/j.jenvp.2010.01.003>

- Xie, S., & Madni, G. R. (2023). Impact of social media on young generation's green consumption behavior through subjective norms and perceived green value. *Sustainability*, 15(4), Article 3739. <https://doi.org/10.3390/su15043739>
- Yadav, R., & Pathak, G. S. (2017). Determinants of consumers' green purchase behavior in a developing nation: Applying and extending the theory of planned behavior. *Ecological Economics*, 134, 114–122. <https://doi.org/10.1016/j.ecolecon.2016.12.019>
- Zafar, A. U., Shen, J., Shahzad, M., & Islam, T. (2021). Relation of impulsive urges and sustainable purchase decisions in the personalized environment of social media. *Sustainable Production and Consumption*, 25, 591–603. <https://doi.org/10.1016/j.spc.2020.11.020>
- Zhao, L., Lee, S. H., & Copeland, L. R. (2019). Social media and Chinese consumers' environmentally sustainable apparel purchase intentions. *Asia Pacific Journal of Marketing and Logistics*, 31(4), 855–874. <https://doi.org/10.1108/APJML-08-2017-0183>
- Zhuang, W., Luo, X., & Riaz, M. U. (2021). On the factors influencing green purchase intention: A meta-analysis approach. *Frontiers in Psychology*, 12, Article 644020. <https://doi.org/10.3389/fpsyg.2021.644020>

The Silent Saboteur: Unraveling the Impact of Smartphone Addiction on International Students' Academic Performance

BIMTECH Business Perspectives

7(2) 212–236, 2026

© The Author(s) 2026

DOI: 10.1177/25819542261483901

bsp.bimtech.ac.in



Ayano Jenga¹ and Meenu Gupta² 

Abstract

The purpose of the study is to investigate the potential impact of smartphone addiction on the academic achievements of foreign students. This study adopts a descriptive research approach and utilizes multiple regression analysis to examine the relationship between smartphone addiction factors and academic performance. Primary data were collected from 132 overseas students using a structured questionnaire. The study revealed that compulsive behavior, abstinence, and tolerance are key factors of smartphone addiction and significantly influence the academic performance of foreign students. However, functional impairment associated with smartphone use showed no significant impact. This study suggests that policymakers and other relevant stakeholders, including educational institutions, can develop targeted interventions and support programs to help students understand and mitigate the adverse effects of smartphone usage on their academic performance. This study contributes original insights by focusing on the impact of smartphone addiction specifically on overseas students' academic performance, an under-explored demographic.

Keywords

Addictive disorders, career development (academic), teaching diverse students

¹ Department of Management, Madda Walabu University, Bale Robe, Oromia, Ethiopia

² Sri Aurobindo College of Commerce and Management, Ludhiana, Punjab, India

Corresponding author:

Meenu Gupta, Sri Aurobindo College of Commerce and Management, Ferozepur Road, Ludhiana, Punjab 142021, India.

E-mail: meenugupta@saccm.in



Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 License (<http://www.creativecommons.org/licenses/by-nc/4.0/>) which permits non-Commercial use, reproduction and distribution of the work without further permission provided the original work is attributed.

Introduction

A smartphone is an advanced mobile gadget made to address common accessibility issues. Smartphones provide a plethora of features beyond making and receiving calls and sending texts. One reason for cellphones' meteoric rise in popularity is their ability to do both simple and complicated tasks with ease. The use of smartphones offers high-quality functionality as well as quick access to information and entertainment for a variety of users, including students. This includes mobile audio and video conversations, mobile teleconferencing, the ability to send and receive emails, and basic internet access. Social media and entertainment are additional applications. There are enormous opportunities for entertainment and meeting new people. With a smartphone, you get the best of both worlds: a mobile phone and a computer. It can access the web using web browsers linked to Wi-Fi and mobile networks. It serves dual purposes, functioning as both an educational tool and a form of entertainment through its myriad uses. Moreover, the proliferation of ubiquitous social media platforms like Facebook and Twitter has contributed to the rapid growth in smartphone ownership across various age groups (Arefin et al., 2017). The advancement of telecommunications technology has a profound impact on students' academic performance. Raza et al. (2020) in their research have well established that excessive dependence on technology has detrimental effects on people's education, moral values, mental and physical health and well-being, especially students. In contrast, it is also a proven fact that smartphones have simplified the lives of students, as they can study diverse topics and access educational materials through e-learning and m-learning.

Addiction was defined as "compulsive, uncontrollable dependence on a substance, habit, or practice to such a degree that cessation causes a severe emotional, mental, or physiological reaction" by Glanze et al. (1998). Addiction is portrayed in many ways. Peele (1985) defined addiction as excessive or compulsive behavior. According to Akers (1991), impatience, withdrawal, and dependence are all examples of psychological demands of a drug that are represented by addiction. Here, the addictive person's habitual behavior explains the psychological demand.

The internet, mobile devices, and smartphones are just a few of the different kinds of technology addiction. Internet addiction symptoms, according to Young (1998), included withdrawal, impatience, loss of control, and impairments in academic, occupational, and social functioning. Brenner (1997) used the Internet-Related Addictive behavior Inventory to identify certain disruptions to everyday living, including insufficient sleep, poor time management, and missing meals. Research on addiction has recently shifted its focus from the internet to mobile phones. Addiction to smartphones differs from addiction to mobile phones. Assessing smartphone addiction requires additional criteria beyond those used for general mobile phone addiction, due to its many unique features (Kwon et al., 2013). Recent research has highlighted four main elements that constitute smartphone addiction: compulsive behaviors, withdrawal, tolerance, and functional impairment (Alageel et al., 2021). Increased smartphone usage exposes students to several repercussions, encompassing both positive and negative aspects. Due to technological advancements, smartphones have become an indispensable part of

the lives of students, having a substantial impact on the behavior of students. Nowadays, in matters related to school tasks or social networking, students depend heavily on their smartphones (Raza et al., 2020). As per the findings of infographic research undertaken by HackCollege.com, 57% of students use smartphones, 60% report being addicted to them, 75% keep their smartphones next to them while sleeping, 88% of them use it to send text messages before they go to bed, 97% of smartphone users use it for social interaction, whereas 40% of them use it to lookup their school activities. Because of heavy reliance on cellphones, the development of students' communication and social skills might suffer in the end.

Young people, especially students, are becoming more and more dependent on technology in almost all facets of their lives; as a result, smartphone addiction is increasing. Consequently, an extensive amount of research is required to determine whether this addiction can be helpful for students or detrimental to their academic accomplishments. Every year, thousands of fatalities and instances of inappropriate behavior occur because people frequently lose consciousness while using cellphones. As smartphone usage continues to grow exponentially, the adverse effects of mobile phone use are escalating with the passage of time. A plethora of research studies spanning diverse populations have been undertaken in this context, substantiating the existence of both favorable and unfavorable correlations between smartphone addiction and students' academic achievements. Lepp et al. (2014) have identified an adverse effect of smartphone addiction on the academic achievements of university students. Despite its detrimental effects on academic achievements, smartphone addiction does have a positive impact on one's overall life satisfaction (Raza et al., 2020; Samaha & Hawi, 2016). This divergence has persisted in the most recent literature rather than resolving with additional research. A 2025 meta-analysis of 63 studies and over 124,000 students across 28 countries revealed only a small, though statistically significant, negative association between technology-related behaviors and academic performance, suggesting that the strong negative associations presumed by past studies may be considerably weaker and less consistent across contexts than was believed (Kuş, 2025). Considering these contradictory findings, ranging from strong negative effects to no direct effect, reveals that the field has not converged on a consistent understanding of how, or even whether, smartphone dependence shapes academic outcomes.

This lack of consensus indicates a clear gap in existing literature. Much of the prior research has treated smartphone addiction as a single, undifferentiated construct, measuring overall frequency or intensity of use without paying attention to its distinct behavioral dimensions comprising compulsive behavior, functional impairment, tolerance, and abstinence, which may have different associations with academic performance. Few studies have examined these dimensions separately, and very few have examined international students, whose academic adjustment, social isolation, and reliance on smartphones for maintaining connection with family and support networks abroad may alter these relationships in ways not captured by studies conducted on domestic populations. This study addresses this research gap by disaggregating smartphone addiction into its constituent behavioral components and examining their distinct effects on the academic performance of international university students, thereby helping to reconcile the divergent findings reported in prior research.

As the effects of smartphone addiction on students' lives are not very clear, this study made an earnest attempt to shed light on the possible impacts of smartphones on the academic performance of international students at a university.

Review of Related Literature

People grappling with "smartphone addiction" or "nomophobia" find their daily lives significantly disrupted due to excessive use of their cellphones. Some of the many negative effects of this addiction include less sleep, decreased productivity, disruptions to social life, and strained relationships. These days, there is a growing apprehension about the potential adverse impact of smartphone use, particularly smartphone dependence and its effect on academic performance. In the literature, poor academic outcomes have been associated with excessive smartphone use. Kuss et al. (2013), in their study of college students, have established that those who were more dependent on smartphones had far worse academic performance. This view is further supported by Lepp et al. (2014) in their research findings, demonstrating that high levels of smartphone use were associated with lower grades in high school students. Junco (2012), Junco and Cotten (2012), and Levine et al. (2012) are just a few of the many studies that have elucidated the adverse effects of this behavior on academic achievements. Research shows that college students are more likely to use their cellphones for leisure purposes than for academic work (Lepp et al., 2013).

Smartphone addiction has been linked to sleep problems, which can also negatively impact academic performance. Empirical studies by Lepp et al. (2014) and Demirci et al. (2015) have established an undisputed relationship between constant smartphone usage and disrupted sleep patterns. This, in turn, has been shown to negatively impact cognition and induce fatigue. Research suggests that the effect of excessive smartphone usage on academic achievements may be moderated by demographic factors like age, gender, and educational level. For example, prior research studies have demonstrated that male college students are more vulnerable to the adverse consequences of smartphone addiction on their academic achievements, as evidenced by Lee et al. (2019). Another study highlighted that high school students who were more dependent on their smartphones for social support performed worse academically, although this was not the case for college students (Lepp et al., 2014). Research suggests that students may be more engaged and productive in class if they are able to limit their use of cellphones. For instance, a Korean study indicated that high school students who participated in smartphone addiction prevention programs had better academic performance. This program's success was attributed, in large part, to its integration of group and individual counseling as well as instruction on responsible smartphone usage (Koo, 2011). Some studies have shown that the duration of smartphone usage and the specific activities conducted on them can play an important role in determining whether they have a negative impact on students' academic achievement. Even certain studies have highlighted that the relation between excessive smartphone usage and academic achievement may vary by subject. To illustrate, Lepp et al. (2014), in their research work targeting high school students, pointed

out that excessive use of smartphones negatively impacted math grades but had no effect on their overall performance. This fact is strongly supported by another study, by establishing that college students who used their smartphones more frequently had lower grades in science courses, but not in other subjects (Kuss & Griffiths, 2011).

Moreover, to measure an individual's degree of smartphone usage, Kwon et al. (2013) established a tool, "The Smartphone Addiction Inventory (SPAI)." Higher scores on the SPAI are indicative of greater smartphone usage. In studies of excessive usage of smartphones, SPAI found to have high reliability and validity (Kwon et al., 2013). Numerous studies have used this tool to measure smartphone usage in different samples. Blaszczynski and Nower (2002) assert that addiction is propelled by an individual's engagement in a particular activity rather than the consumption of a substance. They argued that compulsive behavior, functional impairment, tolerance, and abstinence are distinguishing features of process addictions.

People who suffer from substance abuse disorders, such as drug addiction or alcoholism, exhibit these traits. These notions have been investigated for many years and are well established in the domain of research conducted on addiction.

Nonetheless, it is important to mention that more work is required to fully comprehend how these concepts relate to excessive smartphone use. Hence, in this study, the researchers made an earnest attempt to focus on these factors while studying the effect of smartphone addiction on students' academic achievements. This is particularly important given that prior research has largely treated smartphone addiction as a single, undifferentiated construct and has rarely examined these dimensions among international students specifically, a gap this study aims to address by disaggregating addiction into compulsive behavior, functional impairment, abstinence, and tolerance.

Recent evidence published in 2025 and 2026 reinforces and refines these earlier conclusions. A large-scale meta-analysis of 63 studies encompassing 124,166 students across 28 countries confirmed a small but statistically significant negative association between smartphone addiction, social media use, and video game play on the one hand, and academic performance on the other, highlighting that more technology use continues to be linked with weaker cognitive engagement and poorer academic performance (Kuş, 2025). A subsequent scoping review of 44 studies on university students further reported that smartphone addiction prevalence ranged from 11% to 85% worldwide and remained strongly associated with poorer academic, mental health, and sleep outcomes, reinforcing calls for university-level digital literacy and mental health and wellness programs (Miezah et al., 2026).

Theoretical Framework and Conceptual Justification of Addiction Dimensions

This study is grounded in Griffiths' (2005) components model of addiction, a biopsychosocial framework originally developed to explain substance addictions but was later expanded to include behavioral, or "process," addictions such as gambling, gaming, internet use, and smartphone use. The model proposes that any behavior becomes addictive when it demonstrates six interrelated components:

salience, mood modification, tolerance, withdrawal (unpleasant psychological symptoms upon discontinuation), conflict, and relapse. Because these six elements have been shown to co-occur across otherwise unrelated addictive behaviors, the model provides a theoretically coherent basis for treating smartphone dependence as a genuine behavioral addiction rather than merely a habit or a lifestyle preference.

On the basis of this general framework, Blaszczynski and Nower (2002) argued that process addictions are most reliably distinguished by four observable features: compulsive behavior, functional impairment, tolerance, and abstinence. These four features can be understood as a more parsimonious and usable restatement of Griffiths' six components, condensed for empirical validation in behavioral addiction research: compulsive behavior reflects the salience and relapse components; functional impairment captures the conflict component; tolerance directly mirrors the tolerance component; and abstinence corresponds to the withdrawal component. Kwon et al. (2013) subsequently operationalized this four-dimensional structure specifically for smartphones in the development of the SPAI, the measurement logic on which the hypotheses of the current study are based.

The above discussion elucidates why it is believed that each dimension affects academic performance through a different mechanism rather than a single pathway. Compulsive behavior is expected to divert time and attentional resources that might otherwise be used for studying, consistent with the displacement assumption highlighted in recent studies related to digital technology (King et al., 2025). Functional impairment is expected to function through direct disruption of academic routines, such as missed classes, incomplete assignments, and disrupted sleep, echoing the physical and emotional ill-being pathways studied by Kraut et al. (1998) and Augner and Hacker (2012). Since constant smartphone use gradually consumes more study time and cognitive space without any single significant disturbance, tolerance is anticipated to perform cumulatively. On the other hand, abstinence, in contrast, is supposed to function protectively, aligned well with the components model's withdrawal criterion; duration of voluntary disconnection aids in the restoration of attention capacity and reduces the psychological concern that would otherwise interfere with academic assignments (Kolhe & Naik, 2025; Tromholt, 2016).

Impact of Smartphone on Academic Performance

Compulsive Behavior and Academic Performance

According to the research of O'Guinn and Faber (1989), compulsive behavior is "a response to an uncontrollable drive or desire to obtain, use, or experience a feeling, substance, or activity that leads the individual to repetitively engage in behavior that will ultimately cause harm to the individual and/or others." A fundamental characteristic of this disorder includes behaviors like compulsive eating, shopping, gambling, and drug abuse (Parylak et al., 2011). Symptoms of obsessive-compulsive disorder include extreme compulsive activity. Users are more inclined to check their phones frequently due to the convenience of incentives like social networking and communication. Frequently checking one's phone is now recognized as addictive behavior (Oulasvirta et al., 2012). According to Bianchi and Phillips (2005), people who indulge in excessive smartphone usage experience difficulty in

regulating their time spent on the phone and get easily exhausted by smartphones. Moreover, Matusik and Mickel (2011) have empirically established that perceiving one's compulsive behavior has inevitable increases the likelihood of negative psychological effects like despair and stress. Thus, it is an established fact that prolonged smartphone use would lead to technostress, which in turn may influence performance. Therefore, it is hypothesized that compulsive behavior of students has an adverse effect on their academic performance.

H_1 : Smartphone compulsive behavior has a significant adverse effect on the academic achievements of the students.

Functional Impairment and Academic Performance

Several studies were carried out in different parts of the world to discover the effect of excessive usage of smartphones on academic performance or individual quality of life. There is a growing body of evidence suggesting that excessive smartphone use can have adverse and dysfunctional outcomes for its users (Al-Barashdi et al., 2015; Albursan et al., 2022; Billieux et al., 2015; Chiu, 2014; Farooq et al., 2021; Kim et al., 2019; Toda et al., 2006; Wang et al., 2015; Zeerak et al., 2024). Anxiety levels also tend to rise alongside cell phone use (Chesley, 2005). Kraut et al. (1998) & Augner and Hacker (2012) have identified two ill-beings of excessive smartphone, these are emotional and physical. Lack of sleep or low-quality sleep, as well as general fatigue, are symptoms of physical illness. People who spend the whole day using cellphones may have difficulty falling asleep and staying asleep due to their cellphone addiction (Sohn et al., 2021). About 61.6% of respondents in a large population poll in the UK reported bad sleep, and 68.7% of those who claimed to be addicted to their smartphones also reported having trouble sleeping (Sohn et al., 2021). Research suggests that students' functional impairment due to smartphone addiction has an adverse effect on their academic achievement.

H_2 : Functional impairment has a significant effect on the academic achievements of the students.

Abstinence and Academic Performance

Prior research indicates that conscious and controlled adjustments in daily smartphone usage can positively impact subjective wellbeing. This includes a reduction in depressive and anxiety symptoms, diminished tendencies toward problematic use, and increased life satisfaction. Moreover, increased levels of physical activity and a reduction in smoking behavior characterize the long-term acceptance of such changes, which have been associated with cultivating a healthier living condition. According to a research study (Tromholt, 2016), abstinence from social networking sites might potentially lead to enhanced concentration on other significant pursuits, less reliance on social comparisons, information overload, and fatigue (Maier et al., 2015). Although there is evidence supporting both perspectives, research indicates that abstinence may often provide more pronounced stress-reduction benefits. For instance, in a large study involving 1,095 participants, people who refrained from Facebook for 1 week observed better well-being than

the control groups (Tromholt, 2016). Moreover, it was also proved that activity on Facebook, as opposed to inactivity, might have an adverse impact on people's mood (Sagioglou & Greitemeyer, 2014). Therefore, it is hypothesized that abstinence from smartphones for a few days may have an important influence on the learners' academic performance.

H_3 : Abstinence has a significant effect on the students' academic achievements.

Tolerance and Academic Performance

Tolerance is the unwillingness to act on one's own desire to reduce cell phone use. This trend indicates customers' strong aversion to the adverse effects of prolonged smartphone usage (Afzal & Shah, n.d.). Students fully comprehend the adverse effects of excessive smartphone use, but they continue to do so nevertheless. Despite being aware of the detrimental effects their smartphone addiction is having on their academic achievement and mental wellbeing, they obstinately persist in their addiction (Soyemi et al., 2015). Hence, we made our next hypothesis that tolerance has a negative influence on academic performance.

H_4 : Tolerance has a significant effect on the students' academic achievements.

Contemporary Perspectives (2025–2026)

Latest research also nuances the role of abstinence discussed above. A 2025 systematic review of digital detox practices established that voluntary, periodic disconnection from digital technology provides measurable cognitive and emotional benefits, including improved attention, reduced stress, greater self-reflection, and strengthened social connectedness, extending further support to the view that deliberate abstinence can be protective (Kolhe & Naik, 2025). At the same time, a large sample study of 640 college students revealed that brief, time-specific digital detox periods were difficult for students to sustain and, on average, produced negligible difference in daily mood compared with a control group; however, students who successfully abstain themselves from the use of their phones before bed reported better next-day mood, signifies that the timing of abstinence, and not merely its occurrence, leads to maximum benefits (King et al., 2025). In the domain of tolerance and persistent use, a 2026 study of university students in Jordan found that students continued heavy usage of smartphones despite acknowledging the negative academic and psychological outcomes, reflecting a pattern of tolerance-driven behavior which is consistent with earlier literature (Al-Rajabi et al., 2026). In the backdrop of the above discussion, it is confirmed that compulsive behavior, functional impairment, abstinence, and tolerance are validated and meaningful predictors of academic performance.

Research Hypothesis

H_1 : Smartphone compulsive behavior has a significant effect on the students' academic achievements

- H_2 : Functional impairment has a significant effect on the students' academic achievements.
- H_3 : Abstinence has a significant effect on the students' academic achievements.
- H_4 : Tolerance has a significant effect on the students' academic achievements

Conceptual Framework

The conceptual relationship between variables of excessive smartphone usage and students' academic performance is shown as follows in Figure 1.

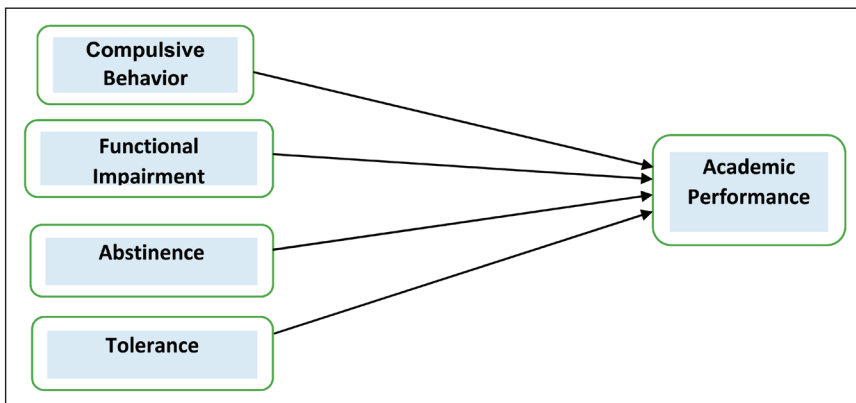


Figure 1. Conceptual Framework of the Relationship Between Smartphone Addiction Dimensions and Academic Performance.

Materials and Methods

Study Design

Due to the impracticability of examining the whole population, a survey research methodology was used for this study. In addition, a cross-sectional design was utilized because data were gathered and examined at a single point in time. The present research adopts a quantitative approach, since data were gathered using survey questionnaires, transformed into numerical form, and then subjected to statistical analysis and evaluation (Raza et al., 2020). Moreover, correlation and regression analyses in this study examine the association between functional impairment (FI), abstinence (AB), tolerance (TL), and compulsive behavior (CB) and academic performance (AP).

Type of Data and Source

In the current research work, quantitative data are being utilized. These data types were gathered from both primary and secondary sources. To collect primary data, a questionnaire was developed and distributed to international students enrolled in

various degree programs at a university in India. Moreover, journal papers, books, the internet, and magazines, among other secondary sources, were reviewed to acquire both theoretical and empirical evidence.

Population and Sampling Design

The target population comprised all international students enrolled in the university and who owned a smartphone at the time of data collection. According to records maintained by the university's Directorate of International Students, a total of 890 foreign students were registered across various degree programs at the time of the study. To determine the minimum adequate sample size, an a priori power analysis was conducted following Cohen (1988) for multiple linear regression with four predictors, $\alpha = 0.05$, and power $(1 - \beta) = 0.80$. For a medium effect size ($f^2 = 0.15$), the minimum required sample was $n = 85$. The achieved sample of $n = 132$ comfortably exceeds this threshold, confirming adequate statistical power to detect medium-sized effects. As a supplementary reference, Yamane's (1967) formula applied at an 8% margin of error yields a comparable figure, further justifying the adequacy of the sample size. A systematic random sampling technique was used. Using the official student register maintained by the Directorate of International Students as the sampling frame, a sampling interval of $k = 7$ (calculated as $890/132$) was applied using the random starting point from within the first interval. Every 7th student on the register was selected as a target respondent. Identified students were later approached in person at classrooms, cafeterias, and hostels to fill the survey instrument, ensuring coverage across departments and residential areas. This procedure gave each student in the population a known and equal opportunity of selection.

Sample Composition and Representativeness

The achieved sample comprised 108 males (81.8%) and 24 females (18.2%), and was dominated by PhD students (56.8%), followed by Master's students (38.6%), with only 4.5% at Bachelor's level. Informal discussion with the university's Directorate of International Students revealed that the majority of international students are male and involved in postgraduate research, suggesting that the sample composition broadly reflects the actual enrollment profile rather than a sampling artifact. While a formal statistical verification of sample representativeness was not done, the observed demographic profile and program-level composition are consistent with the general enrollment profile of international students at the institution, where research-level programs predominantly attract male students from abroad. The skewness of data toward male and PhD-level respondents should therefore be considered while interpreting the findings and generalizing results to female or undergraduate international students.

Methods of Data Collection

The researchers employed Self-administered survey questionnaires to collect the desired data from the target population. The questionnaire was broadly divided into two sections. Section one consists of questions for collecting demographic

information of respondents, such as status, age, education and gender. Section two has 5 sub sections. Compulsive behavior (CB), functional impairment (FI), abstinence (A), tolerance(T) and Academic performance (AP). It consists of a total of 32 questions related to the topic and variables. A five-point Likert scale ranging from Strongly Disagree to Strongly Agree was applied to construct the multiple-item assessment items.

Methods of Data Analysis

After data collection, completeness and accuracy of the questionnaires were checked prior to analysis. Incomplete questionnaires were excluded at the point of collection and replaced, ensuring that all 132 questionnaires entered into analysis were fully completed with no missing values; no imputation was therefore required. Responses were pre-coded and post-coded to systematically categorize answers, and the cleaned dataset was entered into SPSS Version 23 for statistical analysis.

Both descriptive and inferential statistical techniques were employed. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were computed to summarize the demographic characteristics of respondents and the distribution of scores across all study variables. Correlation analysis was subsequently conducted to examine the bivariate relationships between smartphone addiction dimensions and AP. Multiple regression analysis was then carried out to assess the simultaneous predictive effect of compulsive behavior, functional impairment, abstinence, and tolerance on academic performance.

Reliability Analysis

According to Kirk and Miller (1986), reliability is the degree to which findings consistently and reliably reflect the entire population being studied, regardless of the situation. In assessing the reliability of the research, the researchers employed Cronbach's alpha to specify the internal consistency or average correlation, of items in a survey to determine its reliability. Alpha should ideally be between 1 and 0, with a value closer to 1 indicating more dependable results. By using SPSS Version 23 software, the reliability of 30 items has been tested, and the Alpha Coefficient was identified as 0.934 (see Table 1), which is within the threshold as per Nunnally (1967 and 1978). The alpha value of every variable in the study is above 0.7; the items used in the study are reliable. Overall, the reliability analysis of items shows the data is reliable and eligible for further analysis.

Results and Discussions

This section presents the findings of the statistical analyses conducted on data collected from 132 international students. Results are organized sequentially, beginning with the response rate, followed by the demographic profile of

Table 1. Reliability Analysis.

	Cronbach's Alpha	Overall Alpha
CB	0.773	0.934
FI	0.757	
A	0.725	
T	0.749	
AP	0.919	

respondents, descriptive statistics, correlation analysis, and multiple regression results. Of the 132 students approached and consented to participate, all returned fully completed questionnaires. It should be noted that this completion rate reflects responses among those who were approached and agreed to participate; students who were absent, unavailable, or declined to participate were not recorded. Consequently, overall non-response relative to the full population of 890 international students cannot be ascertained, and the rate should be interpreted as reflecting completion among approached participants rather than universal voluntary compliance.

Demographic Profile of Respondents

Table 2 presents the demographic characteristics of the sample. With regard to gender, the sample was predominantly male, comprising 108 male respondents (81.8%) and 24 female respondents (18.2%). In terms of age, the largest proportion of respondents fell within the 26–30 year bracket ($n = 66$, 50.0%), followed by the 31–35 age group ($n = 33$, 25.0%), the 20–25 age group ($n = 21$, 15.9%), the 36–40 age group ($n = 9$, 6.8%), and those above 40 years ($n = 3$, 2.3%), indicating that the sample was largely composed of young to middle-aged adults. Regarding marital status, a slight majority of respondents were married ($n = 69$, 52.3%), with the remaining 63 respondents (47.7%) being single. With respect to academic program, doctoral students constituted the largest group ($n = 75$, 56.8%), followed by Master's students ($n = 51$, 38.6%), with Bachelor's students representing only 4.5% of the sample ($n = 6$). This composition broadly reflects the enrollment profile of international students at the study institution, where postgraduate research programs attract a predominantly male international student body. Findings should therefore be interpreted with caution regarding their generalisability to female or undergraduate international student populations.

Descriptive Statistics

Table 3 presents the descriptive statistics for all study variables. Mean scores were interpreted on a five-point Likert scale, where values closer to 1 indicate strong disagreement and values closer to 5 indicate strong agreement with the items within each construct. The mean scores for compulsive behavior ($M = 2.91$, $SD = 0.69$) and functional impairment ($M = 2.85$, $SD = 0.67$) fell below the scale midpoint of

Table 2. Demographic Characteristics of the Respondents.

Characteristics	Category	No.	%ge
Gender	Male	108	81.8
	Female	24	18.2
Total		132	100.0
Age in years	20–25	21	15.9
	26–30	66	50.0
	31–35	33	25.0
	36–40	9	6.8
	Above 40	3	2.3
Total		132	100.0
Marital status	Single	63	47.7
	Married	69	52.3
Total		132	100.0
Program	Bachelor	6	4.5
	Masters	51	38.6
	PhD	75	56.8
Total		132	100.0

Table 3. Descriptive Statistics.

	N	Mean	Std. Devn.
CB	132	2.9066	0.68711
FI	132	2.8494	0.66803
A	132	3.2273	0.82855
T	132	3.1515	0.85740
AP	132	2.8220	0.99579
Valid N (listwise)	132		

3.0, suggesting that respondents reported relatively low levels of smartphone addiction on these two dimensions. In contrast, the mean scores for abstinence ($M = 3.23$, $SD = 0.83$) and tolerance ($M = 3.15$, $SD = 0.86$) exceeded the scale midpoint, indicating that respondents acknowledged tendencies toward smartphone dependency with respect to these dimensions. Regarding the dependent variable, Academic Performance ($M = 2.82$, $SD = 1.00$) also fell below the midpoint, suggesting that respondents did not strongly agree that smartphone use had negatively affected their academic performance. These descriptive patterns provide an initial indication of the variable distributions prior to inferential analysis.

Correlation Analysis

Table 4 presents the Pearson correlation coefficients between the four dimensions of smartphone addiction and academic performance. All four dimensions: Compulsive Behavior ($r = 0.654$, $p < .01$), functional impairment ($r = 0.490$, $p < .01$), abstinence ($r = 0.630$, $p < .01$), and tolerance ($r = 0.604$, $p < .01$), demonstrated statistically significant positive correlations with academic performance at

Table 4. Correlations Result.

		CB	FI	A	T	AP
AP	Pearson Correlation	0.654**	0.490**	0.630**	0.604**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	
	N	132	132	132	132	132

Note: **Correlation is significant at the 0.01 level (2-tailed).

the 0.01 level. The strongest correlation was observed between compulsive behavior and Academic Performance ($r = 0.654$), followed by abstinence ($r = 0.630$) and tolerance ($r = 0.604$), with functional impairment showing the weakest though still significant association ($r = 0.490$). These findings indicate that all dimensions of smartphone addiction are meaningfully associated with academic performance, providing preliminary support for the hypothesized relationships prior to regression analysis.

Regression Analysis

To further examine the influence of students' smartphone addiction on their academic performance, a multiple regression model was adopted and carried out, and the following regression model was developed and used:

$$\text{Academic Performance (Y)} = \beta_0 + \beta_1 \times 1 + \beta_2 \times 2 + \beta_3 \times 3 + \beta_4 \times 4 + \text{et}$$

Y = dependent variable (poor academic performance)

β_0 = constant

β_1 = coefficient for independent variable ($\times 1$ = compulsive behavior)

β_2 = coefficient for independent variable ($\times 2$ = functional impairment)

β_3 = coefficient for independent variable ($\times 3$ = Abstinence)

β_4 = coefficient for independent variable ($\times 4$ = Tolerance)

et = error term

As regression analysis involves its own assumptions, assessment of those regression assumptions is very important to verify the validity of the model. Consequently, in this study the researchers checked whether the main assumptions were fulfilled or not before conducting the analysis. Those assumptions that were examined in this study were normality, multicollinearity, and heteroscedasticity.

Normality

The normality of the data is tested using skewness and Kurtosis tools. A distribution that is non-normal is indicated by skewness and Kurtosis values that are

greater than certain threshold levels. When it comes to significance levels, the most utilized critical values are ± 2.58 at 1% and ± 1.96 at 5%. The skewness and Kurtosis statistics for all items fall within the recommended range of ± 1.96 , indicating no substantial departure from normality (see Appendix, Table 9). As a result, it suggests that the data is normal and trustworthy for further analysis. This is further supported by the histogram of regression standardized residuals, which approximates a normal curve (see Figure 2).

Multicollinearity

The existence of a multicollinearity issue is indicated by a correlation score above 0.80, a tolerance level less than 0.10, and a variance inflation factor (VIF) over 10 in the correlation matrix (Field, 2009). According to the study's findings, all variables have tolerance levels greater than 0.10 (ranging from 0.358 to 0.455) and VIF values less than 10 (ranging from 2.200 to 2.797), indicating that there is no collinearity between the independent variables that could affect their predictive power. As a result, all independent variables are suitable for the use of regression analysis.

Heteroscedasticity

To assess the assumption of heteroscedasticity, a scatterplot of standardized residuals against standardized predicted values was visually inspected. The residuals were randomly and evenly scattered around zero across the entire range of predicted values, with no visible funnel shape, systematic pattern, or clustering that would indicate non-constant variance.

CMB and Non-response Considerations

Since all predictor and outcome variables were collected from the same respondents at a single point in time using the same questionnaire, common method bias (CMB) was a potential concern. To remove the doubt, Harman's single-factor test was performed by entering all items into an unrotated exploratory factor analysis in SPSS. The first unrotated factor accounted for less than 50% of the total variance as recommended by Podsakoff et al. (2003), signifying that no single factor dominated the variance and that CMB is unlikely to be a major threat to the validity of the findings. Additionally, the conceptual separation of constructs (behavioral dimensions vs. academic outcome) and the use of distinct items across constructs further minimize the risk of CMB-influenced correlations.

As shown in Table 5, the model highlights, with an adjusted R^2 of 0.503, that compulsive behavior, functional impairment, abstinence, and tolerance held by students explain 50.3% of the variation in Academic performance, while 49.7% is explained by other factors not in the model.

ANOVA is used to test the model for overall significance (Table 6). The $p < .01$ indicates that at least one independent variable has an influence on the dependent

Table 5. Regression Result.

Model Summary ^b				
Model	R	R ²	Adjusted R ²	Std. Error of the Estimate
1	0.720 ^a	0.518	0.503	0.70202

Notes: ^aPredictors: (Constant), T, CB, A, FI.

^bDependent variable: AP.

Table 6. ANOVA.^a

Model		Sum of Squares	df	Mean Square	F
1	Regression ^b	67.309	4	16.827	34.144
	Residual	62.590	127	0.493	
	Total	129.900	131		

Notes: ^aDependent Variable: AP.

^bPredictors: (Constant), T, CB, A, FI.

Table 7. Regression Coefficient Results.

		Unstandardized Coefficients		Standardized Coefficients		95.0% Confidence Interval for B		
		B	Std. Error	Beta	T	Sig.	Lower Bound	Upper Bound
1	(Constant)	−0.278	0.298		−0.931	0.353	−0.868	0.312
	CB	0.576	0.148	0.398	3.888	0.000	0.283	0.870
	FI	−0.180	0.153	−0.121	−1.178	0.241	−0.483	0.122
	A	0.304	0.110	0.253	2.765	0.007	0.086	0.521
	T	0.304	0.120	0.262	2.540	0.012	0.067	0.541

variable, students' academic performance. Thus, the overall model is significant with a p value below the 1% level of significance.

The link between the variable of interest and every predictor is revealed by beta coefficients. As depicted in Table 7, except for the functional impairment variable, the remaining variables have significant influence on students' Academic performance. The results demonstrate that compulsive behavior has a significant effect on students' academic performance: a one-standard-deviation increase in compulsive behavior is associated with a 0.398-standard-deviation increase in poor academic performance, holding other predictors constant (standardized $\beta = 0.398$, $t = 3.888$, $p < .001$, per Table 7). This is because compulsive behavior increases the negative effect of smartphone addiction on students' academic performance. Similarly, abstinence ($B = 0.253$, $p = .007$, $t = 2.765$) and tolerance ($B = 0.262$, $p = .012$, $t = 2.54$) also have a significant influence on students' academic performance, whereas functional impairment has an insignificant influence on students' academic performance. The overall result shows that H_1 , H_3 and H_4

Table 8. Hypothesis Result.

Variable	Significance Level	Hypothesis	Result
Compulsive behavior (CB)	Significant	H_1	Supported
Functional impairment (FI)	Insignificant	H_2	Not supported
Abstinence (A)	Significant	H_3	Supported
Tolerance (T)	Significant	H_4	Supported

were supported, as their t -values were greater than 1.96 and $p < 5\%$, whereas H_2 was rejected based on the t -value. A summary of the hypothesis testing results is presented in Table 8.

Conclusion and Practical Implications

The increasing reliance on technology in many aspects of life has led to a surge in smartphone addiction among today's youth. Numerous studies have examined the relation between students' excessive smartphone usage and their low academic performance, and findings have shown both positive and negative associations. As a result, reliable and extensive research is required to determine whether students' smartphone use improves or hinders their academic achievement. The overriding objective of this study is to identify the effect of smartphones on foreign students' academic performance. The study is quantitative since numerical data have been collected and examined using various statistical methods. This study used simple random sampling techniques. The sample size of the study is 132 respondents ($n = 132$).

Regarding the relationship between smartphone addiction and the academic performance of the students, the effect was examined for each of the smartphone addiction factors. Regression analysis was used to examine the effect of smartphone addiction on students' academic performance. Accordingly, compulsive behavior, abstinence and tolerance were found to have a significant effect on the academic achievement of students, whereas functional impairment had an insignificant effect on students' academic achievement.

This study suggests that policymakers and other relevant stakeholders, including educational institutions, can develop targeted interventions such as educational workshops and counseling and support programs to help students understand and mitigate the adverse effects of smartphone usage on their academic performance. These academic institutions should consider drafting policies promoting responsible smartphone use in academic settings. Moreover, Government authorities could launch public health campaigns to educate the public about the risks of smartphone addiction, akin to anti-smoking drives.

Limitations and Scope of Future Research

This study makes a meaningful contribution to understanding the relationship between smartphone addiction dimensions and the academic performance of

international students; however, several limitations should be acknowledged when interpreting its findings, and these reflect directions for future research. First, the cross-sectional design of this study, wherein data were collected at a single point in time, means that causal inferences cannot be drawn from the findings. Although regression analysis identifies the direction and magnitude of associations between compulsive behavior, functional impairment, abstinence, tolerance, and academic performance, it cannot confirm that smartphone addiction causes changes in academic performance, since both variables were measured simultaneously. Longitudinal designs, focusing on smartphone addiction and academic outcomes across an academic semester or year, would be better positioned to establish temporal precedence and causal direction. Second, all variables in this study, including the endogenous variable of academic performance, were measured through self-report questionnaire items rather than actual institutional records such as GPA transcripts or examination scores. Self-reported academic performance is prone to social desirability bias, as respondents may overestimate their academic achievement or underreport their smartphone usage; it could weaken or distort the observed associations. Future studies can fill this gap and supplement self-report measures with objective academic performance records to enhance measurement validity. Third, because all predictor and criterion variables were collected from the same respondents using the same questionnaire at a single time point, the study is vulnerable to CMB (Podsakoff et al., 2003). To partially address this concern, Harman's single-factor test was conducted, and the first unrotated factor accounted for less than 50% of total variance, suggesting that CMB is unlikely to fully account for the observed findings. Nonetheless, future research should consider procedural remedies such as temporal separation of predictor and outcome measurement, or the common latent factor approach within a Structural Equation Modeling (SEM) framework. Fourth, this study was conducted at a single university in India, which restricts the generalisability of the findings to international student populations at other institutions, in other cities, or in other countries. International students' smartphone use patterns and academic experiences may vary substantially depending on institutional culture, country, academic system, and available social support structures. Future studies should extend this inquiry to multiple institutions across different geographic and cultural contexts. Fifth, the sample is heavily skewed toward male respondents (81.8%) and doctoral-level students (56.8%), with female and undergraduate international students substantially underrepresented. Although this likely reflects the actual enrollment profile of the study institution, it restricts the generalisability of findings to these subgroups. Gender differences in smartphone use patterns are well established in prior research, as females tend toward social communication whereas males are more inclined toward gaming and entertainment (Lee et al., 2019). Undergraduate students face different academic pressures compared to postgraduate researchers, meaning the relationships observed here may not hold uniformly across these groups. Future studies should employ proportionate stratified sampling techniques using gender and program to ensure broader demographic representativeness.

Finally, while multiple regression analysis was adequate for testing the directional hypotheses of this study, it does not account for potential indirect associations among variables. Future research should consider applying SEM, which would allow for the simultaneous testing of direct and indirect effects, better control of measurement error, and the inclusion of mediating variables such as psychological wellbeing, self-efficacy, and social support that may explain *how* smartphone addiction dimensions impact academic outcomes. Further expanding the study to include domestic Indian students alongside international students would also allow for meaningful cross-group comparisons.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Meenu Gupta  <https://orcid.org/0009-0002-9755-8467>

References

- Akers, R. L. (1991). Addiction: The troublesome concept. *Journal of Drug Issues*, 21(4), 777–793. <https://doi.org/10.1177/002204269102100407>
- Alageel, A. A., Alyahya, R. A., Bahatheq, Y. A., Alzunaydi, N. A., Alghamdi, R. A., Alrahili, N. M., McIntyre, R. S., & Iacobucci, M. (2021). Smartphone addiction and associated factors among postgraduate students in an Arabic sample: A cross-sectional study. *BMC Psychiatry*, 21(1), Article 302. <https://doi.org/10.1186/s12888-021-03285-0>
- Al-Barashdi, H. S., Bouazza, A., & Jabur, N. H. (2015). Smartphone addiction among university undergraduates: A literature review. *Journal of Scientific Research and Reports*, 4(3), 210–225. <https://doi.org/10.9734/JSRR/2015/12245>
- Albursan, I. S., Mohammad, M. F., Al-Barashdi, H. S., Bakhiet, S. F., Darandari, E., Al-Asqah, S. S., Hammad, H. I., Al-Khadher, M. M., Qara, S., Al-Mutairy, S. H., & Albursan, H. I. (2022). Smartphone addiction among university students in light of the COVID-19 pandemic: Prevalence, relationship to academic procrastination, quality of life, gender and educational stage. *International Journal of Environmental Research and Public Health*, 19(16), Article 10439. <https://doi.org/10.3390/ijerph191610439>
- Al-Rajabi, N., Masadeh, R., ALBashtawy, M., Mahmoud, K. F., Allari, R. S., Othman, E. H., & Jarrah, S. S. (2026). Determinants of smartphone addiction among university students in Jordan. *BMC Psychology*, 14(1), Article 28. <https://doi.org/10.1186/s40359-025-03603-1>
- Arefin, M. S., Islam, M. R., Mustafi, M. A. A., Afrin, S., & Islam, N. (2017). Impact of smartphone addiction on academic performance of business students: A case study. *Independent Journal of Management & Production*, 8(3), 955–975. <https://doi.org/10.14807/ijmp.v8i3.629>

- Augner, C., & Hacker, G. W. (2012). Associations between problematic mobile phone use and psychological parameters in young adults. *International Journal of Public Health*, 57(2), 437–441. <https://doi.org/10.1007/s00038-011-0234-z>
- Bianchi, A., & Phillips, J. G. (2005). Psychological predictors of problem mobile phone use. *CyberPsychology & Behavior*, 8(1), 39–51. <https://doi.org/10.1089/cpb.2005.8.39>
- Billieux, J., Maurage, P., Lopez-Fernandez, O., Kuss, D. J., & Griffiths, M. D. (2015). Can disordered mobile phone use be considered a behavioral addiction? An update on current evidence and a comprehensive model for future research. *Current Addiction Reports*, 2(2), 156–162. <https://doi.org/10.1007/s40429-015-0054-y>
- Blaszczynski, A., & Nower, L. (2002). A pathways model of problem and pathological gambling. *Addiction*, 97(5), 487–499.
- Brenner, V. (1997). Psychology of computer use: XLVII. Parameters of Internet use, abuse and addiction: The first 90 days of the Internet Usage Survey. *Psychological Reports*, 80(3), 879–882. <https://doi.org/10.2466/pr0.1997.80.3.879>
- Chesley, N. (2005). Blurring boundaries? Linking technology use, spillover, individual distress, and family satisfaction. *Journal of Marriage and Family*, 67(5), 1237–1248. <https://doi.org/10.1111/j.1741-3737.2005.00213.x>
- Chiu, S.-I. (2014). The relationship between life stress and smartphone addiction on Taiwanese university student: A mediation model of learning self-efficacy and social self-efficacy. *Computers in Human Behavior*, 34, 49–57. <https://doi.org/10.1016/j.chb.2014.01.024>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Demirci, K., Akgönül, M., & Akpinar, A. (2015). Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *Journal of Behavioral Addictions*, 4(2), 85–92. <https://doi.org/10.1556/2006.4.2015.010>
- Farooq, O., Shah, S. A. M., & Hafeez, S. (2021). Smartphone addiction factors effecting university student performance. *NUML International Journal of Business & Management*, 16(2), 1–13. <https://doi.org/10.52015/nijbm.v16i2.70>
- Field, A. (2009). *Discovering statistics using SPSS* (3rd ed.). Sage Publications.
- Glanze, W. D., Anderson, K., & Anderson, L. E. (Eds.). (1998). *Mosby's medical, nursing, and allied health dictionary* (5th ed.). Mosby.
- Griffiths, M. D. (2005). A “components” model of addiction within a biopsychosocial framework. *Journal of Substance Use*, 10(4), 191–197. <https://doi.org/10.1080/14659890500114359>
- Junco, R. (2012). In-class multitasking and academic performance. *Computers in Human Behavior*, 28(6), 2236–2243.
- Junco, R., & Cotten, S. R. (2012). No A 4 U: The relationship between multitasking and academic performance. *Computers & Education*, 59(2), 505–514.
- Kim, S. G., Park, J., Kim, H. T., Pan, Z., Lee, Y., & McIntyre, R. S. (2019). The relationship between smartphone addiction and symptoms of depression, anxiety, and attention-deficit/hyperactivity in South Korean adolescents. *Annals of General Psychiatry*, 18, Article 1. <https://doi.org/10.1186/s12991-019-0224-8>
- King, D., Moon, K., & Kushlev, K. (2025). Time-specific digital detox interventions: Effects and effectiveness among college students. *Technology, Mind, and Behavior*, 6(3). <https://doi.org/10.1037/tmb0000173>
- Kirk, J., & Miller, M. L. (1986). *Reliability and validity in qualitative research*. Sage.
- Kolhe, D., & Naik, A. R. (2025). Digital detox as a means to enhance eudaimonic well-being. *Frontiers in Human Dynamics*, 7, Article 1572587. <https://doi.org/10.3389/fhumd.2025.1572587>

- Koo, H.-Y. (2011). Development and effects of a prevention program for cell phone addiction in middle school students. *Journal of Korean Academy of Child Health Nursing*, 17(2), 91–99. <https://doi.org/10.4094/jkachn.2011.17.2.91>
- Kraut, R., Patterson, M., Lundmark, V., Kiesler, S., Mukopadhyay, T., & Scherlis, W. (1998). Internet paradox: A social technology that reduces social involvement and psychological well-being? *American Psychologist*, 53(9), 1017–1031. <https://doi.org/10.1037/0003-066X.53.9.1017>
- Kuş, M. (2025). A meta-analysis of the impact of technology related factors on students' academic performance. *Frontiers in Psychology*, 16, Article 1524645. <https://doi.org/10.3389/fpsyg.2025.1524645>
- Kuss, D. J., & Griffiths, M. D. (2011). Online social networking and addiction—A review of the psychological literature. *International Journal of Environmental Research and Public Health*, 8(9), 3528–3552. <https://doi.org/10.3390/ijerph8093528>
- Kuss, D. J., Griffiths, M. D., & Binder, J. F. (2013). Internet addiction in students: Prevalence and risk factors. *Computers in Human Behavior*, 29(3), 959–966.
- Kwon, M., Lee, J.-Y., Won, W.-Y., Park, J.-W., Min, J.-A. (2013). Development and validation of a smartphone addiction scale (SAS). *PLOS ONE*, 8(2), Article e56936. <https://doi.org/10.1371/journal.pone.0056936>
- Lee, Y. K., Chang, C. T., Lin, Y., & Cheng, Z. H. (2019). The dark side of smartphone usage: Psychological traits, compulsive behavior and technostress. *Computers in Human Behavior*, 31, 373–383. <https://doi.org/10.1016/j.chb.2013.10.047>
- Lepp, A., Barkley, J. E., & Karpinski, A. C. (2014). The relationship between cell phone use, academic performance, anxiety, and satisfaction with life in college students. *Computers in Human Behavior*, 31, 343–350.
- Lepp, A., Barkley, J. E., Sanders, G. J., Rebold, M., & Gates, P. (2013). The relationship between cell phone use, physical and sedentary activity, and cardiorespiratory fitness in a sample of U.S. college students. *International Journal of Behavioral Nutrition and Physical Activity*, 10, Article 79.
- Levine, L. E., Waite, B. M., & Bowman, L. L. (2012). Mobile media use, multitasking and distractibility. *International Journal of Cyber Behavior, Psychology and Learning*, 2(3), 15–29.
- Maier, C., Laumer, S., Eckhardt, A., & Weitzel, T. (2015). Giving too much social support: Social overload on social networking sites. *European Journal of Information Systems*, 24(5), 447–464. <https://doi.org/10.1057/ejis.2014.3>
- Matusik, S. F., & Mickel, A. E. (2011). Embracing or embattled by converged mobile devices? Users' experiences with a contemporary connectivity technology. *Human Relations*, 64(8), 1001–1030. <https://doi.org/10.1177/0018726711405552>
- Miezah, D., Brew, T., Graham, M. A., & Obeng, P. (2026). Smartphone addiction among university students: A scoping review of prevalence, correlates and impact. *Human Behavior and Emerging Technologies*, 2026, Article 5511423. <https://doi.org/10.1155/hbe2/5511423>
- Nunnally, J. C. (1967). *Psychometric theory*. McGraw-Hill.
- O'Guinn, T. C., & Faber, R. J. (1989). Compulsive buying: A phenomenological exploration. *Journal of Consumer Research*, 16(2), 147–157. <https://doi.org/10.1086/209204>
- Oulasvirta, A., Rattenbury, T., Ma, L., & Raita, E. (2012). Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing*, 16(1), 105–114. <https://doi.org/10.1007/s00779-011-0412-2>
- Parylak, S. L., Koob, G. F., & Zorrilla, E. P. (2011). The dark side of food addiction. *Physiology & Behavior*, 104(1), 149–156. <https://doi.org/10.1016/j.physbeh.2011.04.063>
- Peele, S. (1985). *The meaning of addiction: Compulsive experience and its interpretation*. Lexington Books.

- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Raza, S. A., Qazi, W., Umer, B., & Khan, K. A. (2020). Influence of social networking sites on life satisfaction among university students: A mediating role of social benefit and social overload. *Health Education, 120*(2), 141–164.
- Sagioglou, C., & Greitemeyer, T. (2014). Facebook's emotional consequences: Why Facebook causes a decrease in mood and why people still use it. *Computers in Human Behavior, 35*, 359–363. <https://doi.org/10.1016/j.chb.2014.03.003>
- Samaha, M., & Hawi, N. S. (2016). Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. *Computers in Human Behavior, 57*, 321–325. <https://doi.org/10.1016/j.chb.2015.12.045>
- Sohn, S. Y., Krasnoff, L., Rees, P., Kalk, N. J., & Carter, B. (2021). The association between smartphone addiction and sleep: A UK cross-sectional study of young adults. *Frontiers in Psychiatry, 12*, Article 629407. <https://doi.org/10.3389/fpsyt.2021.629407>
- Soyemi, J., Oloruntoba, S. A., & Okafor, B. (2015). Analysis of mobile phone impact on student academic performance in tertiary institution. *International Journal of Emerging Technology and Advanced Engineering, 5*(1), 361–365.
- Toda, M., Monden, K., Kubo, K., & Morimoto, K. (2006). Mobile phone dependence and health-related lifestyle of university students. *Social Behavior and Personality, 34*(10), 1277–1284. <https://doi.org/10.2224/sbp.2006.34.10.1277>
- Tromholt, M. (2016). The Facebook experiment: Quitting Facebook leads to higher levels of well-being. *Cyberpsychology, Behavior, and Social Networking, 19*(11), 661–666. <https://doi.org/10.1089/cyber.2016.0259>
- Wang, Y., Niiya, M., Mark, G., Reich, S. M., & Warschauer, M. (2015). Coming of age (digitally): An ecological view of social media use among college students. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing* (pp. 571–582). Association for Computing Machinery.
- Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper & Row.
- Young, K. S. (1998). Internet addiction: The emergence of a new clinical disorder. *CyberPsychology & Behavior, 1*(3), 237–244. <https://doi.org/10.1089/cpb.1998.1.237>
- Zeeraq, Q., Imran, M., Azeez, K., Lokanathan, T. H., & Ismail, I. M. (2024). The effects of smartphone addiction on academic performance among undergraduate medical students in Karnataka, India: A multi-centric study. *Cureus, 16*(6), Article e62796. <https://doi.org/10.7759/cureus.62796>

Appendix

Table 9. Results of Descriptive Statistics.

Descriptive Statistics						
	N	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
I feel very energetic when I use my smartphone, regardless of my level of tiredness	132	1.096	−0.017	0.211	−1.052	0.419
I use smartphone for longer and spend more money on it than I intend to	132	1.076	−0.034	0.211	−0.793	0.419
Although using my smartphone has had negative effects on my interpersonal relationships, the amount of time I spend on the internet remains unreduced	132	1.178	−0.446	0.211	−0.817	0.419
I feel distressed or down once I stop using my smartphone for a certain period.	132	1.140	0.178	0.211	−1.042	0.419
I cannot control the impulse to use my smartphone	132	1.087	0.074	0.211	−0.757	0.419
My recreational activities are reduced because of my smartphone use.	132	1.191	−0.076	0.211	−0.920	0.419
My life would be joyless if I did not have a smartphone	132	1.308	0.333	0.211	−1.143	0.419
Using my smartphone has placed me in dangerous situations: for example, I have used it while crossing the road or while driving	132	1.250	0.799	0.211	−0.458	0.419
I try to spend less time on my smartphone, but my efforts are in unsuccessful	132	1.031	−0.104	0.211	−0.830	0.419
I have slept less than 4 hours more than once because of my smartphone use	132	1.293	0.549	0.211	−0.893	0.419
I find myself using my smartphone at the cost of socializing with my friends	132	1.003	−0.187	0.211	−0.614	0.419
I get aches and soreness in my back or eye discomfort caused by excessive smartphone use.	132	1.160	0.044	0.211	−1.053	0.419

(Table 9 continued)

(Table 9 continued)

Descriptive Statistics						
	N	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
My smartphone use has had certain negative effects on my schoolwork or job performance	132	1.120	-0.261	0.211	-0.860	0.419
My interaction with family members is decreased because of my smartphone use	132	1.111	-0.290	0.211	-0.993	0.419
My smartphone use is a habit and as a result my sleep quality	132	1.035	0.264	0.211	-0.792	0.419
I need to spend an increasing amount of time on my smartphone to achieve the same satisfaction as before	132	.921	0.089	0.211	-0.808	0.419
I feel tired during the daytime due to late-night use of my smartphone	132	1.104	0.275	0.211	-0.602	0.419
I feel uneasy once I stop using my smartphone for a certain period.	132	1.207	-0.061	0.211	-1.183	0.419
The first thing I think about when I wake up each morning is using my smartphone	132	1.174	-0.572	0.211	-0.605	0.419
I feel like I am missing something when I stop using my smartphone for a certain period	132	.992	-0.222	0.211	-1.046	0.419
I feel the urge to use my smartphone again immediately after I stop using it.	132	1.090	0.109	0.211	-1.147	0.419
I have been told more than once that I spend too much time using my smartphone	132	1.025	-0.338	0.211	-0.383	0.419
I find that I am hooked on my smartphone increasingly longer periods	132	1.017	-0.289	0.211	-0.687	0.419
Over the past three months I have substantially increased the amount of time I spend using my smartphone	132	1.108	-0.023	0.211	-0.736	0.419

(Table 9 continued)

(Table 9 continued)

Descriptive Statistics						
	N	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Using a smartphone makes me not to study more efficiently	132	1.255	0.060	0.211	-1.134	0.419
Using a smartphone deteriorate my performance in studying and understanding	132	1.120	0.062	0.211	-1.175	0.419
Using a smartphone decreases my course work productivity.	132	1.135	0.316	0.211	-0.851	0.419
Using a smartphone decreases my research knowledge and skills.	132	1.190	0.193	0.211	-1.132	0.419
Using a smartphone reduces my study effectiveness.	132	1.120	0.136	0.211	-1.126	0.419
Overall, I find a smartphone not useful in my studies and contribute negatively to my academic performance	132	1.254	0.251	0.211	-1.046	0.419
Valid N (listwise)	132					

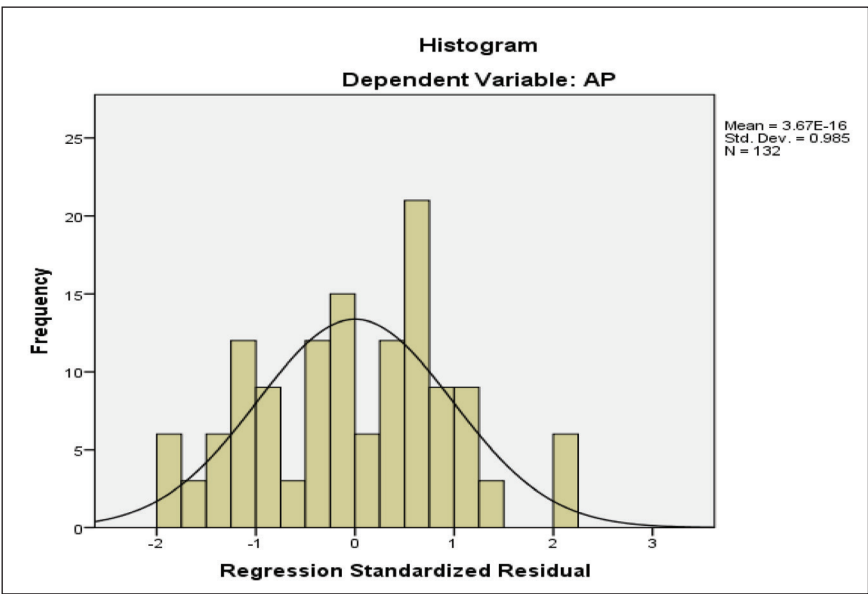


Figure 2. Histogram of Regression Standardized Residuals (Dependent Variable: AP).

Manuscript submission

- The preferred format for your manuscript is MS Word.
- The journal does not consider a paper that has been published elsewhere or that is under submission to another publisher. Authors must attest to this at the time of submission. It is also author's responsibility to disclose any potential conflict of interests regarding their submitted papers.
- Authors will be provided with a copyright form once the contribution is accepted for publication. The submission will be considered as final only after the filled-in and signed copyright form is received.

Basic formatting of the manuscripts

The journal publishes the following article types:

- Original article – 6000–8000 words. This must be accompanied by an abstract of up to 150 words, and 4–6 keywords
- Review essay – 6000–8000 words
- Perspective/viewpoint – 3000–5000 words
- Interview – 2000–3000 words
- Book review – 2000–3000 words

Please refer to the Submission Guidelines on the journal website for details on formatting.

Spelling and numerical usages

- Consistent use of either British or American spelling is advised, but not both at the same time.
- Spell out numbers from one to nine, 10 and above to remain in figures. However, for exact measurements use only figures (e.g. 3 km, 9%). Please use 'thirteenth' instead of '13th century'; use '1960s' instead of 'nineteen sixties'.

Quotations, notes, tables and figures

- British English uses single quotation marks to indicate quotations or dialogue, double quotation marks for quotation inside quotation (nested quotation). American English flips that method and uses double quotation marks to indicate quotations or dialogue, and single quotation marks for nested quotations. Either British or American punctuation patterns should be used and it should not be a mix.
- Notes should be numbered serially and presented at the end of the article. Notes must contain more than a mere reference.
- Tables and figures must be cited in the text, and indicated by number separately (Table 1), not by placement (see Table below). Source details for figures and tables should be mentioned irrespective of whether or not they require permissions.
- All photographs and scanned images should have a resolution of minimum 300 dpi and 1500 pixels, and their format should be TIFF or JPEG. Due permissions should be taken for copyright-protected photographs/images.

References and their text citations

- References and their citations should be given in accordance with APA 7th edition.
- Please ensure that all references mentioned in the reference list are cited in the text and vice versa.

For detailed style guidelines, please visit <https://www.bsp.bimtech.ac.in/>

