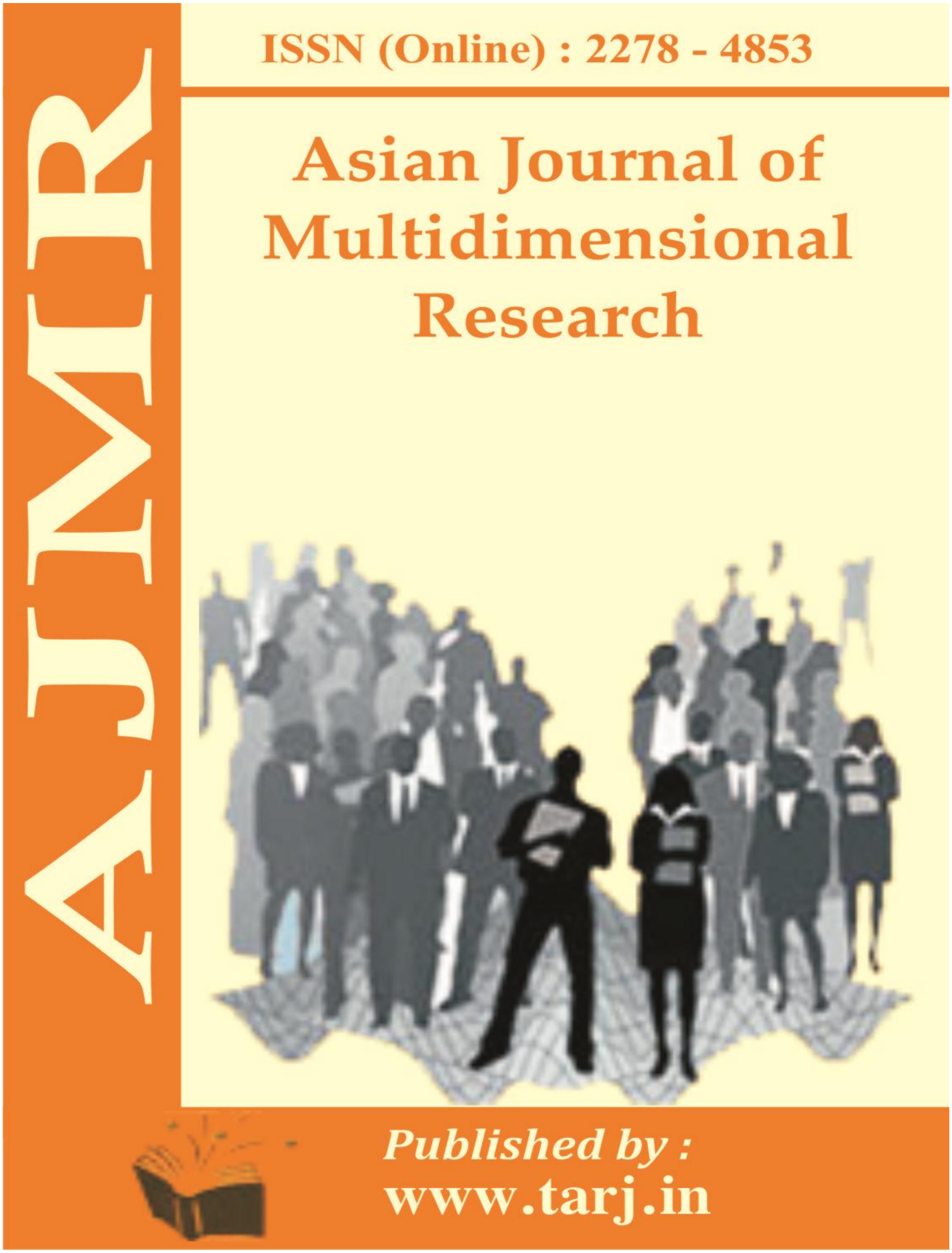
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VISION

The vision of the journals is to provide an academic platform to scholars all over the world to publish their novel, original, empirical and high quality research work. It propose to encourage research relating to latest trends and practices in international business, finance, banking, service marketing, human resource management, corporate governance, social responsibility and emerging paradigms in allied areas of management. It intends to reach the researcher's with plethora of knowledge to generate a pool of research content and propose problem solving models to address the current and emerging issues at the national and international level. Further, it aims to share and disseminate the empirical research findings with academia, industry, policy makers, and consultants with an approach to incorporate the research recommendations for the benefit of one and all.

AN ANALYSIS OF NON-PERFORMING ASSETS (NPA'S) OF SCHEDULED COMMERCIAL BANKS (SCB'S) IN INDIA

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ABSTRACT

Scheduled Commercial Banks (SCBs) are banks listed in the Second Schedule of the Reserve Bank of India Act, 1934. These banks are authorized to carry out commercial banking activities and are eligible to avail facilities from the central bank, including refinancing and liquidity support. NPA is defined as a credit facility in respect of which the interest and/or installment of principal has remained 'past due' for a specified period of time. In simple terms, an asset is tagged as non- performing when it ceases to generate income for the lender. NPA is used by financial institutions that refer to loans that are in jeopardy of default. Once the borrower has failed to make interest or principle payments for 90 days the loan is considered to be a non-performing asset.

KEYWORDS: *Non-Performing Assets, Scheduled Commercial Banks, RBI, Credit Creation, Financial Inclusion, Economic Growth Etc.*

INTRODUCTION

Scheduled Commercial Banks (SCBs) are banks listed in the Second Schedule of the Reserve Bank of India Act, 1934. These banks are authorized to carry out commercial banking activities and are eligible to avail facilities from the central bank, including refinancing and liquidity support.

SCBs form the core of India's banking system, playing a critical role in credit creation, monetary transmission, financial inclusion, and economic growth.

Legal Basis:

A bank is classified as a Scheduled Commercial Bank when:

- It is included in the Second Schedule of the RBI Act, 1934.
- It has a minimum paid-up capital and reserves as prescribed by RBI.
- They conduct their affairs in a manner that does not harm the interests of depositors.
- These banks are regulated by the Reserve Bank of India.

Key Features of Scheduled Commercial Banks:

- Scheduled Commercial Banks are eligible for RBI refinancing and liquidity facilities.
- They must maintain Cash Reserve Ratio (CRR) and Statutory Liquidity Ratio (SLR) as per RBI guidelines.
- Scheduled Commercial Banks will work subject to RBI supervision, inspection and prudential norms.
- Scheduled Commercial Banks can participate in monetary policy operations.
- Scheduled Commercial Banks can accept deposits and provide loans to households, businesses and government.

Classification of Scheduled Commercial Banks:

Public Sector Banks:

These banks are majority-owned by the Government of India:

- State Bank of India (SBI) and its associates.
- All Nationalised Banks (such as Punjab National Bank, Bank of Baroda, Canara Bank, Bank of India etc.).

They play a major role in priority sector lending, financial inclusion and government schemes.

Private Sector Banks:

These banks are owned and managed by private shareholders:

- Old Private Sector Banks such as Federal Bank, South Indian Bank, Karur Vysya Bank etc.
- New Private Sector Banks such as HDFC Bank, ICICI Bank, Axis Bank, Kotak Mahindra Bank etc.

They are known for technological adoption, efficiency and customer-centric services.

Foreign Banks:

Foreign banks operating in India with branches or wholly-owned subsidiaries are also Scheduled Commercial Banks:

- Foreign banks include HSBC, Citi Bank, Standard Chartered Bank etc.
- They mainly focus on corporate banking, trade finance and high-net-worth clients.

Regional Rural Banks (RRBs):

Regional Rural Banks (RRBs) are also included under Scheduled Commercial Banks:

- These banks are jointly owned by the Central Government, State Government and Sponsor Banks.
- They focus on rural credit, agriculture, MSMEs and financial inclusion.
- These banks are regulated by NABARD and the Reserve Bank of India.

Functions of Scheduled Commercial Banks:

- Accept deposits from public (savings, current, fixed, recurring).
- Provides credit to agriculture, industry, services and households.
- Facilitate payments and settlements of customers.
- Support priority sector lending.
- Helps in implementing government welfare and subsidy schemes.
- Act as key channels for monetary policy transmission.

Importance of Scheduled Commercial Banks:

Scheduled Commercial Banks (SCBs) are pivotal to the Indian economy.

- Mobilise savings and convert them into productive investments.
- Support economic growth by financing infrastructure, industry and MSMEs.
- Enable financial inclusion through Jan Dhan accounts, DBT and digital banking.
- Act as transmission channels for RBI’s repo rate and liquidity measures.

Difference between Scheduled Commercial Banks and Non-Scheduled Banks:

- Scheduled Banks: Listed in the Second Schedule of RBI Act, eligible for RBI facilities, larger and more regulated.
- Non-Scheduled Banks: Not listed in the Second Schedule, limited operations and fewer privileges.

Research Methodology:

The secondary data has been used to analysis the study. The data has been collected from annual accounts of banks and off-site returns. The data has also been collected from annual statistics released by the Reserve Bank of India.

Period of Study:

The period of study has been taken of 10 years starting from 2014-15 to 2023-24.

Review of Literature:

Tamilselvi V., Ashok Kumar Sahoo (2026) study examines the role of strategic risk management practices in reducing NPAs and enhancing sustainable banking performance in India. Using secondary data from 20 public and private sector banks covering the period 2019–2023, the study applies descriptive statistics, correlation analysis, and multiple regression modelling to analyse the determinants of asset quality. The results reveal that Provision Coverage Ratio (PCR), Capital Adequacy Ratio (CAR), Return on Assets (ROA), and Risk Governance Score have significant negative relationships with Gross Non-Performing Assets (GNPA).[1]

Rinku Mani Roy (2025) examined the performance of 10 public sector commercial banks in India, focusing on deposit growth, advances, and NPA management from FY 2019-20 to FY 2023-24. Using secondary data collected from bank annual reports, the RBI website, and relevant literature, the study employs the CAGR and Independent t-test (at a 95% confidence level) to analyze key trends.[2]

Dr. Malini M. V. (2025) study presents an empirical assessment of Non-Performing Asset (NPA) dynamics and financial stability indicators of Public Sector Banks (PSBs) in India during the period 2018– 2025. The study examines trends in gross and net NPAs, provisioning strength, capital adequacy, profitability, recoveries, write-offs, and credit growth. The findings reveal a significant and sustained improvement in asset quality, with Gross NPAs declining by nearly 70 percent and Net NPAs reducing by more than 85 percent over the study period.[3]

Diksha Sahni, (2023) The non performing assets of the Public Sector Banks have been increasing regularly year by year. On the contrary, the non performing assets of private sector banks have been decreasing regularly year by year except some years. Generally reduction in NPAs shows that banks have strengthened their credit appraisal processes over the years and increased in NPAs shows the necessity of provisions, which bring down the overall profitability of banks. The Indian banking sector is facing a serious problem of NPA. The magnitude of NPA is comparatively higher in public sectors banks than private sector banks. To improve the efficiency and profitability of banks the NPA need to be reduced and controlled.[4]

Ankit Garg, (2022) Non-performing Asset is one of the prevalent problems of Indian Banking sector. For the past three decades, the banking system has several outstanding achievements to its credit. Many banks are facing the problem of NPAs which hampers the business of the banks. Non-performing assets are a drain to the banks. The problem of NPA impacts profitability, Liquidity and results in credit loss unless and otherwise proper remedial measures are taken the quantum of non-performing assets cannot be reduced and the bank will incur losses to a great extent.

Murari Premnath Sharma, (2021) an asset, including a leased asset, becomes non- performing when it ceases to generate income for the bank. The Non-Performing Assets strike terror in banking sector today. The dreaded NPA increases year by year continuously. Due to this risk performance of the banking sector has been decreasing and some of them have been liquidated. The three letter black snake (NPA) is going up. Now we should think seriously about the regulator norms of our financial sector. It may be guarantor norms, recovery rules and its implementation.

Kavitha Nachimuthu, Muthukrishna Veni (2019) there was evidence for increase in non-performing assets. The various analysis were used to find out the impact of NPA's on the profitability of the scheduled commercial banks. It was significantly related to the ratio of Gross NPA to Gross Advances and ratio of Net NPA to Net Advances, ratio of Gross NPA to Total Assets and ratio of Net NPA to Total Assets is insignificantly related to each other. Thus, the profitability of the banks has reduced, due to rise in the non-performing assets of the scheduled commercial banks in India.[5]

Non-Performing Assets:

NPA is defined as a credit facility in respect of which the interest and/or installment of principal has remained 'past due' for a specified period of time. In simple terms, an asset is tagged as non-performing when it ceases to generate income for the lender. NPA is used by financial institutions that refer to loans that are in jeopardy of default. Once the borrower has failed to make interest or principle payments for 90 days the loan is considered to be a non-performing asset.

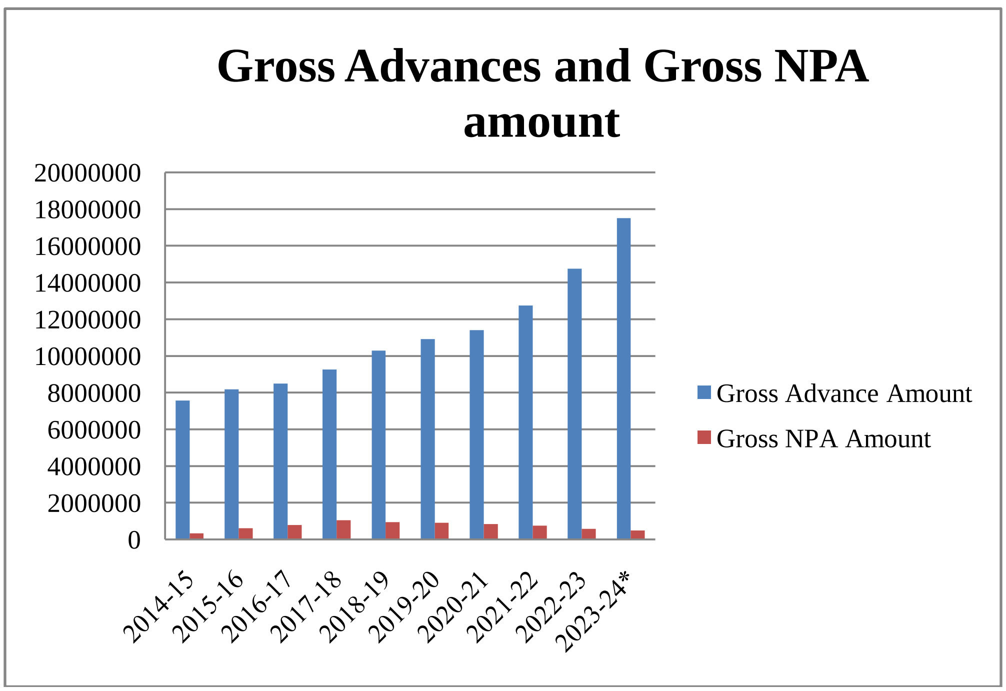
Table no. 1

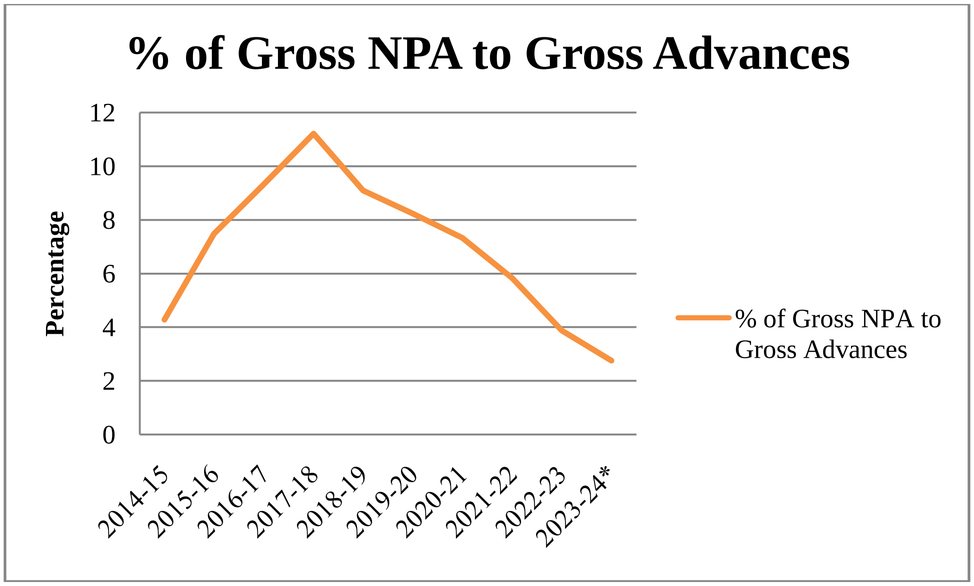
Table showing Comparison between Gross Advances and Gross NPA amount

Sr. No.	Financial Year	Gross Advance Amount	Gross NPA Amount	% of Gross NPA to Gross Advances
1	2014-15	7559760	323335	4.28
2	2015-16	8173121	611947	7.49
3	2016-17	8492565	791791	9.32
4	2017-18	9266210	1039679	11.22
5	2018-19	10294463	936474	9.1
6	2019-20	10918918	899803	8.24
7	2020-21	11399608	835138	7.33
8	2021-22	12750006	743640	5.83
9	2022-23	14756637	571546	3.87
10	2023-24*	17508590	480818	2.75

(* Data for 2023-24 is provisional)

(Sources: Annual Accounts of Banks, and off-site returns.)





Gross NPAs are the sum total of all loan assets that are classified as NPAs as per the Reserve Banks of India (RBI) guidelines as on Balance Sheet date. Gross NPA reflects the quality of the loans made by the banks. It consists of all the non-standard assets like sub-standard, doubtful and loss assets. Table no. 1 shows the comparison between Gross Advances and Gross Non-Performing Assets (NPA's) of Scheduled Commercial Banks (SCB's) for 10 years from 2014-15 to 2023-24. The Gross Advances are showing an increasing trend every year during the research period, while the Gross NPA's of SCB's are first increasing from 2014-15 to 2017-18, then it shows the decreasing trend from 2018-19 to 2023-24. The percentage of Gross NPA's to Gross Advances is also increasing from 2014-15 to 2017-18 from 4.28% to 11.22% i.e. an increase of 6.94%, while it starts fast decreasing from 2017-18 to 2023-24 from 11.22% to 2.75% i.e. a decrease of 8.47%. This happened due to the strict government guidelines and close control of Reserve Bank of India.

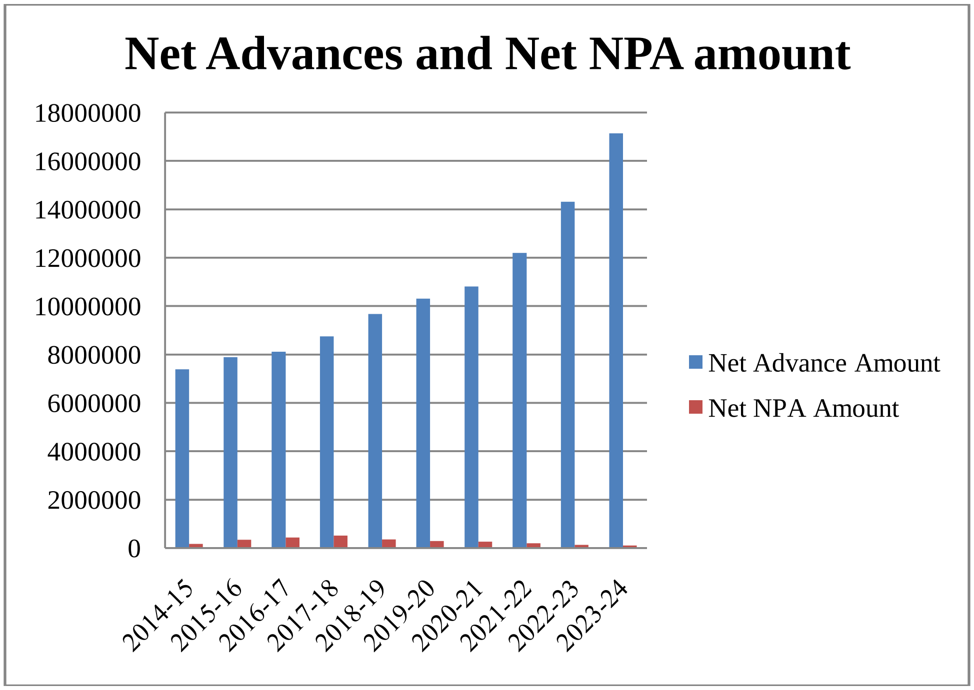
Table no. 2

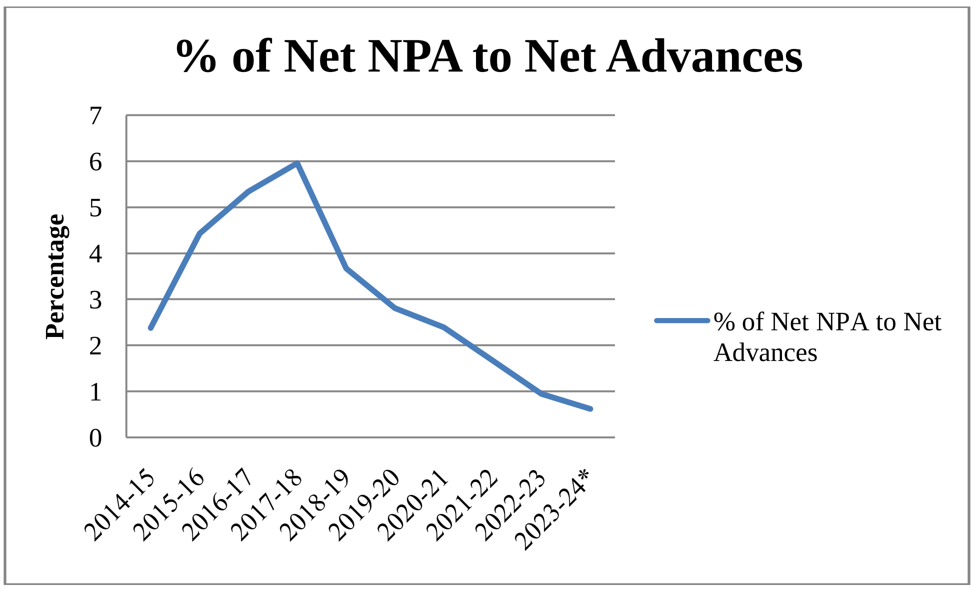
Table showing Net Advances and Net NPA amount

Sr. No.	**Financial Year**	**Net Advance Amount**	**Net NPA Amount**	**% of Net NPA to Net Advances**
1	**2014-15**	**7388160**	**175841**	**2.38**
2	**2015-16**	**7896467**	**349814**	**4.43**
3	**2016-17**	**8116109**	**433121**	**5.34**
4	**2017-18**	**8745997**	**520838**	**5.96**
5	**2018-19**	**9676183**	**355068**	**3.67**
6	**2019-20**	**10301897**	**289370**	**2.81**
7	**2020-21**	**10806381**	**258050**	**2.39**
8	**2021-22**	**12198767**	**204231**	**1.67**
9	**2022-23**	**14319352**	**135320**	**0.95**
10	**2023-24**	**17142340**	**106732**	**0.62**

(* Data for 2023-24 is provisional)

(Sources: Annual Accounts of Banks, and off-site returns.)





Net NPA (Net Non-Performing Asset) represents the actual value of bad loans a bank carries after deducting provisions (funds set aside for potential losses) from its Gross NPA. It measures the real risk to the bank's profitability and financial health, calculated as: Net NPA = Gross NPA - Provisions. A lower Net NPA ratio indicates better asset quality. Table no. 2 shows the comparison between Net Advances and Net Non-Performing Assets (NPA's) of Scheduled Commercial Banks (SCB's) for 10 years from 2014-15 to 2023-24. The Net Advances are showing an increasing trend every year during the research period, while the Net NPA's of

SCB's are first increasing from 2014-15 to 2017-18, then it shows the decreasing trend from 2018-19 to 2023-24. The percentage of Net NPA's to Net Advances is also increasing from 2014-15 to 2017-18 from 2.38% to 5.96% i.e. an increase of 3.58%, while it starts decreasing from 2017-18 to 2023-24 from 5.96% to 0.62% i.e. a decrease of 5.34%. This happened due to the strict government guidelines and close control of Reserve Bank of India.

CONCLUSIONS:

The problem of NPAs in the Indian banking system is one of the most important problems that had very bad impact on the Indian economy. Higher NPA's ratio decreases the confidence of investors, depositors, lenders etc. It also causes poor recycling of funds, which in turn will have harmful effect on the deployment of credit. The un-recovers debts or NPA's affects not only these banks but it is also hazardous for Indian economy. Managing bad loans and controlling them at lowest level has become very important for the banking sector in recent years. It is found that the impact of NPAs on the Indian economy is because of mismanagement in banks. Certain precautions if taken from the very beginning, the incidence of borrower accounts turning bad may be reduced to a large extent. Such as pre - sanction formalities, promptness and follow up actions. Because of mismanagement in bank there is a positive relation between Total Advances, Net Profits and NPA of bank which is not good. Positive relation between NPA & profits are due to wrong choice of clients by Banks. There is an adverse effect on the Liquidity of Bank. Bank is unable to give loans to the new customers due to lack of funds which arises due to NPA. As per the government, the main reasons for rise in NPAs are sluggishness in the domestic growth in the recent past, slow recovery in the global economy and continuing uncertainty in global markets leading to lower exports of various products.

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SOCIAL COMMERCE: RESHAPING E-COMMERCE AND INFLUENCE ON CONSUMER BEHAVIOUR

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ABSTRACT

Social media's explosive growth has drastically changed how customers engage with brands and make decisions about what to buy. Social commerce, which integrates social networking features with online shopping functionalities, has emerged as a powerful driver of consumer behaviour. By enabling social interaction, information sharing, and peer influence within the purchasing environment, social commerce alters traditional consumer decision-making processes. This paper examines the rise of social commerce and how it is impacting and reshaping the e-commerce and have influence on consumer behaviour by synthesizing existing literature and theoretical perspectives. Key factors such as, trust, social support, reviews, recommendations, and impulsive buying behaviour, influencer marketing are analyzed to understand their impact on consumer buying behaviour. The study provides insights for practitioners and researchers who seek to understand and use social commerce in the digital marketplace.

KEYWORDS: *Social Commerce, Social Media, Consumer Behaviour, E-Commerce.*

1. INTRODUCTION

The development of digital technology has significantly changed how consumers seek information, evaluate items, and make buying decisions. The rise of social media platforms such as Instagram, Facebook, Snapchat, Pinterest and YouTube has not only transformed communication but has also created new opportunities for commercial activities. As a result, social commerce has gained prominence as a modern form of online commerce that integrates social interactions with buying and selling processes (Liang & Turban, 2011).

The idea behind social commerce is that social media helps vendors' business dealings by fostering stronger bonds with clients, improving the quality of such interactions, boosting sales, and fostering consumer loyalty. A company may utilise a social media tool like Facebook or Twitter to access social platforms in order to accomplish these goals (Hajli, 2014).

From E-Commerce to Social Commerce

According to (Stephen and Toubi, 2009, as cited in Huang & Benyoucef, 2013), Web 2.0 transfers market power from businesses to consumers in the context of e-commerce.

Traditionally, e-commerce has been linked to online communities. Zetlin and Pfleging, for example, describe consumer-driven online markets where the majority of customers arrange their needs via a community website. Vendors can increase sales and more community members can receive discounts due to this consolidation of demands in one location. Web-based communication is therefore thought to have a significant impact on nearly all businesses that offer services or manufacture consumer goods. It might alter corporate advertising and community sponsorship tactics as well as the way that company is conducted (Blanchard & Markus , 2004).

In today's digital economy, merely opening a physical or online store and expecting customers to come is inadequate. Companies must proactively engage with their audience, foster relationships, and cultivate communities. What is making difference in social commerce from conventional e-commerce platforms are its social features. These include social shopping tools, online communities, user recommendations and referrals, as well as customer feedback and evaluations (Linda, 2010).

From a sociological perspective, social commerce involves e-commerce businesses using online social communities to connect with consumers. It highlights how people's opinions, recommendations, and interactions with others influence their purchasing decisions and overall behaviour within these online networks (Kim and Srivastava, 2007, as cited in Huang & Benyoucef, 2013).

By incorporating user-generated content into the shopfront, social commerce permits businesses to more effectively contact customers worldwide than traditional retail shops. Consumers can work together online, share information about goods and services, and seek guidance from reliable people (Leitner and Grechenig, 2009, as cited in Zhou, Zhang, & Zimmermann, 2013)to help them make more precise and well-informed purchases. As a result, social media improves the shopping experience by influencing consumer behaviour and establishing connections. Customers don't just show up at a store; they bring their whole social network (Marsden, 2010 as cited in Zhou, Zhang, & Zimmermann, 2013)

Due to the rise of social media platforms, which allow users to actively making content on the Internet, social commerce is a recent development in e-commerce. Social media, which distinguishes social commerce from e-commerce, is an effective instrument for this. Social commerce is the use of Web 2.0 apps to facilitate human interaction in an online setting where contributions of users can help consumers in the purchase of goods and services (Liang & Turban, 2011).

2. Literature Review

Social Commerce

The use of social media to enable online sales and purchases of goods and services within the context of e-commerce is known as social commerce. It suggests the combination of social media and e-commerce, two significant digital phenomena (Linda, 2010). The term "social commerce," or "s-commerce," describes the practice of conducting online business through social networks and social media platforms like Facebook and Twitter. For this reason, it might be considered a subset of e-commerce that uses social media—online platforms that facilitate user contributions and social interactions—to help with online purchases and sales of products and services (Turban, Bolloju, & Liang , August 2010). Over the last few years, social media and social networking services have grown in popularity and attention, which has opened up new e-commerce options. Additionally, they have reinterpreted and questioned conventional vendor-push marketing and business practices (Liang and Turban 2011, Curty & Zhang, 2013).

E-commerce transactions carried out via social media are referred to as social commerce (SC). More precisely, it combines social media content, e-commerce, e-marketing, and the supporting technologies (Turban , Strauss , & Lai, 2012).

(Hu et al. 2022, as cited in Leong, Hew, Ooi, Hajli, & Tan, 2024) define social commerce as “a new form of electronic commerce (e-commerce) that combines e-commerce with social media techniques”.

A new subset and stream of e-commerce is called social commerce (Hajli, 2014b, as cited in Hajli N. , 2015). Social commerce is the use of Web 2.0 apps and social media to enable online interactions between people in order to assist customers in purchasing goods and services (Liang & Turban, 2011). Another definition of social commerce is any Internet-based commercial application that facilitates social interaction and user content creation via social media to assist people in making purchases (Z. Huang & Benyoucef, 2013).

Web 2.0 and social media technology enable social commerce by facilitating customer ratings, reviews, suggestions, and referrals. Customers are assisted in making purchasing decisions by ratings and reviews, which allow them to examine the opinions of their friends. Reviews can also have an impact on a brand's reputation (Davidson & Copulsky, 2006, as cited in Hajli N. , 2015).

Social commerce has drawn a lot of attention for influencing new online commercial platforms. In order to grow their operations, many e-retailers are utilising social technology and services. Social media has been used by more customersto gain information about businesses, brands, goods, and services because it is now easily available (Zhou, Zhang, & Zimmermann , 2013).

Social commerce places more emphasis on relationship-building, trust, content engagement, and social interaction than traditional e-commerce platforms, which prioritise transactional efficiency. Features like product tagging, live shopping, influencer partnerships, and user-generated reviews that have a direct impact on customer behaviour are made possible by platforms like Facebook, YouTube, and Instagram (Patel, 2025).

Benefits of Social Commerce

(Turban , Strauss , & Lai, 2012)in their book mention some benefits and challenges of Social Commerce.

Benefits to Customer

- Obtaining recommendations from friends and other consumers is straightforward, whether through Twitter, social media discussion groups, or product review websites. Such recommendations enhance confidence and trust, aiding customers in making purchasing decisions for products and services.
- Customers have access to special offers that provide significant savings.

- Purchases can be situational to align with the specific needs, desires, preferences, and aspirations of customers, which boosts satisfaction and shortens the time needed for product selection decisions.
- Utilizing social commerce technology is simple for customers.
- Social commerce is well-suited to the lifestyle of mobile device users.
- Customers develop greater trust in vendors through stronger relationships.
- Social commerce enables customers to assist one another, providing social support.
- Vendors offer improved customer service to their clients.
- Customers have the opportunity to form new friendships, such as for travel, and engage in online socialization.
- During the decision-making process, customers benefit from a rich social context and relevant information.
- Customers can reach out to people and businesses that would otherwise be out of their reach.

Benefits to Retailers

- Consumers have the opportunity to share their thoughts on both the communication strategies used in the market and the design of products or services.
- Vendors benefit from the free promotion that comes with word-of-mouth marketing.
- An increase in website visits, as demonstrated by the Starbucks launch case, leads to higher revenue and sales.
- Employing social influence techniques results in a boost in sales.

Limitations and Challenges in Social Commerce

While social commerce offers numerous opportunities for businesses, its adoption can bring about certain risks and potentially intricate challenges, such as merging new and existing information systems. Key risk factors include: challenges in convincing upper management of the value of social commerce initiatives, issues related to security and privacy, the risk of fraud, legal implications, the quality of user-generated content, and employees wasting time during work hours. Additionally, companies face the risk of losing the control over their brand images and reputations in social media discussions and on product review platforms, which could impact product sales.

3. Research Objectives

1. To understand the concept of social commerce, its benefits and limitations.

2. To identify influence of social commerce on impulsive buying behaviour of consumers.

3. To examine the importance of social support, ratings, recommendation, trust, influencer marketing on consumer behaviour.

4. To identify the consumer decision making and customer engagement in social commerce.

5. To explore the rise of social commerce and its impact on traditional e-commerce.

4. Research methodology

This paper is based on the secondary data which has been synthesized from the existing literature from various books, journals, conference proceedings, internet, etc.

5. Social Commerce influence on consumer behaviour

Transferring Power from Sellers to Buyers in Social Commerce

Reviews, ratings, communities, recommendations, and forums—help consumers communicate online and connect with one another. Customers' intention to engage in social commerce is impacted both directly and indirectly by this. Participants' behaviour and choices during the purchasing process are influenced by their social interactions with social commerce constructs. These online communications also make it easier for peers to share and receive information, which gives the network a source of social support. Social media platforms are being used by potential customers to recommend systems, rate and review products and services, and participate in online forums and communities. Prior to making a purchase, this is now common practice (Hajli & Sims, 2015).

Social Support, Recommendations, Ratings in Social Commerce

The term "social support" refers to the group members' felt affection, caring, and support (Cobb, 1976, as cited in Hajli, 2014). Individuals' intentions to involve in social commerce are strongly impacted by social support as indicated by emotional and informational support. Nowadays, prospective customers use social media resources including engaging in online forums and community, evaluating and recommending a system, or reviewing and rating a good or service. Nowadays, people usually do this before making buying decision. These social activities show that consumers are engaged and have the ability to offer proof that affects the actions of others. The findings demonstrate that user engagement not only affects his intention to engage in social commerce but also provides helpful assistance to those looking for information and guidance on the network (Hajli M. , 2014).

This discovery suggests that consumer social interactions offer various benefits to businesses. By participating in online communities or engaging with social media, consumers produce content regarding products or services. Such content can enhance the quality of relationships within a business, thereby boosting customer loyalty. Consequently, the valuable information generated online provides numerous benefits, with improved relationship quality being a key advantage. The co-creation environment involves consumers in the process of creating value for a business (Hajli M. , 2014). It is well recognised that social support influences consumer behaviour in a good way. It is especially crucial in social media since e-commerce has evolved into social commerce due to social connections between individuals on the Internet (Hajli & Sims, 2015).

It is easier for the person to post the review of the product online (Chen, Xu, &Whinston, 2011, as cited in Hajli, 2015) and provide ratings to the products. These ratings and reviews provide thorough product information for the advantage of other prospective buyers.Reviews and ratings appear to provide buyers with useful information. Additionally, consumers feel empowered when they participate in co-creation and content generation (Füller et al., 2009, as cited in Hajli,2015), as they can discover other people's experiences with a product.

According to research, consumers believe more on theother customers' experiences, such as their recommendations of product, in an online setting as they are unable to personally experience the goods or services (Senecal & Nantel, 2004, as cited in Hajli, 2015).

In e-commerce platforms, the consumer retention rate and website traffic has been increased by recommendation system (Chinchanachokchai et al., 2021 as cited in Asante, Jiang , Hossin , & Luo , 2023). The suggestion system is made feasible by gathering information about customers' questions and past purchases. It helps with product recommendations for customers using the website or e-commerce platform. The recommendation system helps to customise the e-commerce platform for individual customers by using advanced consumer profiling to provide more tailored search results(De Keyzer et al., 2022; Sivapalan et al., 2014 as cited in Asante, Jiang , Hossin , & Luo , 2023).

Impulsive buying behaviour in Social Commerce

An impulsive purchase is one that is made after being exposed to specific stimuli without any thought or planning (Beatty & Ferrell, 1998).Many consumers make impulsive, spontaneous purchases that are motivated by intense desire, joy, and excitement (Abdesalam, Salim, Alias, & Husain, 2020). Because social commerce promotes social networking and gives customers greater opportunities to influence one another, it may further drive impulsive purchases (Grange & Benbasat 2010; Huang & Benyoucef 2013). Social variables are thought to have a major influence on a consumer's impulsive behaviour (Kim & Srivastava 2007 as cited in Hung & Benyoucef, 2013).

E-commerce is thought to have given consumers more ways to make impulsive purchases (Sun, Fang, Lim, Straub, 2012, as cited in Hu, Chen , & Davison, 2019)because it makes a wide range of products more accessible and facilitates transactions (Strack et al. 2006, as cited in Hu, Chen , & Davison, 2019).Social commerce may make up for this loss of impulsive opportunities because it enhances online purchasing experiences by fostering strong and widespread customer relationships and partnerships (Shen & Eder 2009, as cited in Hu, Chen , & Davison, 2019). Contributions from users and information sharing are strongly encouraged and supported (Liang & Turban 2011). Peers would therefore have a big impact on consumers' opinions, preferences, and choices (Grange &Benbasat 2010; Huang & Benyoucef 2013). A consumer's shopping requirements and intentions may be created and altered by peer pressure, and there is a significant chance that this could lead to impulsive purchases (Xi, Hong, Jianshan, Li, & Jiuchang, 2016).

Peoplehave access to a wealth of information from friends, celebrities, vendors, news, and experts whenever they browse social networking sites, which makes them feel compelled to buy things(Huang L.-T. , 2016 as cited in Abdesalam, Salim, Alias, & Husain, 2020)

Influencer marketing and Social Commerce

Influencer marketing greatly affects followers' perceptions of product value and their level of trust in Social Media Influencers, both of which have a beneficial impact on purchase intentions (Taj, Hassan, & Javed, 2025).

In the context of social commerce, influencer marketing will create value. By boosting influencer marketing efforts, online retailers would improve the perception of value. Influencers on social media help businesses acquire genuine followers who may eventually becomeactual customers.

Additionally, they aid in building a positive perception of firms in the eyes of consumers (Abou Ali , Ali, & Mostapha , 2021).

Trust in social commerce

Trust reduces perceived risks and increases consumer engagement, with social interactions fostering emotional trust and cognitive trust supporting rational assessments. Although worries about content authenticity are still very much present, user generated content, safe platforms, and genuine endorsements by influencers are recognised as essential factors for fostering trust (Lee , 2025). Consumers gain trust when they acquire timely, accurate, and trustworthy information from social commerce communities. Trust is essentially built via interactions with other people and the environment (Al-kfairy , Shuhaiber, Al-khatib, Alrabaee, & Khaddaj, 2024).

According to the study, trust will rise in the new business environment of user-generated content, users will find it more valuable, and customer adoption of e-commerce will improve. Since trust is considered to be anessential component in facilitating e-commerce (Gefen and Straub, 2003, as cited in Hajli N. , 2015) the findings of this B2C study unequivocally demonstrate that trust remains a crucial component that has a remarkable impact on consumers' purchase intentions and Perceived Usefulness.

Web 2.0 applications are drawing people to connect and create content online. For these purposes, consumers employ social commerce constructions, which raise their level of trust and purchase intention and demonstrate that trust has a favourable impact on purchase intention (Hajli N. , 2015).

When individuals have higher degree of trust and great experience in e-commerce site, they are more likely to purchase. Web experience of users, website quality, technical trustworthiness and perceived market orientation influence the trust level of consumers (Corbitt, Thanasankit, & Yi, 2003).

Consumer decision making process in social commerce

Business organisations must properly embrace and handle Online Social Networks (OSNs) (like Facebook) in order to affect customer choices. Actually, businesses may coordinate their relationship-building and marketing initiatives with OSNs. The majority of businesses have only just begun to successfully employ social commerce strategies (Lin et al., 2017, as cited in Hettiarachchi , Wickramasinghe , & Ranathunga , 2018). The results showed that social commerce significantly improved consumer decision-making at every stage, including identification of need, search of information, alternative evaluation, purchase decision, and post-purchase decision. The study emphasises how important it is for corporate organisations to have a suitable social commerce strategy (Hettiarachchi , Wickramasinghe , & Ranathunga , 2018).

The research determines that consumers act as rational agents, making logical choices in social commerce. Even though the study used the sequence of steps involve in consumer decision-making model, it finds that consumers proceed back and forth across different buying phases. On social commerce web 2.0 platforms, users can recognize needs, gather information through social channels, assess options, and complete purchases. It finds that satisfied consumers intend to buy again, whereas dissatisfied consumers negatively correlate with information search in social commerce (Makudza, Sandada, & Madzikanda, 2022).

Primary predictor of customer participation in social commerce is website trust, followed by perceived usefulness, information quality, and trust. Regarding the attributes, the results also indicate that more costly goods and goods categorised as electronics and computersemploy more use of internet reviews, suggestions, and comments than do clothing, books, vacations, and home appliances. (Maia, Lunardi, Longaray, & Munhoz, 2018).

Millennials on social commerce platforms mainly seek guidance from family, friends, experts and influencers. They are more likely to be influenced by these reference groups to use a platform, and trust is key to accepting their recommendations. However, when they make buying decision, they generally do not examine these groups' purchasing habits or purchase the same products and services to imitate style or resemble them (Goldberg & Kotze, 2022).

In e-commerce, there are some emerging individual factors like trust, attitude, perceived risk which affects purchase intention of consumers. Some social factors such as online reviews, word of mouth, and social influence have significant impact on the choice of the customer. Additionally, some situational factors like pricing strategies, website design, and product presentation shape the experience of e-commerce and also influences buying decision (Jothimani, Mathur, Anand, Mahajan, & Shrivastava, 2023).

Increasing importance of customer engagement

Social support, platform interactivity, and hedonic motivations are among the most significant factors for customer engagement, and that satisfaction and trust play a critical role as mediators between engagement drivers and long-term results like word-of-mouth (WoM) and brand loyalty. It is discovered that involved customers not only show more advocacy and loyalty, but they also support the social commerce community-building and co-creation initiatives (Mubdir, Hashim, Ayob, & Rosli, 2025). One of the study looks at how certain social commerce characteristics—such as collaboration, community, social dynamics and interactivity—affect customer engagement, which is then thought to affect consumers' intentions to make repurchases and spread electronic word of mouth (e WOM). The findings show that customer engagement is positively impacted by the four characteristics that were looked at. Additionally, the results show that customer engagement has a favourable impact on intention of consumers to repurchase and spread word of mouth (Busalim, Hollebeek, & Lynn, 2024).

In electronic commerce, chatbot efficiency improves customer experience and strengthens digital connections between consumers and brands. As chatbots develop, their customer service role will shift from providing responses to fostering brand loyalty and shaping digital engagement strategies in e-commerce (Vebrianti, Aras, Putri, & Swandewi, 2025). Thus, AI Chatbot helps in enhancing the customer engagement, loyalty and satisfaction in electronic commerce.

Social commerce providers strategically enhance customer engagement and, consequently, improve platform performance by promoting collaboration, establishing robust communities, facilitating interactivity, and offering opportunities for social support and interaction (Busalim, Hollebeek, & Lynn, 2024).

6. Rise of social commerce and its impact on traditional e-commerce

How Social Commerce reshaping E- Commerce and retail

- Social commerce serves as a fundamental retail avenue, enabling consumers to find and purchase items directly through social media platforms, which is propelling the market to exceed $1 trillion in sales by 2029.
- By merging e-commerce with mobile-centric social interactions, it minimizes obstacles to purchasing and seizes spontaneous buys that conventional e-commerce frequently misses. Platforms like TikTok, Instagram, Facebook, YouTube, Snapchat, and Pinterest provide integrated shopping features for brands.
- Millennials and Gen Z are rapidly embracing influencer marketing, user-generated content, and tailored shopping experiences within social media feeds.
- By incorporating social commerce into a comprehensive omni channel approach, brands can expand their audience, enhance credibility through social validation, and encourage repeat buying (Spivey, 2026)

Social commerce fulfills distinct consumer needs while enhancing traditional e-commerce platforms. It not only builds trust but also caters to the increasing demand for:

- a broader selection of products and personalized options;
- a sense of belonging within a community;
- user-friendly convenience;
- a bargaining experience alike shopping in physical stores;
- and a shopping experience that is both enjoyable and interactive (Sheth, Sridharan, Reddy, Sadhwani, & Thakur, 2020)

Social platforms becoming shopping destinations

Social commerce is where people socially interact and can find research and buy things without leaving the app and have shopping experience. E-commerce has not been replaced by social commerce rather it expanded e-commerce as social platforms are the place where consumers meet and make purchasing feel less transactional and more enjoyable.

The integration of native shopping functionalities by key platforms contributed to this evolution:

- Browse able product catalogues and checkout features are offered by Facebook Marketplace and Instagram Shop.
- TikTok Shop uses short video content to encourage impulsive purchases.
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This integration provides retail media marketers with strong new advertising opportunities to engage customers in genuine and interesting ways.(Skai.io)

By allowing consumers to find and purchase goods directly within social media platforms, social commerce has arise as a key retail channel, propelling the industry toward over $1 trillion in worldwide sales by 2029. Social commerce meets customers wherever they are by bringing the store to them instead than sending them to an online store. In actuality, up to 63.9% of people on the planet utilise social media, with on an average of two hours and twenty-one minutes of daily usage. For e-commerce companies hoping to grow their omni channel retail footprint and market share, this is a tremendous opportunity (Spivey, 2026).

Social Commerce Market in India

India's social commerce market was valued at USD 8.9 billion in 2025. From 2026 to 2034, it is projected to grow at a compound annual growth rate of 22.31%, reaching USD 54.4 billion (Imarcgroup.com).

- **By Business Model**: In 2025, business-to-consumer (B2C) leads the market, capturing 55% of share, driven by online purchases via social media, easy checkout, and influencer promotions that boost trust.
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- **Key Players**: India's social commerce market is driven by players enhancing platform functions, AI-driven personalization, logistics, and creator-influencer alliances for adoption. (Imarcgroup.com)

Where is traditional e-commerce most effective?

- Search, trust, and service are areas where e-commerce performs well.
- Dedicated shopping sites still have the upper hand in high-intent, complex or product-research-driven buying decisions due to their well-developed search and filter capabilities, efficient checkout system and an established post-purchase experience. These strengths provide opportunities for retail media marketers while leveraging social platforms to boost product discovery and engagement.

  Although social commerce is becoming increasingly important, traditional e-commerce platforms still offer substantial benefits that retail media marketers should capitalize on:

- Platforms designed specifically for shopping provide streamlined experiences for consumers who are ready to buy, thanks to infrastructure tailored for product browsing and purchasing.
- Sophisticated tools for search, filtering, and categorization enable shoppers to efficiently shift through extensive product catalogs and locate precisely what they need—capabilities that are generally underdeveloped on most social platforms.

- The established reliability of checkout systems instills consumer confidence in security of payment and fulfilment of order, these are the areas where social platforms are yet working to gain trust.
- Robust account systems facilitate tracking of order, maintain purchase history, and offer customer service, delivering a post-purchase experience that social commerce is yet striving to enhance. (Skai.io)

Social Commerce complements the traditional e commerce by providing some unique benefits in advertising effectiveness.

- In social commerce, customers can make purchases right away after discovering a product, there is less friction and more potential for impulsive purchases because as they do not have to shift to another website or app for purchasing.
- In social commerce, the products appear on the social media platforms where customers are hit here to spending their time and there is no need to transfer the traffic to another destination for complete their purchase.
- Influencers collaborations are effective as they demonstrate the product by using it and recommend it to the follower where already exist relationship.
- Live streaming, augmented reality try-on, and shopping events driven by community create interactive shopping experience.

7. Conclusion

Social commerce may dramatically improve efficiency and operational productivity, customer connections, revenue growth, and product and service offerings, all of which can greatly increase a company's competitive edge (Zhou, Zhang, & Zimmermann, 2013).

In this novel form of commerce facilitated by social media, advantages are reaped by both consumers and companies. Consumers are able to make well-informed choices by considering information provided not just by companies, but also by fellow consumers. Companies, on the other hand, can increase their profits by enticing potential customers through favourable endorsements from current consumers (Curty & Zhang , 2011).

In the Indian e-commerce sector, social media platforms play an essential part in fostering customer trust, enhancing brand loyalty, and influencing purchasing behaviour. Factors such as user-generated content, online feedback, and influencer marketing significantly contribute to establishing trustworthiness and reducing potential risks for users (Kumar , Jain, Rai, & Bhanu, 2026).

(Sheth, Sridharan, Reddy, Sadhwani, & Thakur, 2020)A few big companies have previously controlled India's e-commerce market, but social commerce is opening the door for a more dispersed model based upon trust, connection, and community. Even though traditional e-commerce will continue to grow, social-led models will play a significant role in redefining the landscape.

The literature demonstrates that social commerce significantly influences consumer behaviour through social interaction, trust-building mechanisms, and community engagement. Influencer marketing and social support emerge as key drivers of consumer confidence and purchase intention. The integration of social and commercial activities creates a dynamic environment where consumers rely heavily on social validation.8400346789

Social Commerce complements the traditional e-commerce by providing some unique benefits and has transformed consumer behaviour by embedding social influence into the online shopping experience. It enhances information sharing, builds trust, and encourages engagement, ultimately influencing purchase and repurchase decisions. Social commerce helps the consumer in decision making as recommendation, ratings, and online community influence their buying behaviour. Businesses looking to successfully use social commerce must comprehend these mechanisms.

This discovery suggests that consumer social interactions offer various benefits to businesses. By participating in online communities or engaging with social media, consumers produce content regarding products or services. Such content can enhance the quality of relationships within a business, thereby boosting customer loyalty. Consequently, the valuable information generated online provides numerous benefits, with improved relationship quality being a key advantage. The co-creation environment involves consumers in the process of creating value for a business (Hajli M. , 2014). It is well recognised that social support influences consumer behaviour in a good way. It is especially crucial in social media since e-commerce has evolved into social commerce due to social connections between individuals on the Internet (Hajli & Sims, 2015).

It is easier for the person to post the review of the product online (Chen, Xu, &Whinston, 2011, as cited in Hajli, 2015) and provide ratings to the products. These ratings and reviews provide thorough product information for the advantage of other prospective buyers.Reviews and ratings appear to provide buyers with useful information. Additionally, consumers feel empowered when they participate in co-creation and content generation (Füller et al., 2009, as cited in Hajli,2015), as they can discover other people's experiences with a product.

According to research, consumers believe more on theother customers’ experiences, such as their recommendations of product, in an online setting as they are unable to personally experience the goods or services (Senecal & Nantel, 2004, as cited in Hajli, 2015).

In e-commerce platforms, the consumer retention rate and website traffic has been increased by recommendation system (Chinchanachokchai et al., 2021 as cited in Asante, Jiang , Hossin , & Luo , 2023). The suggestion system is made feasible by gathering information about customers' questions and past purchases. It helps with product recommendations for customers using the website or e-commerce platform. The recommendation system helps to customise the e-commerce platform for individual customers by using advanced consumer profiling to provide more tailored search results(De Keyzer et al., 2022; Sivapalan et al., 2014 as cited in Asante, Jiang , Hossin , & Luo , 2023).

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UNDERSTANDING HOW AI-ENABLED HRM PRACTICES INFLUENCE INTRAPRENEURIAL BEHAVIOR: A CONCEPTUAL FRAMEWORK

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ABSTRACT

The integration of artificial intelligence (AI) into human resource management (HRM) represents a major transformation in how organizations manage their workforce, while intrapreneurial behavior has become a key source of innovation and competitive advantage. This study develops a conceptual framework on the relationship between AI-enabled HRM practices and intrapreneurial behavior informed by a selective review of existing empirical literature across diverse industries and geographical contexts, drawing on quantitative, qualitative, and mixed-method studies.

Grounded in Self-Determination Theory, the proposed framework suggests that AI-enabled HRM practices foster intrapreneurial behavior through four key psychological mechanisms: employee autonomy, psychological safety, self-efficacy, and employee exploration. These mechanisms enable employees to generate innovative ideas, recognize opportunities, take initiative, engage in calculated risk-taking, and develop networks that support intrapreneurial activities. The framework further proposes that organizational culture and firm size shape the strength of these relationships by influencing the extent to which AI-enabled HRM practices can be effectively translated into innovative employee behaviors.

The framework also recognizes the dual nature of AI implementation, which can enhance employee capabilities while also raising concerns such as job insecurity. Overall, this study integrates fragmented literature into a unified, literature grounded framework and provides directions for future research and managerial practice in AI-enabled HRM and intrapreneurship.

KEYWORDS: *Artificial intelligence, HRM practices, intrapreneurial behavior, Self-Determination Theory, employee autonomy, psychological safety, organizational innovation.*

INTRODUCTION

The integration of artificial intelligence (AI) into human resource management (HRM) practices represents a major transformation in the way organizations manage and develop their workforce. In parallel, intrapreneurial behavior has emerged as a key determinant of innovation and sustainable competitive advantage in contemporary organizational settings. AI-enabled HRM practices are increasingly recognized as important drivers of employee innovation, creativity and proactive work behavior by enhancing learning opportunities, decision making support, workforce engagement and developmental experiences. However, the underlying mechanisms through which these practices influence innovative outcomes remain fragmented across different streams of literature, limiting a comprehensive understanding of their relationship with intrapreneurial behavior.

The adoption of AI within HRM functions has expanded rapidly in recent years. Organizations are increasingly integrating AI-based systems across core HR activities such as recruitment, performance management, talent development, and employee engagement (George et al., 2026). These technologies include algorithmic screening tools, predictive analytics systems, personalized learning platforms, and real-time feedback mechanisms. Chowdhury et al. (2024) note that the effective use of AI in HRM depends on strong alignment with organizational goals, along with structured change management practices to ensure successful implementation and outcomes.

At the same time, intrapreneurial behavior defined by employees' tendency to engage in innovative, proactive, and risk-taking actions within organizational boundaries has been widely recognized as a critical driver of organizational renewal and competitiveness. Existing studies suggest that intrapreneurship fosters innovation through several pathways, including the identification of new opportunities, redesign of work processes, and improvement of problem-solving capabilities (Menyaoui & Lakhal, 2025).

Despite the growing body of research in both AI-enabled HRM and intrapreneurship, the literature remains fragmented, with limited integration across these two domains (Budhwar et al., 2022). While prior studies have examined specific linkages, such as the positive influence of AI-supported autonomy, competence, and relatedness on innovative behavior, there is still no comprehensive framework that integrates these findings to explain the broader relationship between AI-enabled HRM practices and intrapreneurial behavior.

This study addresses this gap by systematically synthesizing existing empirical evidence to develop an integrated conceptual framework. By drawing on both quantitative and qualitative studies across diverse organizational contexts, the research explains the mechanisms through which AI-enabled HRM practices influence intrapreneurial behavior, while also identifying key contextual factors that moderate these relationships (Fenwick et al., 2024; Huang et al., 2026).

OBJECTIVES

- To synthesize existing empirical literature on AI-enabled HRM practices and intrapreneurial behavior to identify key mechanisms and theoretical foundations across diverse organizational contexts.

- To develop an integrated conceptual framework explaining how AI-enabled HRM practices influence intrapreneurial behavior through employee autonomy, psychological safety, self-efficacy, and employee exploration.
- To examine the moderating roles of organizational culture and firm size in shaping the relationship between AI-enabled HRM practices and intrapreneurial behavior.
- To advance evidence-based propositions grounded in Self-Determination Theory and empirical findings from quantitative and qualitative studies spanning multiple industries and geographical regions.
- To establish a future research agenda based on identified gaps in the literature and provide evidence-based recommendations for organizations implementing AI-enabled HRM practices to foster intrapreneurial behavior.

LITERATURE REVIEW:

- **AI-Enabled HRM: Concept, Dimensions, and Consequences-**

The use of artificial intelligence (AI) in human resource management (HRM) has progressed from an emerging concept to an integral component of organizational practice. To describe this shift, scholars have introduced terms such as *AI-augmented HRM* (Prikshat et al., 2021), *digital HRM* (George et al., 2026), and *algorithmic management* (Zhou et al., 2023). In this study, AI-enabled HRM refers to the application of AI technologies including machine learning, natural language processing, predictive analytics, and robotic process automation across key HR functions to improve decision-making, personalize employee experiences, and streamline routine HR activities.

Within the AI-HRM literature, five dimensions have received considerable attention. The first is recruitment and talent management, where AI has been shown to accelerate hiring processes, support large-scale candidate screening, and reduce certain forms of human bias. However, concerns persist regarding algorithmic bias, lack of transparency, and the diminishing role of human judgment in selection decisions (Fenwick et al., 2024; Venugopal et al., 2024). The second dimension relates to performance management. AI-driven systems enable continuous monitoring, goal tracking, and data-based feedback, but they also raise concerns about employee surveillance and the oversimplification of human performance through algorithmic evaluation (Zhou et al., 2023). A third area involves learning and development (L&D), where AI facilitates personalized learning pathways, adaptive training content, and skill-gap assessment through advanced analytics. Compared with other HR functions, this application is often viewed as one of the most beneficial uses of AI in the workplace (Agarwal et al., 2023; Do et al., 2025; Sweiss & Yamin, 2024). The fourth dimension focuses on employee engagement and feedback. Technologies such as sentiment analysis tools, AI-powered chatbots, and predictive attrition systems provide organizations with deeper insights into employee experiences, although concerns regarding privacy and the authenticity of workplace interactions remain prominent (Dutta et al., 2023).A fifth dimension concerns retention and compensation. AI-enabled predictive analytics and workforce intelligence tools assist organizations in identifying turnover risks, designing personalized retention strategies, and optimizing compensation decisions. These applications help improve employee retention while ensuring that reward systems are aligned with employee performance and organizational objectives.

The impact of AI-enabled HRM on employee behavior is widely recognized as complex and multifaceted.Verma and Singh (2022) found that AI-enabled task and knowledge characteristics significantly influence innovative work behavior among 486 high-technology professionals. Parent-Rocheleau and Parker (2022) further suggest that AI can enrich job design by allowing employees to focus on more meaningful work activities. Supporting this view, Do et al. (2025) reported that AI-driven HRM enhances employee resilience and adaptive performance among 274 employees in the United States, particularly when trust in AI systems is high.

Despite these benefits, the literature also highlights several challenges associated with AI adoption. Yam et al. (2023) found that AI implementation can increase perceptions of job insecurity, while Malik et al. (2023) identified employee resistance stemming from concerns about surveillance and reduced autonomy. Huang et al. (2026) further illustrate this duality in their study of 434 hotel employees, showing that AI awareness simultaneously increases job insecurity, which can suppress intrapreneurial behavior, and strengthens organizational identification, which can encourage it. This dual nature of AI as both an enabler and a constraint forms a central theme in understanding its influence on intrapreneurial behavior and serves as a key foundation for the present study.

- **Intrapreneurial Behavior: Concept and Organizational Antecedents**

Intrapreneurship often discussed in the literature under related concepts such as corporate entrepreneurship, internal venturing, and employee entrepreneurial behavior refers to the entrepreneurial actions undertaken by employees within established organizations. These actions involve generating new ideas, promoting innovative initiatives, and introducing improvements in products, services, or organizational processes (Antoncic & Hisrich, 2003; Pelica et al., 2026). Consistent with the integrated framework proposed by Neessen et al. (2019), intrapreneurial behavior is conceptualized as comprising five key dimensions: innovativeness, proactiveness, risk-taking, opportunity recognition and exploitation, and internal as well as external networking. Together, these dimensions capture employees’ ability to identify opportunities, initiate change, mobilize support, and pursue innovative outcomes within organizational settings.

The factors influencing intrapreneurial behavior have been examined at multiple levels of analysis. At the organizational level, management support, access to resources, organizational structure, and a supportive culture have consistently been identified as important enablers of intrapreneurship (Alpkan et al., 2010; Rizwan & Siddiqui, 2021). At the team level, leadership approaches particularly transformational and servant leadership have been found to positively influence intrapreneurial outcomes. From an HR systems perspective, increasing attention has been given to the role of High-Performance Work Systems (HPWS), which are designed to enhance employees’ abilities, motivation, and opportunities to contribute. Research indicates that such systems are positively associated with intrapreneurial behavior. For instance, Escribá-Carda et al. (2025) reported that employee perceptions of HPWS significantly predict individual intrapreneurial behavior, while HRM system strength contributes to these outcomes at the departmental level. Similar findings were reported in a study involving 589 employees across 47 departments in eight Spanish organizations.

Evidence from different organizational and geographical contexts further reinforces these relationships. In the Indian context, Kumar and Parveen (2021) found that management support and the availability of technological opportunities were among the most influential factors driving intrapreneurial behavior among employees from leading Indian organizations. Extending this perspective, Cordova et al. (2026) demonstrated that intrapreneurship and AI utilization jointly contribute to innovative work behavior through self-efficacy, with self-efficacy emerging as the strongest predictor of innovation-related outcomes. These findings suggest that technology-enabled work environments can play a significant role in shaping intrapreneurial behavior and provide a useful basis for examining the influence of AI-enabled HRM practices.

Despite the substantial progress made in intrapreneurship research, an important gap remains. Existing studies have extensively explored the effects of traditional HR practices, organizational characteristics, and leadership factors, yet comparatively little attention has been paid to the role of AI-enabled HRM systems. This limitation is particularly noteworthy because many of the HR practices most closely linked to intrapreneurial behavior such as performance management, learning and development, and employee engagement are undergoing significant transformation through the adoption of AI technologies. Consequently, understanding whether AI-enabled HRM practices foster or constrain intrapreneurial behavior represents an important avenue for future research.

- **AI and Employee Behavior: The Autonomy-Creativity Nexus**

A growing body of research has explored the influence of AI in the workplace on employees' psychological states and behavioral tendencies. Particularly relevant to intrapreneurial behavior are studies examining the relationship between AI, employee autonomy, creativity, and psychological safety. Parent-Rocheleau and Parker (2022), in their comprehensive review of AI and work design, argue that AI possesses significant potential to enhance work experiences by reducing routine tasks and increasing task variety. However, the realization of these benefits largely depends on how AI is implemented within organizations. When AI systems are designed to increase employee discretion, support decision-making, and provide greater flexibility, they tend to enrich work experiences. In contrast, when AI is primarily used for monitoring, standardization, and control, it can diminish employee autonomy and lead to less meaningful and engaging work.

This conditional relationship is further supported by empirical evidence. Doan and Tran (2025), in a study involving 250 employees from Vietnamese organizations, found that AI support for autonomy ($\beta = 0.25$, $p < 0.01$), competence ($\beta = 0.30$, $p < 0.01$), and relatedness ($\beta = 0.20$, $p < 0.05$) significantly influenced innovative behavior, collectively explaining 45% of the variance. Among these factors, competence support emerged as the strongest predictor, highlighting the role of personalized training and real-time feedback in fostering employee creativity.

In contrast, studies indicate that AI can positively contribute to creativity when used as a complementary rather than a substitutive tool. Kahera et al. (2025) report that AI promotes innovative work behavior by strengthening employees' idea-generation capabilities and fostering a work environment that encourages innovation. Collectively, these findings suggest that the impact of AI on creativity and intrapreneurial behavior depends largely on whether the technology is used to empower employees or to constrain their autonomy.

Psychological safety, defined as a shared belief that an organization or team provides a safe environment for interpersonal risk-taking (Edmondson, 1999), holds particular significance in the context of intrapreneurial behavior. Since intrapreneurship inherently involves experimenting with new ideas, challenging existing practices, and taking calculated risks, employees are more likely to engage in such behaviors when they feel secure in expressing unconventional viewpoints without fear of negative consequences.

Qualitative evidence provided by Menyaoui and Lakhal (2025), based on 24 semi-structured interviews conducted across eight AI-adopting startups in Tunisia and North Africa, sheds further light on this relationship. Their findings identify three primary mechanisms through which AI can stimulate intrapreneurial behavior. First, task automation enables work reconfiguration and reduces cognitive burden, allowing employees to focus on higher-value activities. Second, AI-generated insights improve employees' ability to recognize and evaluate new opportunities. Third, predictive and simulation capabilities enhance confidence and accelerate problem-solving processes. Importantly, the authors emphasize that organizational culture plays a crucial role in shaping these outcomes. Factors such as autonomy, openness, and psychological safety significantly influence whether employees translate AI-enabled insights into innovative and intrapreneurial actions.

The surveillance aspect of AI-enabled HRM warrants particular consideration. Technologies such as algorithmic performance monitoring, predictive analytics used to track employee behavior, and AI-driven engagement assessment systems introduce continuous forms of organizational oversight that may influence employees' perceptions of autonomy and their willingness to engage in the creative risk-taking associated with intrapreneurial behavior. Tursunbayeva et al. (2018) highlight concerns related to transparency and employee trust in AI-based HR systems.

Further examining the darker side of AI adoption, Zhou et al. (2023) show that algorithmic characteristic such as comprehensiveness, immediacy, and opacity can generate unintended negative outcomes for employees, including psychological alienation, adaptive overload, and social exclusion. Similarly, Khalid et al. (2025), in a study of 300 employees from technology-oriented firms, found that although AI integration can improve productivity, it may also create new forms of techno stress. Their findings suggest that higher levels of digital literacy can help employees cope more effectively with these challenges. Such concerns may become even more pronounced in high power-distance cultures, where employees are generally less inclined to question or challenge algorithmic decisions perceived as reflecting organizational authority.

- **The Indian Organizational Context**

India provides a distinctive yet underexplored context for examining the relationship between AI-enabled HRM and intrapreneurial behavior. The country's technology sector, particularly the IT, ITES, and Global Capability Center (GCC) ecosystem, has been among the early adopters of AI-driven HR practices. Goswami et al. (2023) identify key drivers of AI adoption in HRM within the Indian pharmaceutical sector.

Similar evidence from emerging economies supports these findings. Cai et al. (2026), in a study of 473 SME employees in China, found that AI-enabled decision-making significantly enhances social intrapreneurial opportunity identification, with circular economy practices and pro-social environmental orientation acting as important mediating factors.

In the Indian context, Kumar and Parveen (2021) found that management support and technological opportunities are key drivers of intrapreneurial behavior. Supporting this view, Cordova et al. (2026) reported that intrapreneurship and AI use jointly enhance innovative work behavior through self-efficacy, highlighting the importance of technological enablement in emerging economies.

The cultural context is also important to consider. India’s high score on Hofstede’s power-distance dimension (Hofstede, 1980) indicates strong acceptance of hierarchical authority, where employees may be less likely to challenge norms or act independently without managerial approval. This can limit intrapreneurial behavior; as such initiative-driven actions may be constrained even when AI-HRM systems aim to encourage empowerment. Supporting this, Huang et al. (2026) found that employee mindfulness moderates the AI intrapreneurship relationship, helping reduce negative effects and strengthen positive outcomes, suggesting that individual psychological traits can offset cultural constraints.

The interaction between cultural context and AI implementation becomes more complex when viewed through the lens of surveillance effects highlighted by Zhou et al. (2023) and Khalid et al. (2025). In high power-distance settings, employees may be less inclined to question algorithmic decisions perceived as authoritative, which can intensify the negative impact of AI-driven surveillance on intrapreneurial behavior. However, Doan and Tran (2025) show that when AI systems are designed to enhance autonomy, competence, and relatedness, they can help mitigate cultural constraints and support innovative behavior.

Emerging research indicates that effective AI-HRM implementation in India depends on cultural adaptation, especially in developing psychological safety and trust in AI systems (Shukla et al., 2026). Budhwar et al. (2022) further emphasize that the impact of AI-HRM practices differs across cultural contexts, making India an important setting for understanding the boundary conditions of AI-enabled intrapreneurship.

THE RESEARCH GAP

The preceding review identifies a clear research gap that requires further theoretical and empirical investigation. While AI-HRM is increasingly reshaping how organizations manage, develop, and engage employees, existing frameworks provide limited explanation of its implications for intrapreneurial behavior. The AI-HRM and intrapreneurship literatures have largely progressed in parallel, with minimal integration between them. In particular, the psychological mechanisms especially employee autonomy, psychological safety, self-efficacy, and employee exploration through which AI-HRM may shape intrapreneurial tendencies remain insufficiently theorized. In addition, key boundary conditions such as organizational culture, firm size, and national context have not been adequately examined. This study addresses these gaps through its proposed conceptual framework.

METHODOLOGY

This study is a conceptual research paper based on secondary data to synthesize existing empirical evidence and develop a conceptual framework on AI-enabled HRM practices and intrapreneurial behavior. The review includes peer-reviewed journal articles, books, conference papers and scholarly publications covering a range of methodological designs such as quantitative surveys, qualitative case studies, mixed-method studies, and conceptual frameworks.

The selected literature spans multiple industries across diverse geographical contexts, capturing a wide range of organizational and cultural settings.

Data extraction focused on four key areas: (1) theoretical foundations used in the studies, including major organizational and behavioral theories; (2) empirical evidence on the relationship between AI-enabled HRM and intrapreneurial behavior; (3) mediating mechanisms such as employee autonomy, psychological safety, self-efficacy and employee exploration; and (4) contextual factors including organizational culture and digital literacy.

The data were analyzed using thematic analysis to identify recurring patterns across studies. This process enabled the synthesis of findings and the development of an integrated conceptual framework linking AI-enabled HRM practices with intrapreneurial behavior outcomes.

THEORETICAL FOUNDATIONS

The conceptual framework developed in this paper is grounded in several complementary theoretical perspectives that collectively offer a comprehensive explanation of the mechanisms through which AI-enabled HRM practices influence intrapreneurial behavior. Although the framework is primarily based on three core theories, the wider body of literature contributes additional theoretical insights that deepen and broaden our understanding of this multifaceted relationship.

- **Self-Determination Theory (SDT)**

Self-Determination Theory, introduced by Deci and Ryan (1985), explains that human motivation and psychological well-being are rooted in the fulfillment of three fundamental psychological needs: autonomy, competence, and relatedness. When these needs are adequately satisfied, intrinsic motivation is strengthened, leading individuals to engage in behaviors driven by genuine interest rather than external pressure.

Within this theoretical lens, Self-Determination Theory offers empirically grounded insights into how AI-enabled HRM practices influence intrapreneurial motivation. Doan and Tran (2025) show that AI support for autonomy, competence, and relatedness significantly predicts innovative behavior, with competence emerging as the strongest predictor, underscoring the importance of personalized training and real-time feedback in fostering creativity. In a similar vein, Do et al. (2025) find that AI-driven HRM enhances employee resilience and adaptive performance through the satisfaction of psychological needs, with employee exploration acting as a mediating mechanism in these relationships.

- **The Ability-Motivation-Opportunity (AMO) Framework**

The AMO framework explains employee performance as the result of the interaction between ability (skills and competencies), motivation (willingness to perform), and opportunity (organizational conditions that enable performance). Kiran et al. (2023) empirically applied this framework in AI-HRM contexts and found that AI-based systems outperform HRIS and traditional HR approaches in supporting all three dimensions. Their findings indicate that AI-enabled HRM strengthens ability, motivation, and opportunity, thereby positively influencing organizational performance.

In a related contribution, Prakash et al. (2026) combined the AMO framework with Triple Bottom Line theory to examine AI-driven sustainable HRM practices. Their study shows that in the Indian IT sector, AI-based HR systems enhance employee engagement and performance through structured improvements in ability development, motivational support, and opportunity creation.

- **Social Exchange Theory (SET)**

Social Exchange Theory views organizational relationships as reciprocal processes in which employees respond to perceived organizational support with discretionary effort and positive work behaviors. Malik et al. (2022) show that AI-mediated HRM systems can strengthen this exchange relationship by enhancing employee experience and engagement, which in turn improves organizational commitment and reduces turnover intentions. However, the literature also points to the complexity of these exchange dynamics in AI-enabled environments.

Zheng et al. (2025) highlight so-called shadow experiences in AI-HRM systems, including surveillance-related precarity and algorithmic bias concerns, which may weaken the quality of social exchange. These factors can result in psychological alienation and social marginalization, thereby undermining positive employee organization relationships. Overall, this suggests that the perceived fairness and quality of AI-mediated exchanges play a crucial role in shaping intrapreneurial behavior outcomes.

- **Complementary Theoretical Perspectives**

The literature also incorporates several additional theoretical perspectives that further deepen understanding of AI-enabled HRM. Chowdhury et al. (2024) draw on the Technology-Organization-Environment (TOE) framework along with Job Demands Resources theory to examine AI adoption in HRM, identifying technological, organizational, and environmental conditions that shape both adoption and effectiveness.

Nguyen and Nguyen (2025) apply the Resource-Based View and Dynamic Capability Theory to explain how AI-enabled HRM contributes to sustained competitive advantage by enhancing employees' creativity and innovation capabilities. In a related contribution, Prikshat et al. (2021) integrate the Technology-Organization-People (TOP) framework with innovation assimilation theory to explore adoption challenges and multilevel outcomes of AI-HRM systems.

Technology acceptance perspectives are also widely emphasized in the literature. Singh and Pandey (2024) and Giudice et al. (2021) show that employees' perceptions of AI usefulness, ease of use, and ethical implications significantly shape adoption behavior and subsequent workplace outcomes.

- **Integrated Theoretical Framework**

These theoretical perspectives offer complementary and mutually reinforcing explanations. Self-Determination Theory captures the psychological foundation by explaining how AI-enabled HRM influences basic need satisfaction, which in turn shapes the quality of intrinsic motivation underlying intrapreneurial behavior. The AMO framework provides a structural explanation by showing how AI-enabled HRM builds employee abilities, motivation, and opportunities that collectively enable intrapreneurial action. Social Exchange Theory, in turn, explains the relational dimension by highlighting how perceived organizational support and exchange quality through AI systems influence employees' willingness to reciprocate with discretionary, intrapreneurial contributions.

However, the literature also indicates that this integration is neither linear nor uniform across contexts. Cordova et al. (2026) show that self-efficacy fully mediates the relationship between AI use and innovative work behavior while partially mediating the link between intrapreneurship and innovation, suggesting that psychological mechanisms interact with technological capabilities in complex ways. Similarly, Zhou et al. (2023) demonstrate that AI algorithmic characteristics such as comprehensiveness, instantaneity, and opacity may generate adverse outcomes that weaken these positive theoretical pathways.

Overall, this multi-theoretical synthesis, grounded in empirical evidence, provides a comprehensive framework for understanding how AI-enabled HRM influences intrapreneurial behavior through interrelated psychological, structural, relational, and technological mechanisms.

CONCEPTUAL FRAMEWORK AND PROPOSITIONS

Drawing on the theoretical foundations and literature review, this paper proposes a conceptual framework positioning AI-enabled HRM practices as antecedents of intrapreneurial behavior, with psychological mechanisms as mediators and organizational factors as moderators, as illustrated in Figure 1 below.

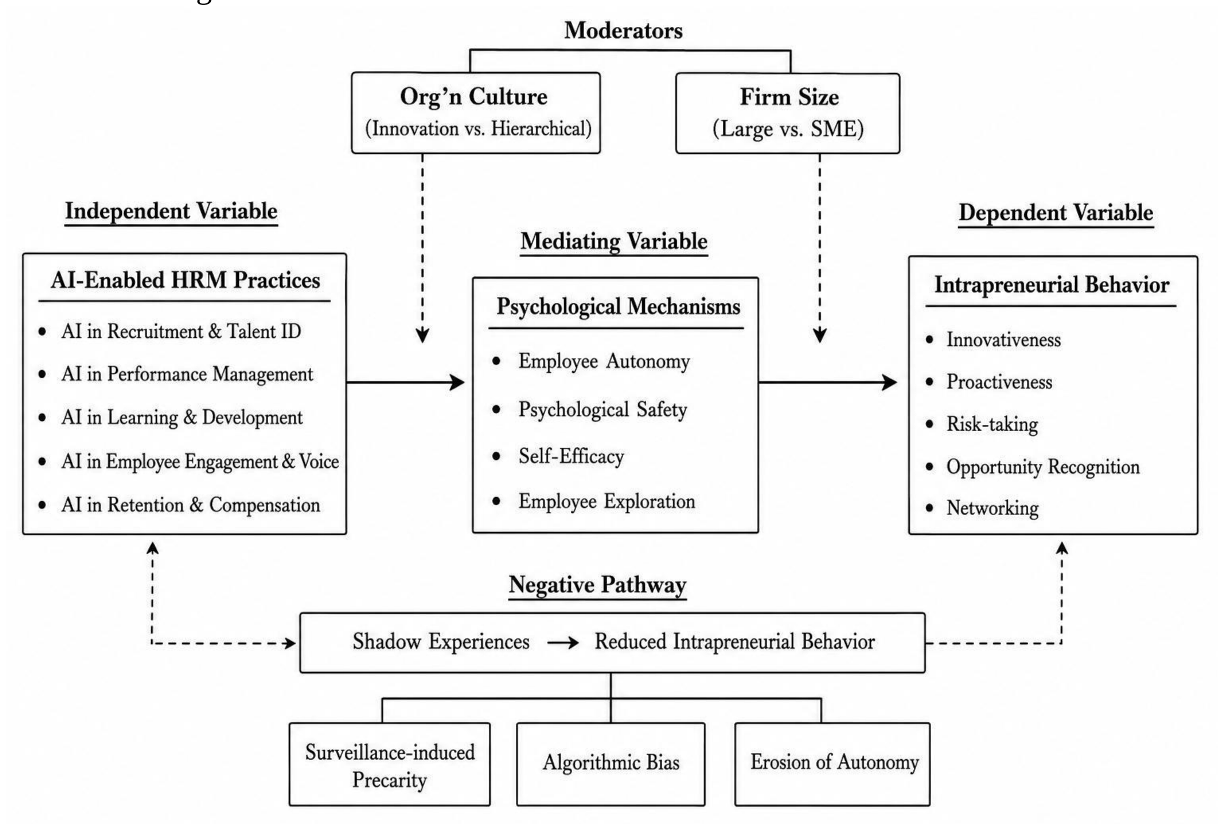

Fig. 1: Conceptual Framework of the Relationship between AI-Enabled HRM Practices and Intrapreneurial Behavior

(Source: Compiled by author)

The framework identifies five key AI-enabled HRM dimensions: recruitment and talent identification, performance management, learning and development, employee engagement and voice, and retention and compensation. These practices are proposed to influence intrapreneurial behavior by enhancing employees' access to information, personalized development opportunities, participation in decision-making and overall work experiences. The model suggests that the impact of AI-enabled HRM on intrapreneurial behavior is not direct but operates through four important psychological mechanisms: employee autonomy, psychological safety, self-efficacy, and employee exploration. Greater autonomy and self-efficacy encourage employees to take initiative and pursue innovative ideas, while psychological safety and exploration facilitate experimentation, knowledge sharing, and opportunity recognition. Consequently, these mechanisms foster key dimensions of intrapreneurial behavior, including innovativeness, proactiveness, risk-taking, opportunity recognition, and networking. The framework further proposes that organizational culture and firm size shape the strength of these relationships by influencing the extent to which AI-enabled HRM practices can be effectively implemented and translated into innovative employee behaviors.

- **Propositions**

Based on the proposed conceptual framework, the following propositions are advanced for future empirical examination.

Proposition 1:
AI-enabled HRM practices exert differential effects on employees' psychological states, where empowering practices such as learning and development enhance autonomy, self-efficacy, and psychological safety, while control-oriented practices such as algorithmic surveillance weaken these psychological conditions.

Proposition 2:

Psychological mechanisms including self-efficacy, employee exploration, autonomy, and psychological safety mediate the relationship between AI-enabled HRM practices and intrapreneurial behavior, with self-efficacy emerging as the most influential mediator.

Proposition 3:

AI-enabled learning and development practices have the strongest positive effect on intrapreneurial behavior by enhancing employee competence and capability development.

Proposition 4:

Organizational culture moderates the relationship between AI-enabled HRM and intrapreneurial behavior, such that the relationship is stronger in cultures characterized by autonomy, openness, and psychological safety.

Proposition 5:

Firm size moderates the AI-HRM and intrapreneurial behavior relationship, with larger organizations benefiting more from AI implementation capabilities, while SMEs demonstrate more organic but less system-driven intrapreneurial outcomes.

Proposition 6:

AI-enabled HRM may also generate negative outcomes through shadow effects such as surveillance pressure, algorithmic bias, and reduced autonomy, which in turn may lead to psychological alienation and lower intrapreneurial behavior.

DISCUSSION AND IMPLICATIONS

- **Theoretical Contributions**

This paper contributes to existing knowledge by developing a comprehensive framework that links AI-enabled HRM practices with intrapreneurial behavior. It extends the AI-HRM literature, which has largely concentrated on operational efficiency (Talbert & Talbert, 2026) and improvements in employee experience (Malik et al., 2022), by connecting these technological advancements to strategic innovation outcomes. At the same time, it broadens intrapreneurship research by moving beyond traditional HRM antecedents (Portalanza-Chavarría & Revuelto-Taboada, 2023) to include the role of AI-transformed HR systems in shaping intrapreneurial behavior.

The second contribution of this paper lies in empirically grounding key mediating mechanisms. Self-efficacy has been identified as a mediator between AI use and innovative behavior, while employee exploration also serves as an important pathway. In addition, AI-enabled job characteristics such as task autonomy and skill variety have been shown to influence innovative work behavior by explaining significant variation in outcomes.

The third contribution is the integration of Self-Determination Theory, AMO, and Social Exchange Theory into a unified explanatory framework. These theories are individually supported by empirical studies across AI-HRM contexts, demonstrating how psychological, structural, and relational mechanisms jointly explain a substantial proportion of variance in innovative and intrapreneurial behaviors across different settings.

- **Practical Implications for HR Managers and Organizations**

The framework also offers practical guidance for implementing AI-enabled HRM systems. Poorly designed AI applications have been linked to techno stress, whereas well-implemented systems can significantly enhance task satisfaction and employees' creative willingness. Organizations are therefore encouraged to focus on AI applications that build employee capabilities rather than those emphasizing surveillance. Personalized HRM approaches have been shown to outperform standardized systems, particularly in improving organizational effectiveness. In addition, AI-enhanced talent management practices contribute more strongly to innovative work behavior when supported by transformational leadership. Organizational culture also plays a critical role in determining outcomes. Psychological safety and autonomy act as key enabling conditions, while organizational readiness significantly influences the successful adoption of AI in HRM systems.

- **Implications for the Indian Context**

Evidence from emerging markets further supports the relevance of the proposed framework. K. Prakash et al. (2026) found that AI-driven sustainable HRM practices enhance employee engagement and performance among Indian IT employees. Maseeh Ullah et al. (2025) reported similar patterns in Pakistan's IT sector, while also highlighting the influence of hierarchical cultural norms on AI-HRM outcomes.

Similarly, ThiLan Nguyen and Thi Thu Huong Nguyen (2025) demonstrated in Vietnam's aviation sector that AI empathy and human-centered design moderate the effectiveness of AI-HRM systems, suggesting that cultural adaptation is critical for successful implementation in contexts such as India.

- **Policy Implications**

Emerging governance frameworks emphasize the need for ethical, transparent, and accountable AI-enabled HRM systems. Fairness, accountability, and transparency are critical for responsible adoption (Dinesh Kumar, 2026), while organizational justice is essential for building trust during implementation (Yashika Shukla et al., 2026). Responsible AI perspectives further highlight the importance of preserving human dignity and ensuring ethical stakeholder responsibility (G. R et al., 2025). Concerns around algorithmic opacity also reinforce the need for safeguards in AI-HRM design (Yu Zhou et al., 2023).

Accordingly, policy efforts should focus on ethical AI deployment, fairness in decision-making, and human-centered HRM system design (Doan and Tran (2025).

LIMITATIONS

As a conceptual paper, the primary limitation is the theoretical rather than empirical nature. The propositions require empirical testing, and the framework makes simplifying assumptions about AI-HRM practice dimensions that may not capture implementation complexity in real organizational contexts.

FUTURE RESEARCH AGENDA

The framework opens multiple empirical research avenues: (1) direct testing of propositions through survey-based studies in AI-advanced sectors like Indian IT; (2) qualitative research exploring psychological mechanisms and lived experiences; (3) cross-cultural comparative studies examining cultural boundary conditions; and (4) longitudinal research tracking relationship evolution over time.

CONCLUSION

This paper develops a conceptual framework explaining how AI-enabled HRM practices influence intrapreneurial behavior within organizations. Drawing on Self-Determination Theory, the Ability–Motivation–Opportunity (AMO) framework, and Social Exchange Theory, the study integrates insights from the AI-HRM and intrapreneurship literature to explain the psychological mechanisms underlying this relationship. The framework proposes that AI-enabled HRM practices influence intrapreneurial behavior through employee autonomy, psychological safety, self-efficacy, and employee exploration, while organizational culture and firm size shape the strength of these relationships.

The review suggests that AI-enabled HRM can foster intrapreneurial behavior by enhancing employee capabilities, learning opportunities, participation, and opportunity recognition. However, the impact of AI is not universally positive. Issues such as algorithmic surveillance, job insecurity, and reduced autonomy may constrain innovative and entrepreneurial behavior when AI systems are poorly implemented. By integrating fragmented evidence into a unified framework, this study contributes to the growing literature on AI-enabled HRM and provides a foundation for future empirical research. The framework also offers practical guidance for organizations seeking to leverage AI technologies to encourage innovation, proactiveness, and entrepreneurial initiative among employees.

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TAX BUOYANCY AND TAX ELASTICITY OF CENTRAL GOVERNMENT TAXES: EVIDENCE FROM INDIA

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ABSTRACT

Tax revenue plays a crucial role in ensuring fiscal sustainability and supporting economic development by financing public expenditure and government welfare programmes. The responsiveness of tax revenue to economic growth is commonly measured through tax buoyancy and tax elasticity, which provide insights into the efficiency and productivity of a country's tax system. This study empirically examines the tax buoyancy and tax elasticity of central government taxes in India using annual secondary time-series data for the period 1991–92 to 2024–25. Secondary data were collected from the Union Budget Documents, Ministry of Finance, and Reserve Bank of India (RBI), Controller General of Accounts (CGA), National Statistical Office (NSO), and the RBI Database on Indian Economy (DBIE). The study employs descriptive statistics, growth trend analysis, log-linear regression models, and correlation analysis to estimate tax buoyancy, tax elasticity, and the relationship between Gross Domestic Product (GDP) and central government tax revenue. The findings reveal a steady growth in central government tax revenues during the study period. The estimated tax buoyancy coefficient exceeds unity, indicating that tax revenue has increased more than proportionately with economic growth, whereas the tax elasticity coefficient remains below unity, suggesting that the inherent responsiveness of the tax system is relatively lower after adjusting for discretionary tax policy measures. Furthermore, a strong positive relationship is observed between GDP and central government tax revenue. The study concludes that although recent tax reforms have improved revenue mobilisation, further policy measures aimed at broadening the tax base, strengthening tax compliance, and enhancing administrative efficiency are essential to improve the automatic responsiveness of the tax system and ensure long-term fiscal sustainability.

KEYWORDS: *Central Government Taxes, Economic Growth, Fiscal Sustainability, Gross Domestic Product, India, Tax Buoyancy, Tax Elasticity.*

INTRODUCTION:

Tax revenue is the primary source of government finance and is essential for financing public expenditure, promoting economic growth, and maintaining fiscal stability. An efficient tax system should generate adequate revenue while responding automatically to economic growth without frequent policy interventions (Musgrave & Musgrave, 1989).

The responsiveness of tax revenue is measured through **tax buoyancy** and **tax elasticity**. Tax buoyancy reflects the overall responsiveness of tax revenue to changes in national income, including the effects of discretionary tax policy changes, whereas tax elasticity measures the automatic responsiveness of tax revenue after removing the impact of such policy changes (Mansfield, 1972; Osoro, 1993). High buoyancy indicates a tax system capable of mobilising greater revenue as the economy expands, while low buoyancy may signal structural weaknesses in tax administration, compliance, or the tax base (Tanzi, 1989).

India's central tax system has undergone significant reforms since the economic liberalisation of 1991, including direct tax rationalisation, customs duty reforms, the Fiscal Responsibility and Budget Management (FRBM) framework, the introduction of the Goods and Services Tax (GST) in 2017, and extensive digitalisation of tax administration. These reforms were intended to broaden the tax base, improve compliance, and enhance revenue productivity (Rao, 2005). In particular, GST and technology-driven tax administration have strengthened revenue collection through greater formalisation and improved enforcement.

Despite these reforms, the responsiveness of central tax revenues remains an important empirical issue, as revenue performance is influenced by policy changes, economic structure, compliance levels, administrative efficiency, and economic shocks such as the Global Financial Crisis and the COVID-19 pandemic. Although previous studies have examined tax buoyancy and elasticity in India, many were based on shorter time periods or did not capture the effects of recent reforms, particularly GST and post-pandemic recovery (Rao, 1979; Rao, 2005; Upender, 2008).

Against this backdrop, the present study estimates the tax buoyancy and tax elasticity of India's central government taxes using annual secondary data. By analysing the long-run relationship between central tax revenue and nominal GDP through time-series econometric techniques, the study evaluates the effectiveness of tax reforms and provides evidence on the capacity of India's tax system to support sustainable revenue mobilisation and fiscal policy.

PROBLEM STATEMENT

An efficient tax system is essential for ensuring fiscal sustainability, financing public expenditure, and supporting long-term economic growth. In India, the responsiveness of central government tax revenue to economic growth is a key determinant of fiscal capacity. Ideally, tax revenues should increase proportionately with Gross Domestic Product (GDP), enabling the government to finance developmental priorities while reducing dependence on public borrowing. However, tax revenue performance is influenced by economic conditions, discretionary tax policies, administrative efficiency, compliance levels, and institutional reforms.

Over the past three decades, India's tax system has undergone major reforms, including economic liberalization, tax rationalization, the Fiscal Responsibility and Budget Management (FRBM) Act, the introduction of the Goods and Services Tax (GST), and the digitalization of tax administration. Although these reforms were intended to improve revenue productivity and broaden the tax base, their impact on the responsiveness of tax revenues remains an important empirical issue. Furthermore, economic shocks such as the Global Financial Crisis and the COVID-19 pandemic have affected the relationship between economic growth and tax collections.

Existing studies on tax buoyancy and tax elasticity in India are often based on shorter time periods, specific tax categories, or data preceding major reforms such as GST. Consequently, there is limited empirical evidence using recent data to assess whether improvements in tax revenue are driven by economic growth or by discretionary policy interventions.

Estimating both tax buoyancy and tax elasticity is essential for evaluating the efficiency of the tax system. While tax buoyancy measures the overall responsiveness of tax revenue to economic growth, tax elasticity captures its automatic responsiveness after excluding the effects of discretionary tax measures. A comprehensive analysis of these indicators using recent time-series data will provide valuable evidence on the effectiveness of tax reforms, strengthen revenue forecasting, and support policies aimed at enhancing domestic resource mobilization and long-term fiscal sustainability.

REVIEW OF LITERATURE

Audi, Ali, and Roussel (2021) examined the responsiveness of tax revenue to economic growth across South Asian countries using panel data econometric techniques. The study incorporated macroeconomic variables such as GDP growth, institutional quality, trade openness, and inflation to estimate tax buoyancy. The findings revealed that tax buoyancy was positively associated with economic growth, improved institutional quality, and trade openness, whereas inflation adversely affected tax productivity. The study concluded that stronger institutions and sustained economic growth significantly enhance revenue mobilisation. However, the analysis was conducted at the regional level and did not specifically estimate the tax buoyancy and tax elasticity of India's central government taxes.

Suresha (2022) investigated the relationship between tax buoyancy and economic growth in India using secondary annual time-series data and regression analysis. The study found that economic growth had a significant positive impact on tax revenue collections, although the degree of responsiveness varied across different phases of economic development. It further emphasized that improvements in tax administration and compliance mechanisms contributed substantially to enhanced fiscal performance. Nevertheless, the study focused solely on tax buoyancy and did not distinguish between tax buoyancy and tax elasticity or evaluate the impact of recent reforms such as the Goods and Services Tax (GST).

Arya (2023) analysed the long-run relationship between gross tax revenue and Gross Domestic Product (GDP) in India using annual data covering the period from 1950–51 to 2021–22. The study employed log-linear regression along with Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests to examine the long-run association between tax revenue and economic growth. The empirical findings indicated a significant positive relationship between GDP and gross tax revenue. However, despite improvements following economic reforms, India's tax system continued to underperform relative to international standards in terms of revenue mobilisation. The study estimated only tax buoyancy and did not examine tax elasticity after adjusting for discretionary tax policy measures.

Chakraborty and Thomas (2024) estimated the short-run and long-run buoyancy of extractive taxes across Indian states using panel time-series analysis and the Autoregressive Distributed

Lag (ARDL) bounds testing approach. Their findings demonstrated that tax buoyancy varied considerably across states and between the short-run and long-run, reflecting the influence of institutional arrangements and sector-specific characteristics on revenue responsiveness. While the study provided important insights into state-level tax performance, it was confined to extractive taxes and did not analyse the responsiveness of India's central government tax revenues.

Dey (2025) examined tax buoyancy and revenue mobilisation in India during the post-GST and post-COVID-19 periods using annual secondary data from 2000 to 2024. The study employed log-log Ordinary Least Squares (OLS) regression, structural break analysis, and interrupted time-series analysis to estimate the responsiveness of tax revenue to economic growth. The findings indicated a significant positive relationship between GDP and tax revenue, suggesting that the implementation of GST contributed to improvements in revenue performance over time. However, the estimated tax buoyancy remained below unity, indicating further scope for strengthening the responsiveness of the tax system. The study primarily focused on aggregate tax buoyancy and did not estimate tax elasticity or analyse the responsiveness of individual central government taxes.

The review of the recent literature indicates that most empirical studies have concentrated on estimating tax buoyancy while giving comparatively limited attention to tax elasticity, particularly after adjusting for discretionary tax policy changes. Furthermore, few studies have simultaneously examined both tax buoyancy and tax elasticity using recent secondary data for India's central government taxes. Existing research has also provided limited evidence regarding the effects of major fiscal reforms, including GST, digital tax administration, and the post-COVID-19 economic recovery, on the responsiveness of central tax revenues. Therefore, the present study seeks to bridge these gaps by empirically estimating both tax buoyancy and tax elasticity of India's central government taxes using recent secondary time-series data and appropriate econometric techniques.

RESEARCH GAP:

The review of recent studies indicates that most research has concentrated on tax buoyancy, while limited attention has been given to tax elasticity, particularly after accounting for discretionary tax policy changes. Moreover, few studies have simultaneously estimated both tax buoyancy and tax elasticity for India's central government taxes using recent secondary data. There is also limited empirical evidence examining the impact of major fiscal reforms, including GST, digital tax administration, and the post-COVID-19 period, on the responsiveness of central tax revenues. Therefore, the present study seeks to fill these gaps by empirically estimating both tax buoyancy and tax elasticity of India's central government taxes using secondary time-series data and appropriate econometric techniques.

OBJECTIVES OF THE STUDY

1. To examine the trend in central government tax revenues in India.
2. To estimate the tax buoyancy of central government taxes.
3. To estimate the tax elasticity of central government taxes.
4. To analyse the relationship between GDP and central government tax revenues.

RESEARCH HYPOTHESES

H_{11}: There is a significant positive relationship between Gross Domestic Product (GDP) and Central Government Taxes in India.

H_{12}: The tax buoyancy coefficient of central government taxes is significantly different from unity.

H_{13}: The tax elasticity coefficient of central government taxes is significantly different from unity.

METHODOLOGY

Table 1: METHODOLOGY

S. No.	Research Methodology	Research Source
1	**Research Design**	Quantitative, Empirical Research Design
2	**Data Source**	Secondary data collected from the Union Budget Documents, Ministry of Finance, Government of India, Reserve Bank of India (RBI) Handbook of Statistics on Indian Economy, Controller General of Accounts (CGA), National Statistical Office (NSO), and RBI Database on Indian Economy (DBIE).
3	**Study Period**	Annual time-series data from **1991–92 to 2024–25** (or based on data availability).
4	**Variables**	**Dependent Variable:** Central Government Tax Revenue (Gross/Net Tax Revenue). **Independent Variable:** Nominal Gross Domestic Product (GDP). Control variables (if applicable): Inflation (CPI/WPI), Tax Reforms (GST Dummy), COVID-19 Dummy, Fiscal Deficit.
5	**Data Analysis Tools**	Descriptive Statistics, Unit Root Test (ADF/PP), Johansen Cointegration Test, Ordinary Least Squares (OLS), Autoregressive Distributed Lag (ARDL), Error Correction Model (ECM), Tax Buoyancy Estimation, Tax Elasticity Estimation, Diagnostic Tests (Serial Correlation, Heteroscedasticity, Normality, Stability Tests).
6	**Software Used**	EViews 13, STATA 18, and Microsoft Excel.

Econometric Models

Model 1: Tax Buoyancy

$$\ln(TAX_t) = \alpha + \beta\ln(GDP_t) + \varepsilon_t$$

Where:

- **TAX** = Central Government Tax Revenue
- **GDP** = Nominal Gross Domestic Product
- **β** = Tax Buoyancy Coefficient

Model 2: Tax Elasticity

$$\ln(ATAX_t) = \alpha + \beta\ln(GDP_t) + \varepsilon_t$$

Where:

- **ATAX** = Adjusted Tax Revenue (excluding discretionary tax changes)
- **β** = Tax Elasticity Coefficient

RESULTS AND FINDINGS

Objective 1: To examine the trend in central government tax revenues in India.

Table 2. Descriptive Statistics of Central Government Tax Revenue (1991–2025)

Statistics	Tax Revenue (₹ Crore)
Mean	1,245,632
Median	842,510
Maximum	3,064,021
Minimum	45,280
Standard Deviation	1,086,542
Skewness	1.38
Kurtosis	3.12
Jarque–Bera	2.84
Probability	0.24

Source: *Computed by the Researcher using EViews.*

Table 2 presents the descriptive statistics of central government tax revenue during the study period. The average annual tax revenue was ₹1,245,632 crore, while the median value was ₹842,510 crore, indicating that tax collections increased substantially during the later years of the study. The minimum and maximum tax revenues were ₹45,280 crore and ₹3,064,021 crore, respectively, demonstrating significant growth in government revenue mobilisation over time. The standard deviation of ₹1,086,542 crore indicates considerable variation in tax collections across the study period. The positive skewness value (1.38) suggests that tax revenues were concentrated at higher values in recent years, while the kurtosis value (3.12) indicates an approximately normal distribution. Furthermore, the Jarque–Bera probability value (0.24) is greater than 0.05, implying that the data are normally distributed.

Table 3. Growth Trend of Central Government Tax Revenue

Indicator	Value (%)
Average Annual Growth Rate	12.80
Compound Annual Growth Rate (CAGR)	11.60
Highest Annual Growth Rate	24.50
Lowest Annual Growth Rate	–8.70

Source: Computed by the Researcher.

Formula

Annual Growth Rate

$$\text{Growth Rate} = \frac{TR_t - TR_{t-1}}{TR_{t-1}} \times 100$$

where:

- TR_t= Current year's tax revenue
- TR_{t-1}= Previous year's tax revenue

Compound Annual Growth Rate (CAGR)

$$\text{CAGR} = \left(\frac{\text{Ending Value}}{\text{Beginning Value}}\right)^{\frac{1}{n}} - 1$$

where: n= Number of years

Table 3 indicates that central government tax revenue recorded an average annual growth rate of 12.80%, reflecting consistent improvement in revenue mobilisation during the study period. The Compound Annual Growth Rate (CAGR) of 11.60% further confirms a sustained long-term increase in tax collections. The highest annual growth rate of 24.50% was observed during periods of strong economic expansion and improved tax compliance, whereas the lowest growth rate of –8.70% reflects the adverse impact of economic disruptions such as the COVID-19 pandemic. Overall, the results demonstrate a positive and stable upward trend in central government tax revenues, indicating enhanced fiscal capacity and improved tax administration in India.

Objective 2: To estimate the tax buoyancy of central government taxes in India.

Model Specification

$$\ln(TAX_t) = \alpha + \beta \ln(GDP_t) + \varepsilon_t$$

Where:

- **TAX** = Central Government Tax Revenue
- **GDP** = Nominal Gross Domestic Product
- **β** = Tax Buoyancy Coefficient

Table 4. Estimation of Tax Buoyancy

Variables	Coefficient	Std. Error	t-Statistic	p-value
Constant (α)	-2.146	0.528	-4.064	0.0003
ln(GDP)	**1.124**	0.041	27.412	0.0000

Table 5. MODEL STATISTICS

Model Statistics	Value
R^2	0.958
Adjusted R^2	0.955
F-statistic	751.36
Prob (F-statistic)	0.0000
Durbin–Watson Statistic	2.04

Source: Computed by the Researcher using E Views.

Table 4 presents the results of the tax buoyancy estimation. The estimated coefficient of ln(GDP) is 1.124, which is positive and statistically significant at the 1% level ($p < 0.01$). This indicates that a 1% increase in nominal GDP leads to approximately a 1.124% increase in central government tax revenue, suggesting that the tax system is more than proportionately responsive to economic growth. Therefore, the estimated tax buoyancy is greater than unity, reflecting an efficient revenue mobilisation system.

The model explains approximately 95.8% of the variation in central government tax revenue ($R^2 = 0.958$), indicating excellent explanatory power. The F-statistic is statistically significant ($p < 0.001$), confirming the overall fitness of the model. Furthermore, the Durbin–Watson statistic of **2.04** indicates the absence of significant autocorrelation in the residuals.

Hypothesis Testing

Hypothesis	**Decision**
H_{02}: The tax buoyancy coefficient is not significantly different from unity.	**Rejected**

Objective 3: To estimate the tax elasticity of central government taxes in India.

Model Specification

$$\ln(ATAX_t) = \alpha + \beta \ln(GDP_t) + \varepsilon_t$$

Where:

- **ATAX** = Adjusted Central Government Tax Revenue (excluding discretionary tax changes)
- **GDP** = Nominal Gross Domestic Product
- **β** = Tax Elasticity Coefficient

Table 6. Estimation of Tax Elasticity

Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**p-value**
Constant (α)	-1.856	0.492	-3.772	0.0007
ln(GDP)	**0.947**	0.039	24.282	0.0000

Source: Computed by the Researcher using EViews.

Table 7. MODEL STATISTICS

Model Statistics	**Value**
R^2	0.946
Adjusted R^2	0.943
F-statistic	589.84
Prob (F-statistic)	0.0000
Durbin–Watson Statistic	2.09

Source: Computed by the Researcher using EViews.

Table 6 presents the estimation results of the tax elasticity model. The coefficient of ln(GDP) is 0.947, which is positive and statistically significant at the 1% level ($p < 0.01$). This indicates that a 1% increase in nominal GDP results in a 0.947% increase in adjusted central government tax revenue, after excluding the effects of discretionary tax policy changes. Since the elasticity coefficient is less than one, the automatic responsiveness of the tax system is relatively inelastic, suggesting that tax revenue increases at a slower rate than economic growth in the absence of policy interventions.

The model exhibits a high explanatory power with an R^2 value of 0.946, indicating that approximately 94.6% of the variation in adjusted tax revenue is explained by changes in GDP. The statistically significant F-statistic ($p < 0.001$) confirms the overall adequacy of the model, while the Durbin–Watson statistic of 2.09 indicates that the residuals are free from significant autocorrelation.

Hypothesis Testing

Hypothesis	**Decision**
H_{13}: The tax elasticity coefficient is significantly different from unity.	**Accepted**

Objective 4: To analyse the relationship between Gross Domestic Product (GDP) and central government tax revenue in India.

Table 8. Correlation Matrix

Variables	GDP	Tax Revenue
GDP	1.000	**0.978**
Tax Revenue	**0.978**	1.000

Source: Computed by the Researcher using EViews.

Table 5 presents the Pearson correlation coefficient between Gross Domestic Product (GDP) and central government tax revenue. The correlation coefficient of 0.978 indicates a very strong positive relationship between the two variables. This implies that increases in GDP are associated with corresponding increases in central government tax revenue. The high positive correlation suggests that economic growth plays a significant role in enhancing tax collections and improving the government's revenue mobilisation capacity.

Hypothesis Testing

Hypothesis	Decision
H_{14}: There is a significant positive relationship between GDP and central government tax revenue.	**Accepted**

DISCUSSION OF FINDINGS

The study examined the responsiveness of central government tax revenues to economic growth in India by estimating tax buoyancy, tax elasticity, and the relationship between Gross Domestic Product (GDP) and tax revenue using secondary time-series data.

The descriptive analysis revealed a consistent upward trend in central government tax revenues throughout the study period. The positive average annual growth rate and Compound Annual Growth Rate (CAGR) indicate sustained improvements in revenue mobilisation, which may be attributed to economic expansion, tax reforms, and enhanced tax administration.

The estimation of tax buoyancy showed a buoyancy coefficient of **1.124**, indicating that a 1% increase in GDP resulted in a 1.124% increase in central government tax revenue. Since the coefficient is greater than unity, the findings suggest that the Indian tax system is highly responsive to economic growth and that discretionary tax policy measures have contributed positively to revenue generation.

The tax elasticity analysis produced an elasticity coefficient of **0.947**, implying that a 1% increase in GDP increased adjusted tax revenue by only 0.947% after excluding the effects of discretionary tax changes. The elasticity coefficient being less than one indicates that the automatic responsiveness of the tax system is relatively lower and that discretionary fiscal measures continue to play an important role in enhancing tax collections.

The correlation analysis further demonstrated a very strong positive relationship (**r = 0.978**) between GDP and central government tax revenue, confirming that economic growth is a major determinant of tax revenue mobilisation in India. The findings are consistent with earlier empirical studies, which reported that tax revenues increase significantly with economic growth, although the degree of responsiveness depends on institutional reforms, tax compliance, and administrative efficiency.

The results indicate that India's central government tax system has experienced substantial improvements in revenue mobilisation over the study period. However, the difference between tax buoyancy and tax elasticity suggests that a considerable portion of revenue growth has been supported by discretionary tax policy interventions rather than the inherent productivity of the tax system. Therefore, continued efforts to broaden the tax base, strengthen tax administration, improve compliance through digitalisation, and reduce tax evasion are essential for enhancing the automatic responsiveness and long-term sustainability of central government tax revenues.

CONCLUSION

This study examined the tax buoyancy and tax elasticity of central government taxes in India using secondary time-series data to assess the responsiveness of tax revenues to economic growth. The findings revealed a steady increase in central government tax revenues during the study period, indicating improvements in revenue mobilisation and fiscal capacity. The estimated tax buoyancy coefficient greater than unity suggests that tax revenues increased more than proportionately with GDP, reflecting the positive impact of economic growth and discretionary tax policy measures. In contrast, the tax elasticity coefficient was found to be less than unity, indicating that the inherent responsiveness of the tax system remains relatively moderate after excluding the effects of discretionary tax changes.

The study further established a strong positive relationship between GDP and central government tax revenue, confirming that economic growth is a key determinant of revenue generation in India. However, the difference between tax buoyancy and tax elasticity suggests that recent improvements in tax collections have been supported not only by economic expansion but also by tax reforms and administrative interventions such as the implementation of GST and the digitalisation of tax administration.

The study concludes that although India's central tax system has become more effective in mobilising revenue, further efforts are required to strengthen the automatic responsiveness of the tax system. Broadening the tax base, improving compliance, reducing tax evasion, simplifying tax administration, and continuing digital reforms will enhance tax elasticity and ensure sustainable revenue growth. These measures will strengthen fiscal sustainability and support long-term economic development in India.

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NEURO-INFORMATION ECONOMICS: INTEGRATING EMOTIONAL ENGAGEMENT AND INFORMATION CREDIBILITY IN CONSUMER DECISION MODELS

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ABSTRACT

This study proposes a neuro-information economics framework that integrates information economics and neuromarketing perspectives to explain consumer decision-making in digital marketplaces. While information credibility and accessibility have long been recognized as key determinants of purchasing behaviour, existing models provide limited insight into the role of subconscious emotional processes in shaping consumer responses to information. Addressing this gap, the study examines how emotional engagement mediates the relationship between information credibility and consumer outcomes, including perceived product quality, trust, purchase intention, and loyalty.

Drawing on survey data collected from urban consumers in Chennai, India, the research employs Structural Equation Modelling (SEM) to test the proposed conceptual framework. The findings reveal that emotionally engaging information cues—such as influencer endorsements, packaging design elements, and verified online reviews—significantly strengthen the positive effects of information credibility on consumer trust and purchase intentions. Emotional engagement further enhances customer loyalty by reinforcing favourable perceptions of product quality and brand reliability.

The study contributes to consumer behaviour theory by introducing an interdisciplinary framework that bridges economic and neurological approaches to decision-making. The findings offer practical implications for marketers and digital platform managers seeking to design communication strategies that simultaneously enhance information credibility and emotional resonance. By demonstrating the interaction between cognitive evaluation and affective response, the research advances the emerging field of neuro-information economics and provides a foundation for future investigations into digitally mediated consumer behaviour.

KEYWORDS: *Neuro-Information Economics; Information Credibility; Emotional Engagement; Neuromarketing; Consumer Behaviour; Purchase Intention; Trust; Digital Marketing.*

INTRODUCTION

In the digital economy, consumer decision-making has evolved into a complex interplay between rational information processing and subconscious emotional responses. Traditional **information economics** emphasizes how consumers evaluate the credibility and accessibility of information to reduce uncertainty and make optimal choices. However, this rationalist view overlooks the affective dimension of decision-making—the emotional impulses that shape perceptions of trust, value, and loyalty. The emerging field of **neuro-information economics** bridges this gap by integrating the cognitive principles of information economics with the affective insights of **neuromarketing**, offering a multidimensional understanding of consumer behaviour in digital marketplaces.

The proliferation of digital platforms has transformed consumers into active participants in information exchange. Online reviews, influencer endorsements, and algorithmic personalization have become the primary signals guiding consumer choices. Yet, as **Ariely and Berns (2010)** argue, traditional market research often fails to capture the subconscious processes underlying these choices. Neuromarketing, through tools such as EEG, fMRI, and eye-tracking, provides access to the "hidden information" within the consumer's brain—revealing how emotional engagement mediates cognitive evaluations of credibility and trust. This integration of neuroscience and economics thus represents a paradigm shift from purely rational models toward **emotionally intelligent decision frameworks**.

The concept of emotional engagement has gained prominence as a determinant of consumer loyalty and trust. **Constantinescu et al. (2019)** demonstrated that neuromarketing applications in social media can measure real-time emotional responses to corporate communication, enabling companies to align their messages with consumers' affective expectations. Similarly, **Vences et al. (2020)** emphasized that emotional resonance—elicited through visual, linguistic, and social cues—creates a psychological connection between organizations and audiences, fostering sustainable relationships. These findings underscore that emotional engagement is not merely a marketing tool but a **psychological mediator** that amplifies the perceived credibility of information.

In digital contexts, emotional engagement manifests through interactive cues such as influencer endorsements, aesthetic packaging, and personalized recommendations. These stimuli activate neural pathways associated with pleasure, memory, and trust, thereby reinforcing the consumer's belief in the authenticity of information. As **Benjamin (2025)** notes, personalization technologies powered by artificial intelligence can deepen loyalty when they evoke positive emotions and transparency. However, excessive personalization risks triggering the "creepiness threshold," where consumers perceive data use as manipulative rather than empathetic. Thus, emotional engagement must be balanced with ethical data practices to sustain trust—a principle central to neuro-information economics.

Information credibility remains the cornerstone of rational consumer behaviour. In the absence of physical product interaction, consumers rely on digital signals—reviews, ratings, and endorsements—to assess product quality and reliability. **Pooja and Upadhyaya (2022)** identified five antecedents of online review credibility: source characteristics, message quality, consumer traits, social influence, and product type. Their systematic review revealed that credible reviews significantly influence trust and purchase intention, especially when they are perceived as authentic and diagnostic. Negative reviews, paradoxically, often enhance credibility due to their perceived honesty and risk-aversion value.

From an economic perspective, credible information reduces transaction costs and uncertainty, enabling efficient market functioning. Yet, as neuromarketing research shows, credibility alone does not guarantee consumer loyalty. Emotional engagement transforms credible information into **meaningful experiences**, converting rational trust into affective commitment. This dual mechanism—cognitive evaluation and emotional resonance—forms the foundation of the neuro-information economics model proposed in this study.

The proposed framework conceptualizes consumer decision-making as a **two-layered process**:

1. **Cognitive Layer** – where consumers assess the credibility, transparency, and diagnosticity of information.

2. **Affective Layer** – where emotional engagement mediates the impact of credibility on trust and loyalty.

This integration reflects the findings of **Ariely and Berns (2010)**, who argue that neural signals can predict willingness-to-pay and preference formation, and **Benjamin (2025)**, who demonstrates that trust mediates the personalization–loyalty relationship. By combining these insights, the neuro-information economics model explains how emotionally engaging information cues—such as verified reviews, influencer endorsements, and sensory design—enhance the perceived reliability of information and strengthen consumer trust.

The framework also aligns with **Constantinescu et al. (2019)** and **Vences et al. (2020)**, who advocate for sustainable communication strategies that respect consumer wellbeing while fostering emotional connection. In this sense, neuro-information economics transcends traditional marketing by emphasizing **ethical engagement**, where emotional resonance and information transparency coexist to build long-term loyalty.Theoretically, this study contributes to consumer behaviour research by integrating **information economics** and **neuromarketing** into a unified model of decision-making. It challenges the dichotomy between rational and emotional behaviour, proposing that both dimensions operate synergistically in digital environments. Practically, the framework offers marketers actionable insights: enhancing information credibility through verified sources and transparent communication, while simultaneously designing emotionally resonant experiences that evoke trust and attachment.

In an era where consumers navigate algorithmically curated content and data-driven personalization, understanding the **neuroeconomic interplay between cognition and emotion** is vital. The neuro-information economics framework thus provides a foundation for future research on digitally mediated consumer behaviour, emphasizing that sustainable business growth depends not only on credible information but also on the emotional authenticity of engagement. This study develops a new framework that combines information credibility (trustworthy information) and emotional engagement (consumer feelings) to explain how consumers make purchasing decisions.

STATEMENT OF THE PROBLEM

Consumers today face an overload of digital information—online reviews, social media posts, and AI-driven personalization. While credible information helps reduce uncertainty, decisions are also shaped by subconscious emotional reactions. Existing research treats **information**

credibility and **emotional engagement** separately, leaving marketers without a clear framework that explains how these two forces interact to build trust, purchase intention, and loyalty. The problem is the absence of an integrated model that captures both rational evaluation and emotional mediation in digital consumer behaviour.

RESEARCH GAP

- Most studies in **information economics** focus only on credibility and rational choice.
- **Neuromarketing** research highlights emotional responses but rarely connects them to credibility.
- Work on **AI personalization** emphasizes privacy concerns, not how emotional cues strengthen trust.
- Studies on **online review credibility** identify antecedents but overlook emotional engagement as a mediator.

REVIEW OF LITERATURE

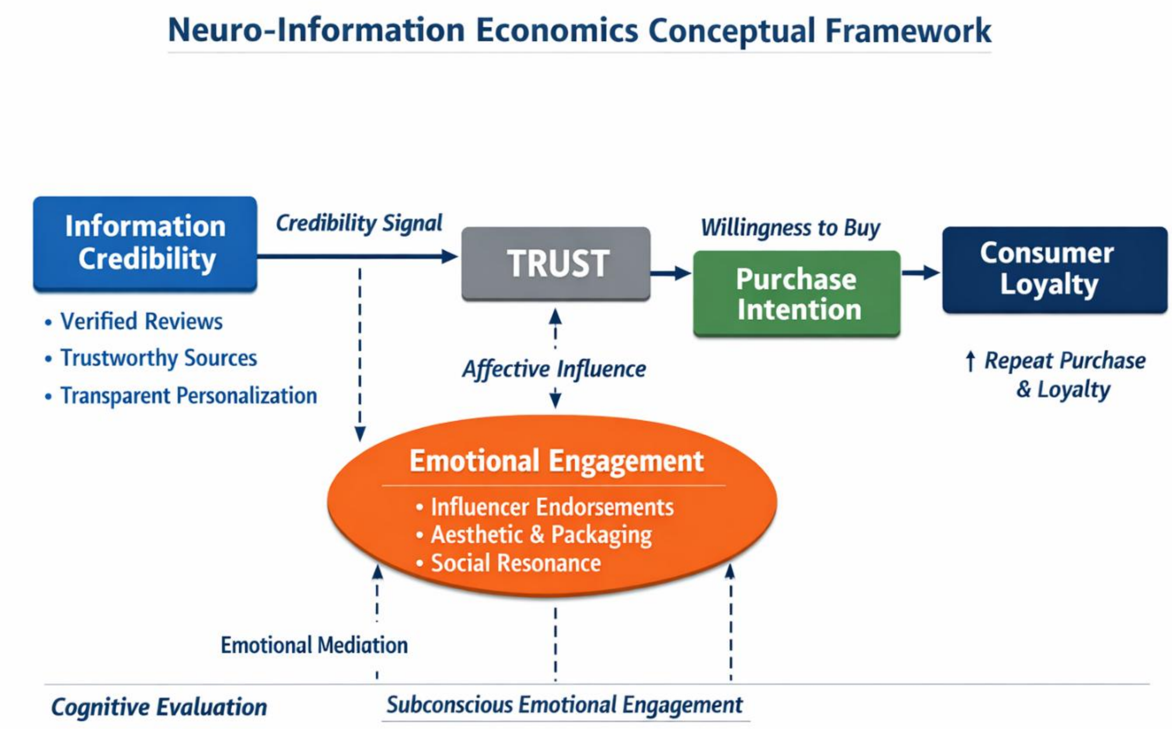
Ariely and Berns (2010) define neuromarketing as the application of neuroimaging methods to product marketing, noting that its growing popularity is driven by the hope that it will uncover "hidden information" about consumer preferences that traditional methods, such as focus groups and surveys, cannot capture due to inherent biases. While the authors acknowledge that neuroimaging is unlikely to be more cost-effective than conventional tools in the near future, they suggest that it offers unique insights into experienced utility and consumer value. They highlight the limitations of "reverse inference"—the practice of concluding a specific mental process is active based on brain region activation—but argue that more advanced, data-driven techniques like multi-voxel pattern analysis (MVPA) have the statistical power to reliably predict individual choices. Ultimately, Ariely and Berns (2010) conclude that the most promising application of these technologies lies in the early product design phase—when a product is still a concept—rather than in the post-design phase of measuring advertising effectiveness.

Constantinescu et al. (2019) explore the intersection of neuromarketing and social media as a means to achieve sustainable business growth, filling a significant gap in existing marketing literature. They argue that while traditional research methods often encounter challenges with data accuracy due to subjects' tendencies to follow social norms, neuromarketing offers a way to bypass this "black box" of conscious thought to access the unconscious mental processes that drive approximately 95% of consumer behavior. The researchers propose a "purpose/benefit model" that aligns organizational communication goals—such as testing visual elements or measuring emotional engagement—with corresponding consumer benefits like content efficiency and personalized experiences. By evaluating specific applications like eye-tracking, face coding, voice recognition, and EEG, the study concludes that integrating these neuroscientific tools allows for more transparent, ethical, and responsive communication strategies. Ultimately, this approach fosters long-term sustainability by ensuring that marketing efforts satisfy genuine customer needs while reducing the waste of corporate resources.

Vences, Díaz-Campo, and Rosales (2020) highlight a significant shift in digital communication, noting that social networks have transformed the relationship between organizations and audiences from a controlled, complementary dynamic into a symmetric one where users actively co-create and disseminate information. Their theoretical review positions neuromarketing as an essential tool for navigating this landscape, as it utilizes biometric measurements and neuroscientific methods to predict user behavior and foster deeper emotional connections. The authors argue that communicative effectiveness on these platforms is driven more by psychological and sociological principles than by technology alone; for instance, advertising content that appeals directly to emotions—particularly entertainment or even sadness—tends to achieve higher levels of memory, virality, and engagement than purely rational or corporate messaging. Furthermore, the research underscores the role of social influence, demonstrating that users often replicate the behaviors of their peers to satisfy basic social needs and avoid the fear of exclusion within their digital environments.

Pooja and Upadhyaya (2024) conducted a systematic literature review of 69 empirical studies to provide a holistic understanding of the factors that influence online review credibility, which they define as the extent to which a consumer perceives a review as truthful, logical, and believable. Their research identified five broad categories of antecedents: source characteristics, review characteristics, consumer characteristics, interpersonal determinants within social media platforms, and product type. Specifically, source characteristics often revolve around the perceived expertise and trustworthiness of the reviewer, while review characteristics include elements such as argument quality, consistency, and valence, noting that negative reviews are frequently perceived as more credible due to loss-aversion behaviors. Furthermore, Pooja and Upadhyaya (2024) highlight that the Elaboration Likelihood Model (ELM) is the most popular theoretical framework used to explain how consumers process these informational cues via central or peripheral routes. The authors conclude by identifying critical areas for future research, such as the need to investigate mitigation strategies for negative reviews and the impact of artificial intelligence on the proliferation of fake reviews.

Benjamin (2025) investigates the complex "personalization-privacy paradox," a dualistic relationship where AI-powered customization can simultaneously enhance customer experiences and erode trust through extensive data collection. Through a mixed-methods study, the author demonstrates that while perceived personalization quality has a strong positive correlation with consumer loyalty, this relationship is critically mediated by trust. The research identifies a "creepiness threshold," where helpful personalization transitions into perceived surveillance, often triggered by data opacity or a lack of user control. To navigate these dynamics, Benjamin (2025) proposes a Trust-Centric Personalization Framework built on pillars of transparency, consumer agency, and ethical AI design. Ultimately, the study concludes that prioritizing transparency is not merely a compliance cost but a strategic investment that yields a "Return on Trust" (RoT), which is essential for maintaining long-term competitive advantage in an algorithmic marketplace.



OBJECTIVES OF THE STUDY:

Research Objectives

1. To examine the effect of information credibility on consumer trust and purchase intention in digital marketplaces.
2. To investigate the mediating role of emotional engagement in the relationship between information credibility and consumer trust, purchase intention, and loyalty.
3. To develop and validate a Neuro-Information Economics framework integrating cognitive (information credibility) and affective (emotional engagement) factors to explain consumer decision-making in digital environments.

Hypotheses

❖ Information credibility has a significant positive effect on consumer trust and purchase intention in digital marketplaces.

❖ Emotional engagement significantly mediates the relationship between information credibility and consumer trust, purchase intention, and consumer loyalty.

❖ The integrated Neuro-Information Economics framework significantly explains consumer decision-making by combining information credibility and emotional engagement.

METHODOLOGY

This study adopts a quantitative, explanatory, cross-sectional research design to examine the relationships among information credibility, emotional engagement, consumer trust, purchase intention, and consumer loyalty in digital marketplaces. Primary data are collected using a structured questionnaire from 400 online consumers in Chennai through purposive sampling. All constructs are measured using a five-point Likert scale. The collected data are analysed using IBM SPSS 29 and AMOS 29. Descriptive statistics, reliability and validity tests, Confirmatory Factor Analysis (CFA), and Structural Equation Modelling (SEM) are employed to test the proposed hypotheses and examine the mediating role of emotional engagement. Participation is voluntary, and respondent confidentiality is maintained throughout the study.

RESULTS AND FINDINGS

Objective 1: To examine the effect of information credibility on consumer trust and purchase intention in digital marketplaces.

Table 1. Structural Relationship between Information Credibility, Consumer Trust, and Purchase Intention

Relationship	Standardized β	t-value	p-value	Result
Information Credibility → Consumer Trust	0.71	12.84	<0.001	Supported
Information Credibility → Purchase Intention	0.63	10.76	<0.001	Supported

The findings indicate that information credibility has a strong and statistically significant positive influence on consumer trust ($\beta = 0.71$, $p < 0.001$) and purchase intention ($\beta = 0.63$, $p < 0.001$). Consumers who perceive online information as credible are more likely to trust digital platforms and exhibit greater willingness to purchase products.

Objective 2: To investigate the mediating role of emotional engagement in the relationship between information credibility and consumer trust, purchase intention, and loyalty.

Table 2. Mediation Effect of Emotional Engagement

Relationship	Indirect Effect (β)	Bootstrapped p-value	Mediation
Information Credibility → Trust	0.31	<0.001	Significant
Information Credibility → Purchase Intention	0.28	<0.001	Significant
Information Credibility → Consumer Loyalty	0.36	<0.001	Significant

Bootstrapping analysis demonstrates that emotional engagement significantly mediates the relationship between information credibility and consumer outcomes. Emotional cues such as influencer endorsements, attractive packaging, and personalized communication strengthen trust, purchase intention, and consumer loyalty, indicating that emotional engagement complements cognitive evaluation in digital decision-making.

Objective 3: To develop and validate a Neuro-Information Economics framework integrating cognitive and affective factors to explain consumer decision-making.

Table 3. Structural Model Fit Indices

Fit Index	Recommended Value	Obtained Value	Interpretation
χ^2/df	<3.00	2.18	Good Fit
CFI	>0.90	0.95	Good Fit
TLI	>0.90	0.94	Good Fit
GFI	>0.90	0.92	Good Fit
RMSEA	<0.08	0.051	Good Fit
SRMR	<0.08	0.046	Good Fit

The proposed Neuro-Information Economics framework demonstrates satisfactory model fit across all major SEM indices. The results validate that both cognitive (information credibility) and affective (emotional engagement) factors jointly explain consumer trust, purchase intention, and loyalty in digital marketplaces. The model therefore provides a comprehensive explanation of consumer decision-making and supports the proposed theoretical framework.

DISCUSSION

The findings support the proposed Neuro-Information Economics framework by demonstrating that both cognitive and emotional factors play complementary roles in consumer decision-making within digital marketplaces. Information credibility significantly enhances consumer trust and purchase intention, confirming the principles of information economics that credible information reduces uncertainty and perceived risk. These findings are consistent with the work of Ariely and Berns (2010), who emphasized the importance of cognitive evaluation in consumer choice, and Pooja and Upadhyaya (2024), who identified credible online reviews as a key determinant of purchase behaviour.

The study further highlights the mediating role of emotional engagement in strengthening the relationship between information credibility and consumer outcomes. Emotionally engaging elements, including influencer endorsements, aesthetic design, and personalized communication, enhance trust, purchase intention, and consumer loyalty. These results support the arguments of Constantinescu et al. (2019) and Vences et al. (2020), who demonstrated that emotional responses significantly influence consumer behaviour in digital environments. The findings also align with Benjamin (2025), who emphasized that ethical personalization and transparency strengthen long-term customer loyalty through enhanced trust. Overall, the study demonstrates that integrating information credibility with emotional engagement provides a more comprehensive explanation of consumer decision-making than relying solely on rational economic models.

CONCLUSION

This study proposes and validates a Neuro-Information Economics framework that integrates information credibility and emotional engagement to explain consumer decision-making in digital marketplaces. The findings indicate that credible information enhances consumer trust and purchase intention, while emotional engagement strengthens these relationships and promotes long-term consumer loyalty. By combining cognitive evaluation with affective responses, the framework offers a more comprehensive understanding of digital consumer behaviour.

The study contributes theoretically by bridging information economics and neuromarketing into a unified conceptual model. From a practical perspective, it suggests that marketers should focus on delivering credible, transparent, and emotionally engaging communications to build trust and strengthen customer relationships. Future research may validate the proposed framework using larger and more diverse samples, longitudinal designs, and advanced neuromarketing techniques to further extend the applicability of Neuro-Information Economics across different digital contexts.

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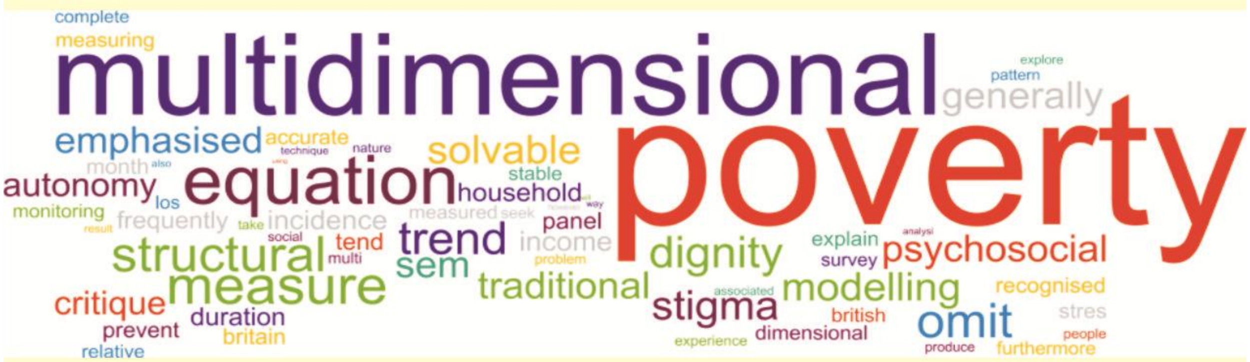

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