SURVEY

A Journal of Management and Welfare Studies

ISSN: 0586-0008 Volume: 65, Issue: 01 • January - March, 2026

IISWBM, Kolkata
SURVEY
Volume : 65, Issue 01 • January - March, 2026

From The Editor's Desk

It is with considerable satisfaction that we present the latest issue of SURVEY: A Management Research Journal of IISWBM. This issue continues our commitment to disseminating rigorous and impactful scholarship that advances the frontiers of management research and practice. The journal seeks to integrate theoretical insights with empirical validation, thereby contributing to evidence-based management and informed decision-making.

SURVEY is a peer-reviewed quarterly publication dedicated to fostering high-quality academic discourse across a wide spectrum of management-related domains. These include, but are not limited to, business management, human resource management, data science, public systems, commerce, economics, sports management, law, and social welfare. By maintaining a multidisciplinary orientation, the journal facilitates cross-fertilization of ideas and encourages the development of integrative frameworks that address complex organizational and societal challenges.

A defining characteristic of the journal is its openness to diverse methodological approaches and epistemological perspectives. Both quantitative and qualitative inquiries as well as mixed-methods research are welcomed, provided they demonstrate analytical rigor and conceptual clarity. In this context, SURVEY serves as an intellectual platform for the generation, validation, and dissemination of knowledge that is both theoretically robust and practically relevant.

The articles featured in this issue reflect a broad array of contemporary themes in management science offering nuanced analyses and innovative perspectives. Collectively, they contribute to a deeper understanding of emerging trends, managerial effectiveness and policy implications in a dynamic and evolving environment.

We express our sincere appreciation to the contributing authors for their scholarly efforts and to the reviewers for their critical evaluations and constructive feedback, which have been instrumental in maintaining the academic integrity of this publication. We also extend our gratitude to our readers for their continued engagement and support. We encourage them to actively participate in this ongoing dialogue by sharing their insights and perspectives on the issues discussed herein.

Looking ahead, we invite researchers and practitioners to contribute original, methodologically sound and conceptually innovative work to future issues of SURVEY, thereby strengthening its role as a leading forum for management research and intellectual exchange.

Prof. (Dr.) K. M. Agrawal
Editor-in-Chief, SURVEY &
Director, IISWBM, Kolkata

SURVEY
A Journal of Management and Welfare Studies
Volume: 65, Issue: 01 • January - March, 2026

CONTENTS

Exploring the Entrepreneurial Intentions of Business Students: Insights from Select HEIs of Kolkata

S. Kavitha[1] and Abhik Kumar Mukherjee[2]

ABSTRACT

This study explores the entrepreneurial intentions of undergraduate and postgraduate students in business-related disciplines at select higher education institutions (HEIs) in Kolkata, a major educational hub in eastern India, through the lens of Ajzen's (1991) Theory of Planned Behaviour. It examines the role of three key components-attitude towards entrepreneurship, subjective norms, and perceived behavioural control-in explaining students' entrepreneurial intentions. Additionally, it examines differences in entrepreneurial intentions based on gender and family business background. Data for the study were collected using a structured questionnaire based on the Entrepreneurial Intention scale of Linan & Chen (2009) and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

The findings reveal that attitude towards entrepreneurship was the most significant contributor, followed by perceived behavioural control, in shaping students' intentions, whereas subjective norms had no statistically significant impact on intentions. Attitude towards entrepreneurship strongly predicts entrepreneurial intentions for both students of both genders, with a stronger impact on male students. Notably, perceived control significantly and positively influences entrepreneurial intentions solely among female students. Both attitude and perceived control significantly shape entrepreneurial intentions, regardless of students' family-business background. This research provides useful insights into factors shaping entrepreneurial intentions in Kolkata, a prominent hub in eastern India's educational ecosystem, and offers implications for HEIs and policymakers.

The study is limited to a specific geographic location and is cross-sectional, which limits the generalisability of the results. Future research could employ mixed-methods to explore entrepreneurial intentions across different academic disciplines and employ longitudinal designs to provide a more comprehensive understanding.

Keywords: *Entrepreneurial Intention; Theory of Planned Behaviour; Higher Education Institutions; Entrepreneurship Education; Kolkata*

1. Introduction

Entrepreneurship is recognised as a prerequisite for societal growth (Zahra & Wright, 2015; Ratten & Jones, 2021) and employment creation (Baumol & Strom, 2007; Kuratko, 2005). Much of the literature has examined why some individuals become entrepreneurs while others do not (Loi et al., 2023; Krueger et al., 2000). Recent research has shifted towards understanding entrepreneurial behaviour and its antecedents, with entrepreneurial intention (EI) identified as a crucial precursor (Krueger et al., 2000; Liñán & Fayolle, 2015). Since the 1990s, EI has emerged as a consolidated research area within entrepreneurship (Liñán & Fayolle, 2015; Nájera-Sánchez et al., 2022; Maheshwari et al., 2023).

As part of the multi-stage entrepreneurial process, EI development is vital (Cui & Bell, 2022) and central to explaining entrepreneurial behaviour (Liñán & Fayolle, 2015). Stronger intentions increase the likelihood of entrepreneurial activity or start-up creation (Moriano et al., 2012). Research on EI has gained global traction,

[1]Doctoral Scholar, Department of Business Administration, The University of Burdwan, West Bengal
[2]Assistant Professor, Department of Business Administration, The University of Burdwan, West Bengal

particularly within higher education institutions (HEIs) (Loi et al., 2023; Maheshwari et al., 2023; Nájera-Sánchez et al., 2022). HEIs provide a critical environment for fostering EI, as education equips individuals with the skills, knowledge, and attitudes necessary for entrepreneurial action. Historically, well-educated individuals have shown greater success in creating and sustaining ventures (Nabi et al., 2018). Students at HEIs, being at formative career stages, are especially receptive to developing entrepreneurial mindsets (Saxena, 2021; Manimala & Thomas, 2017).

Several studies have identified factors influencing entrepreneurial intention among students (Liñán et al., 2011; Maheshwari et al., 2023; Schlaegel & Koenig, 2014). The most prominent factors-attitude towards entrepreneurship, subjective norms, and perceived behavioural control-are derived from Ajzen's (1991) Theory of Planned Behaviour and are widely considered key predictors of entrepreneurial intention. Ajzen's framework provides robust theoretical support for understanding how intentions are formed through the interaction of these three antecedents (Maheshwari, 2023; Moriano et al., 2012).

In India, EI has been studied through cross-cultural comparisons (Moriano et al., 2012; Trivedi, 2017; Seth et al., 2018; Olarewaju et al., 2022) and within HEIs, which dominate the literature. Some studies measure EI levels among students (Mishra & Singh, 2022; Anwar et al., 2021; Jena, 2020; Tiwari et al., 2020), while others examine the role of entrepreneurship education (Paray & Kumar, 2020; Anwar, 2021; Pandit et al., 2018). Emerging themes include gender differences (Chaudhuri et al., 2022; Anwar, 2021; Srivastava & Misra, 2017), disciplinary and regional variations (Jena, 2020; Mishra & Singh, 2022; Roy & Das, 2022; Kumar et al., 2021; Vasumathi et al., 2023), social and sustainable entrepreneurship (Gupta & Matharu, 2022; Tiwari et al., 2020), and technology integration (Chatterjee et al., 2020; Aboobaker et al., 2023).

The Global Entrepreneurship Monitor (GEM) India report (2026) measures EI as the proportion of adults (18-64) who intend to start a business within three years. This figure has fluctuated, exceeding 30% in 2019, and currently stands at 25.6% for 2025-26. With growing support from HEIs and government initiatives, India has emphasised student entrepreneurship in the last decade (Chhabra et al., 2021; Saxena, 2021). Yet, eastern India remains underexplored. Kolkata, as a major metropolitan and educational hub, offers a valuable context to address this gap.

Accordingly, this study seeks to examine, within the urban context of Kolkata, whether attitude towards entrepreneurship (ATE), perceived behavioural control (PBC), and subjective norms (SN) affect entrepreneurial intentions among students enrolled in undergraduate and postgraduate programs in commerce, business administration, or management at specific higher education institutions. The study is particularly relevant for institutions offering business and commerce programmes, as these students are exposed to entrepreneurship courses as a part of their curriculum. Understanding the impact of these variables on entrepreneurial intention can help stakeholders design targeted interventions to strengthen specific areas, thereby enhancing students' overall entrepreneurial intention. In addition, the study investigates how the components of the Theory of Planned Behaviour relate to entrepreneurial intentions, while also examining differences across gender and family business background.

2. Review of select literature, theoretical framework and hypotheses development

2.1 Entrepreneurial Intention

Scholars have long sought to explain why only some individuals pursue entrepreneurship and what ignites the entrepreneurial spark (Anwar et al., 2021; Loi et al., 2023). Early research emphasised traits, portraying entrepreneurs as possessing enduring characteristics such as need for achievement (McClelland, 1961), locus of control, risk-taking propensity, and tolerance for ambiguity (Brockhaus & Horwitz, 1986; Neck & Greene, 2011). However, trait-based models produced mixed results (Sarasvathy & Venkataraman, 2010; Landström et al., 2012) and limited explanatory power (Krueger et al., 2000; Liñán & Fayolle, 2015), prompting a shift towards process and cognitive approaches (Landström et al., 2012). Entrepreneurship came to be seen as a deliberate, intentional activity shaped by cognitive models of behaviour (Neck & Greene, 2011; Krueger et al., 2000; Liñán & Fayolle, 2015).

Pioneering works by Shapero (1984) and Bird (1988) established entrepreneurial intention (EI) as a precursor to behaviour. Shapero's Entrepreneurial Event Model and subsequent theories from social psychology, including self-efficacy (Bandura, 1982) and Ajzen's (1991) Theory of Planned Behaviour (TPB), became central to EI research (Krueger et al., 2000). Ajzen's framework, in particular, provided a cornerstone for understanding how intentions form through attitude, subjective norms, and perceived behavioural control (Schlaegel & Koenig, 2014). By the 1990s, intention-based models gained traction (Krueger et al., 2000), supported by multidisciplinary approaches (Loi et al., 2023).

EI has since emerged as a crucial field of study (Donaldson et al., 2021; Loi et al., 2023), widely recognised as the most vital predictor of entrepreneurial behaviour, which is volitional (Rauch & Hulsink, 2015) and planned (Ajzen, 1991; Krueger et al., 2000). It is particularly useful where behaviour is atypical, deliberate, not regularly observable, or subject to time lags (Krueger et al., 2000).

Operationalising EI remains important. Liñán & Fayolle (2015) highlighted definitional challenges, while Bae et al. (2014) defined EI as an individual's inclination and commitment to pursue entrepreneurial activities, such as starting a business. Among various frameworks, Ajzen's Theory of Planned Behaviour has emerged as the dominant model in EI research (Schlaegel & Koenig, 2014).

2.2 Theory of Planned Behaviour (TPB)

The TPB, put forward by Ajzen (1991), is an extensively used model of human behaviour. It explains intentions through three antecedents: attitude towards entrepreneurship, subjective norms, and perceived behavioural control. TPB integrates psychological constructs such as attitudes, social norms, and self-efficacy, offering a comprehensive framework for predicting entrepreneurial behaviour (Schlaegel & Koenig, 2014; Rauch & Hulsink, 2015; Liñán & Fayolle, 2015). With its three predictive components, TPB is considered a robust model for understanding entrepreneurial intention (Krueger et al., 2000) and extends the earlier Theory of Reasoned Action (Ajzen & Fishbein, 1980).

Entrepreneurial intention acts as the immediate precursor of behaviour, mediating the relationship between attitudinal constructs and actual entrepreneurial action (Fayolle et al., 2006; Krueger et al., 2000; Souitaris et al., 2007). Exogenous factors, like education., personalities, characteristics, or role models influence behaviour indirectly by shaping perceptions and attitudes, which in turn drive intentions (Krueger et al., 2000; Rauch & Hulsink, 2015). These intentions serve as the catalyst for entrepreneurial behaviour (Souitaris et al., 2007).

2.3 Attitude Towards Entrepreneurship

The first component, attitude towards entrepreneurship (ATE), reflects perceptions of the desirability of entrepreneurial behaviour. It captures an individual's preference for entrepreneurship over organisational employment (Souitaris et al., 2007). ATE is influenced by beliefs and stored information in memory, shaping perceptions of entrepreneurship as a viable career option (Ajzen, 1991; Fayolle et al., 2006). In essence, it stems from the conviction that starting a business is a viable career alternative (Krueger et al., 2000; Rauch & Hulsink, 2015).

2.4 Subjective Norms

Subjective norms (SN) measures an individual's perceived social expectations from significant others-family, peers, or friends-regarding entrepreneurial behaviour (Ajzen, 1991). They also capture an individual's motivation to comply with these opinions (Krueger et al., 2000). SN thus represent perceived social pressure (Liñán et al., 2011) or societal influence (Fayolle & Gailly, 2015). Positive perceptions from reference groups can strengthen entrepreneurial intention (Krueger et al., 2000). However, empirical studies show that social norms often exert a weaker influence on intentions in certain contexts (Ajzen, 1991), particularly among individuals with proactive attitudes (Rauch & Hulsink, 2015). Despite this, most literature retains SN as a key antecedent of entrepreneurial intention.

2.5 Perceived Behavioural Control

The final aspect of perceived behavioural control, or PBC, relates to how an individual perceives the ease or difficulty of performing the behaviour or act as an entrepreneur and their confidence in their ability to carry it out and sustain it (Fayolle et al., 2006). It arises from an individual's belief that becoming an entrepreneur is a realistic possibility (Rauch & Hulsink, 2015; Zhao et al., 2005). It aligns with Bandura's (1987) concept of self-efficacy, reflecting the perceived ability to execute tasks as an entrepreneur and is crucial for predicting entrepreneurial intentions (Ajzen, 1991).PBC was clarified in TPB to account for the involuntary elements that may be present in all behaviour (Ajzen, 1991; Zhao et al., 2005; Fayolle & Gailly, 2015).

2.6 Theory of Planned Behaviour Antecedents predicting Entrepreneurial Intention

The three antecedents-ATE, SN and PBC-are central to understanding entrepreneurial intention, as they explain the psychological drivers of behaviour (Ajzen, 1991; Liñán & Chen, 2009). Intentions are strong predictors of action, with attitudes consistently influencing intentions (Ajzen, 1991; Kim & Hunter, 1993; Krueger et al., 2000). Depending on the behaviour and context, one or more antecedents may dominate (Heuer & Liñán, 2013). A positive ATE is often crucial (Armitage & Conner, 2001), while SN shape perceptions of approval from significant others, encouraging or discouraging entrepreneurial behaviour. PBC, closely linked to self-efficacy (Bandura, 1987), strongly predicts entrepreneurial intention, as higher confidence enhances the likelihood of undertaking entrepreneurial tasks (Armitage & Conner, 2001; Fayolle & Gailly, 2015). This leads to the exploration of the following hypotheses:

H1: Attitude towards entrepreneurship significantly influences entrepreneurial intention.

H2: Subjective norms significantly influence entrepreneurial intention.

H3: Perceived behavioural control significantly influences entrepreneurial intention.

This is illustrated in Figure 1 below.

2.7 Entrepreneurial Intention and grouping variables

Intentions represent the motivation to engage in behaviour, and the antecedents of the Theory of Planned Behaviour (TPB) can be shaped by situational and demographic factors (Krueger et al., 2000; Fayolle & Gailly, 2015; Rauch & Hulsink, 2015). Several studies highlight the role of demographics in the entrepreneurial intention-TPB link, with gender shown to significantly influence entrepreneurial intention (Nguyen, 2018; Smith et al., 2016; Wilson et al., 2007; Zhao et al., 2005). This study, therefore, examines whether gender differences affect entrepreneurial intention through TPB antecedents.

Family background is another important factor, as an entrepreneurial family environment may either encourage or discourage entrepreneurial intention (Nguyen, 2018; Georgescu & Herman, 2020). Accordingly, this study investigates whether entrepreneurial intention differs between students with and without a family business background (Figure 1).

H4: EI through ATE, SN, and PBC, varies significantly between male and female students.

H5: EI through ATE, SN, and PBC varies significantly between students with or without family business background.

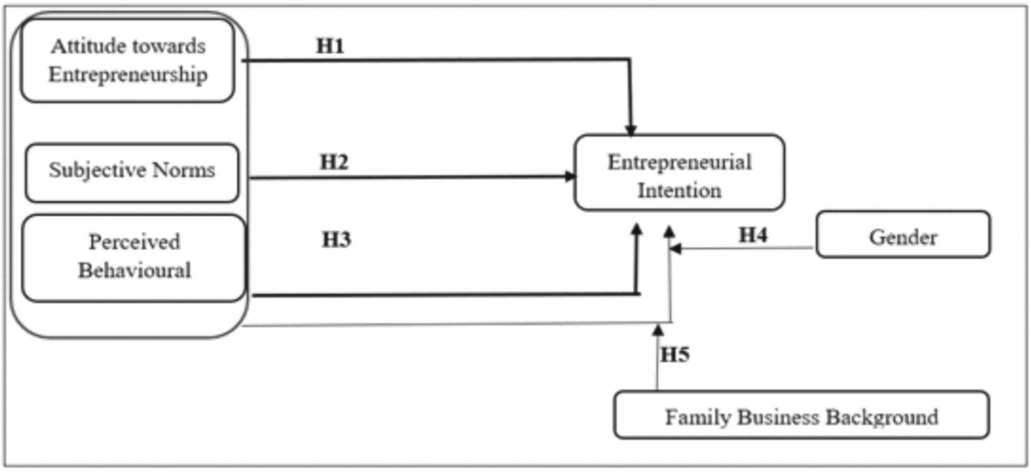

Figure 1. The proposed research model

Source: Author's own work

3. Methodology

3.1 Sample and data collection

This is a quantitative cross-sectional study, in which data were collected from students pursuing business-related undergraduate and postgraduate programmes, such as those in commerce (Bachelor of Commerce/B. Com and Master of Commerce/M. Com) and business studies, business administration, or management, from select HEIs in Kolkata. The respondents were enrolled in the prominent state and private universities and their affiliated colleges. Participants were informed about the research objectives and assured of the anonymity and confidentiality of their responses, and their informed consent was obtained (Podsakoff et al., 2003). A structured survey questionnaire, based on the Entrepreneurial Intention scale of Linan & Chen (2009), was used to collect data, which was shared electronically. Data were collected from students across all semesters using purposive and convenience sampling techniques. A total of 381 valid responses were received. The distribution of students is shown in Table 1.

3.2 Measures and procedures

The questionnaire used empirically validated scales from existing literature. The scale developed by Liñán and Chen (2009) was used to measure the three TPB components: Attitudes Toward Entrepreneurship (ATE), Subjective Norms (SN), Perceived Behavioural Control (PBC), and Entrepreneurial Intention (EI). All four constructs were measured using a five-point Likert scale.

The partial least squares-structural equation modelling (PLS-SEM) technique was employed, and SmartPLS4 software was used for data analysis, as per Hair et al. (2022). In recent years, this technique has been extensively used in EI research for data analysis (Kaur & Chawla, 2024). The described constructs were measured as reflective and prevalent in existing literature (Nowinski et al., 2019; Nguyen et al., 2022).

To analyse inferential statistics and moderation within a research model, this study employed multi-group analysis (MGA) using partial least squares path modelling (PLSPM) option available with SmartPLS. When group memberships are known, MGA enables researchers to test for differences between them across two similar models (Hair et al., 2022). Before evaluating the MGA, measurement invariance was examined through the MICOM (measurement invariance of the composite model) technique (Cheah et al., 2020; Henseler et al., 2016).

4. Results

4.1 Details of demographic data

Table 1 provides a comprehensive view the demographic characteristics of the data collected.

Table 1. Details of demographic data collected

Variable	Category	Distribution	Percentage (%)	Total
Gender	Male	64	17%	381
	Female	317	83%	
Family Business Background	Yes	185	49%	381
	No	196	51%	

Source: Author's own work

As shown above, 381 valid respondents completed the survey. Among them, a substantial number of respondents-83% were female and 17% were male. In terms of family business background, the data showed parity: 49% had a family business background and 51% did not.

4.2 Measurement model assessment

This process involves analyzing the outer model, including reliability and validity tests. To assess construct reliability, Cronbach's Alpha and Composite Reliability (CR) are used; convergent validity is evaluated through Average Variance Extracted (AVE) (Hair et al., 2019). Constructs are deemed reliable if composite reliability exceeds 0.70, Cronbach's Alpha is above 0.60, and AVE is 0.5 or more (Hair et al., 2019). In this case, all three factors surpass the threshold levels, as shown in Table 2, indicating the reliability of all four constructs: ATE, SN, PBC, and EI.

Table 2. Construct Validity and Reliability

Constructs	Cronbach's alpha	Composite reliability (CR)	Average variance extracted (AVE)
ATE	0.898	0.904	0.710
PBC	0.859	0.868	0.637
SN	0.830	0.840	0.744
EI	0.939	0.940	0.767

Source: Generated from authors' own PLS-SEM results

To assess Discriminant Validity, the Fornell-Larcker criterion is used. This criterion states that the square root of each construct's AVE (highlighted for each construct in Table 3) should be greater than its correlation with any other construct, thereby confirming discriminant validity (Fornell and Larcker, 1981).

To further assess discriminant validity, the HTMT (Heterotrait-Monotrait) ratios were examined. All ratios were below the 0.90 threshold, ensuring the absence of multicollinearity (Hair et al., 2019), as demonstrated in Table 3.

The data satisfied all outer model criteria, confirming adequate validity and reliability. This validation enabled progression to inner- or structural-model analysis. Figure 2 presents the research model and PLS results, displaying the path coefficients and outer loadings.

Table 3. Discriminant Validity

Fornell-Larcker Criterion

Constructs	**ATE**	**EI**	**PBC**	**SN**
ATE	0.842			
EI	0.751	0.876		
PBC	0.655	0.642	0.798	
SN	0.553	0.491	0.556	0.862
Heterotrait-monotrait ratio (HTMT) - Matrix				
Constructs	ATE	EI	PBC	SN
ATE				
EI	0.811			
PBC	0.725	0.702		
SN	0.627	0.542	0.631	

Source: Generated from Authors' Own PLS-SEM Results

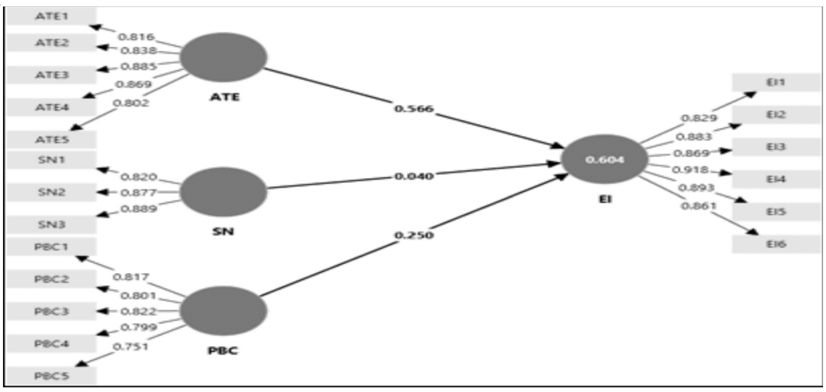

Figure 2. SEM Model

Source: Generated from authors' own PLS-SEM results

Figure 2 Measurement and Structural Model without Output as shown in SmartPLS4.0

4.3 Structural Model Assessment

Next, the structural model was analysed by initially studying the model-fit indicators. The SRMR value (0.074) indicates an acceptable model fit, as it is below the 0.08 threshold. However, the NFI (0.831) indicates a moderate fit, as it falls below the commonly accepted threshold of 0.90 to 1 for robust model fit (Hair et al., 2019). This was followed by the Bootstrapping procedure, which allows testing the statistical significance of various paths.

The results of bootstrapped hypothesis testing, including path coefficients, t-test values, and their significance, are presented in Table 4. The table also includes remarks on the nature of the established causal relationships between the constructs and analysis of effect sizes using f^2 values. Based on the significance, path coefficients, and t-statistics, it can be concluded that ATE positively and significantly influences EI, followed by PBC, which also has a significant impact. However, the direct impact of SN on EI is not significant. The ATE-EI relationship emerges as the most impactful, with a large effect size ($f^2 = 0.420$), making it the most critical predictor of EI, followed by PBC, with a medium effect size ($f^2 = 0.081$) that significantly contributes to explaining EI variance. The role of SN in explaining EI variance is not significant or discernible in the given context, and it has a small effect size ($f^2 = 0.002$).

Table 4. Path coefficients; Effect size and Hypotheses testing

List	Path coefficients	T statistics	P values	Effect size f-square	Hypotheses & Remarks
ATE -> EI	0.566	11.337	0.000	0.420	H1 Supported; Strong, positive, and significant effect
PBC -> EI	0.250	5.321	0.000	0.081	H2 Supported; Positive and significant effect
SN -> EI	0.040	0.890	0.374	0.002	H3 Not Supported; Non-significant

Source: Generated from Authors' Own Pls-Sem Results

An important metric for assessing the quality of the model is the Coefficient of Determination (R^2). The R^2 value for Entrepreneurial Intentions (EI) is 0.604, indicating that the model explains approximately 60.4% of the variance in EI through the combined influence of ATE, SN, and PBC. The Q^2predict value of 0.596, calculated using PLSPredict in SmartPLS 4 (Hair et al., 2019), confirms that the model has predictive relevance for the endogenous construct EI, indicating that the constructs ATE, SN, and PBC are reliable predictors of EI. These values have been shown in Table 5.

Table 5. R-Square and Q2 predict values

Constructs	R-square	Q^2 predict
EI	0.604	0.596

Source: Generated from Authors' Own Pls-Sem Results

4.4 Multi-Group Analysis (MGA)

To investigate the hypotheses H4 and H5, this study utilised the multi-group analysis (MGA) technique. The MGA option in PLS-SEM allows testing whether predefined data groups (e.g., gender, family background) differ significantly in their group-specific parameter estimates, including differences among TPB antecedents across groups (Hair et al., 2022). It is a useful technique to examine differences in the structural relationships among ATE, SN, PBC, and EI across groups defined by gender (male/female) and family business background (yes/no). The MGA specifically focused on whether these paths vary significantly across groups, providing insights into the effects of these demographic factors on relationships within the theoretical model. Before conducting MGA, the measurement invariance of composite models (MICOM) procedure must be followed (Hair et al., 2022; Cheah et al., 2020; Henseler et al., 2016).

The Measurement Invariance of Composite Models (MICOM) process was used to verify that the measurement model was consistent across groups- gender and family business background (Cheah et al., 2020; Henseler et al., 2016). This is shown in Table 6. The first step is Configural Invariance, which holds across all groups (Gender and Family Background). Specifically, the mode of measurement, the structure of the constructs, and the statements or indicators used to measure are equivalent across groups, indicating configural invariance, which is the first condition for proceeding with MGA.

Next, the Compositional Invariance is checked, which assesses equality of means and variances from the SmartPLS MICOM results. Compositional invariance is established across all groups for the given data (Gender, Family Background) and all constructs (ATE, PBC, EI, SN). In case of both gender and family background, partial invariance is established for all constructs-EI, ATE, PBC and SN, making it suitable to proceed with the MGA bootstrapping procedure.

Table 6. Measurement invariance result using MGA permutation

Comparison Groups	Construct	Configural Invariance	Compositional Invariance		
			Original correlation	**Permutation p value**	**Partial Invariance established**
Gender	ATE	Yes	1.000	0.652	Yes
	PBC	Yes	0.998	0.488	Yes
	EI	Yes	1.000	0.680	Yes
	SN	Yes	1.000	0.884	Yes
Family background	ATE	Yes	1.000	0.610	Yes
	EI	Yes	1.000	0.631	Yes
	PBC	Yes	1.000	0.823	Yes
	SN	Yes	0.995	0.101	Yes

Following the MICOM procedure, MGA bootstrapping was conducted to examine differences in path coefficients across the two predefined groups. The first set of results concerns gender, in which the analysis assessed whether the structural relationships among ATE, SN, PBC, and EI differ significantly between male and female students.

4.4.1 MGA Results for differences based on Gender

Table 7. Multiple Group Comparisons Based on Gender

Path	Female (β)	Female (p)	Male (β)	Male (p)	Remarks	Hypothesis Conclusion
ATE →EI	0.548	0.000	0.658	0.000	Significant for both groups	H4 supported partially, with gender-specific differences evident in the relationships between ATE and EI for both male and female; PBC & EI path being significant for females; SN & EI path not significant for both groups
PBC → EI	0.270	0.000	0.148	0.085	Significant for females only	
SN →EI	0.015	0.752	0.176	0.126	Not Significant for either group	

Source: Generated from Authors' Own Pls-Sem Results

The connection between ATE and EI is significant for both male and female students, but the relationship is somewhat stronger among male students, as indicated by the β-values. PBC to EI is significant for females but not for males, indicating a gender-specific influence of PBC on EI. The SN-EI path shows no significant difference for either gender. Thus, H4 is only partially supported, as EI through ATE, SN, and PBC varies across gender, and it affects EI through ATE and partially through PBC but not SN.

4.4.2 MGA Results for differences based on Family Business Background

The second set of results examines the structural relationships among ATE, SN, PBC, and EI and whether they differ significantly between students with and without a family business background. This comparison provides insights into how exposure to an entrepreneurial environment within the family may shape the strength of these paths and influence overall entrepreneurial intention.

Table 8. Multiple Group Comparisons Based on Family Business Background

Path	Family Business (p)	Family Business (p)	No Family Business (β)	No Family Business (p)	Remarks	Hypothesis Conclusion
ATE →EI	0.537	0.000	0.575	0.000	Significant for both groups	H6 is supported partially, with between ATE and EI link being both family business and non-family business students; the PBC-EI path is also equally significant for both groups; the SN-EI path is not significant for either group.
PBC →EI	0.279	0.000	0.224	0.001	significant for both groups	
SN →EI	0.014	0.885	0.077	0.233	Not Significant for either group	

Source: Generated from Authors' Own Pls-Sem Results

Hypothesis H5 is partially supported, with the ATE-EI and PBC-EI link being significant across both groups. The family business background significantly influences the relationship between PBC and EI, with students from family businesses showing a slightly stronger association. The significance of ATE-EI is the same for both groups, but the difference is small, with students without a family business background having a slightly stronger relationship. SN do not significantly affect entrepreneurial intentions for either group.

5. Discussion

The objective of this study was to examine whether the entrepreneurial intentions (EI) of undergraduate and postgraduate students in business-related programmes at select higher education institutions are directly influenced by the three components of the Theory of Planned Behaviour (TPB): attitude towards entrepreneurship (ATE), subjective norms (SN), and perceived behavioural control (PBC).

The findings are largely consistent with extant literature, which shows that attitudes are the most reliable predictor of intentions (Ajzen, 1991; Krueger et al., 2000). However, as noted by Heuer & Liñán (2013), situational context and behavioural characteristics can alter the relative strength of antecedents. In this study, subjective norms were found to exert only a weak influence on EI, consistent with earlier findings (Ajzen, 1991; Heuer & Liñán, 2013; Rauch & Hulsink, 2015). Ajzen (1991) attributes this to the limited role of social pressure in shaping entrepreneurial intention, particularly among proactive individuals who rely more on self-belief and self-efficacy than external approval.

Group comparisons further enrich these insights. For gender, ATE significantly influenced EI among both male and female students, though the effect was slightly stronger for males. PBC, reflecting self-efficacy, was particularly significant for female students, aligning with prior findings that women's entrepreneurial intentions are often shaped by confidence in their ability to perform entrepreneurial tasks (Wilson et al., 2007). SN, however, showed no significant effect across gender, reinforcing its weaker role in predicting EI.

In the family business background, both ATE and PBC significantly influenced EI among students with and without entrepreneurial family exposure, but the magnitude of these effects did not differ substantially between groups. This suggests that while family background may provide exposure to entrepreneurial practices, it does not necessarily alter the strength of attitudinal or control beliefs in shaping intention. Moreover, SN again showed no significant relationship with EI, indicating that family business background does not enhance the role of perceived social approval in entrepreneurial decision-making.

Overall, these results highlight the primacy of ATE and PBC in predicting EI, while SN remains comparatively weak. They also suggest that demographic factors such as gender and family background influence the relative strength of these antecedents, but do not fundamentally alter the underlying TPB framework.

6. Conclusion, Limitations and Future Implications

This study examined the impact of the three antecedents of the Theory of Planned Behaviour-attitude towards entrepreneurship (ATE), subjective norms (SN), and perceived behavioural control (PBC)-on the entrepreneurial intentions (EI) of undergraduate and postgraduate students in commerce and management programmes at select higher education institutions in Kolkata. The findings highlight the significant role of ATE and PBC in shaping EI, while SN exerts minimal influence. Gender analysis revealed that ATE significantly impacts both male and female students, with a slightly stronger effect among males, whereas PBC plays a more decisive role for females, reflecting the importance of self-efficacy in their entrepreneurial decision-making. Family business background showed limited overall significance, with PBC exerting a slightly stronger influence among students with entrepreneurial family exposure, but no substantial differences were observed in the effects of ATE or SN.

These results suggest that interventions aimed at strengthening entrepreneurial attitudes and self-efficacy are likely to be more effective in fostering EI than those targeting social norms, which remain comparatively weak predictors. For higher education institutions, this underscores the importance of designing curricula and extracurricular activities that build confidence in entrepreneurial skills and reinforce positive attitudes towards entrepreneurship.

This study, however, has limitations. First, it assumes that ATE, SN, and PBC independently influence EI, without exploring potential interactions among them. Second, it is geographically limited to select institutions in Kolkata and is cross-sectional, which may not reflect the diversity of students across India. Third, relying on self-reported data can lead to potential biases. Finally, the sample predominantly includes students from business and commerce programmes, restricting generalisability to other disciplines. Future studies could improve by integrating qualitative methods, such as interviews or focus group discussions, to gain a deeper understanding of the factors influencing EI.

Further studies should explore how ATE, SN, and PBC interact to influence EI, and include students from diverse regions and academic fields to enhance generalisability. Longitudinal designs would allow tracking changes in EI over time, while examining the impact of targeted interventions-such as entrepreneurship education courses or extracurricular entrepreneurial activities-would provide practical insights. The New Education Policy (2020), aligned with the Sustainable Development Goals and Global Entrepreneurship Monitor recommendations, emphasises early entrepreneurship education to build skills, knowledge, and attitudes. This policy context makes the exploration of EI in Indian higher education both timely and promising, offering scope for impactful research and practice.

References

Aboobaker, N., D., R., & K.A., Z. (2023). Fostering entrepreneurial mindsets: The impact of learning motivation, personal innovativeness, technological self-efficacy, and human capital on entrepreneurial intention. *Journal of International Education in Business, 16*(3), 312-333. https://doi.org/10.1108/jieb-10-2022-0071

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-t

Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Englewood Cliffs, NJ: Prentice-Hall.

Anwar, I., Jamal, M. T., Saleem, I., & Thoudam, P. (2021). Traits and entrepreneurial intention: Testing the mediating role of entrepreneurial attitude and self-efficacy. *J. for International Business and Entrepreneurship Development, 13*(1), 40. https://doi.org/10.1504/jibed.2021.112276

Armitage, C. J., & Conner, M. (2001). Efficacy of the Theory of Planned Behaviour: A meta-analytic review. *British Journal of Social Psychology, 40*(4), 471-499. https://doi.org/10.1348/014466601164939

Bae, T. J., Qian, S., Miao, C., & Fiet, J. O. (2014). The Relationship between Entrepreneurship Education and Entrepreneurial Intentions: A meta-analytic review. *Entrepreneurship Theory and Practice, 38*(2), 217-254. https://doi.org/10.1111/etap.12095

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist, 37*, 122-147.

Baumol, W. J., & Strom, R. J. (2007). Entrepreneurship and economic growth. *Strategic Entrepreneurship Journal, 1*(3-4), 233-237. https://doi.org/10.1002/sej.26

Bird, B. (1988). Implementing entrepreneurial ideas: The case for intention. *Academy of Management Review, 13*(3), 442-453

Brockhaus, R. H., & Horwitz, P. S. (1986). The Psychology of the Entrepreneur. In D. L. Sexton & R. W. Smilor, D. L. Sexton & R. W. Smilor (Eds.), The art and science of entrepreneurship (pp. 25--48). Cambridge, MA: Ballinger.

Chatterjee, S., Dutta Gupta, S., & Upadhyay, P. (2020). Technology adoption and entrepreneurial orientation for rural women: Evidence from India. Technological Forecasting and Social Change, 160, 120236. https://doi.org/10.1016/j.techfore.2020.120236

Chaudhuri, S., Agrawal, A. K., Chatterjee, S., & Hussain, Z. (2022). Examining the role of gender on family business entrepreneurial intention: Influence of government support and technology usage. Journal of Family Business Management, 13(3), 665-686. https://doi.org/10.1108/jfbm-04-2022-0052

Cheah, J.-H., Thurasamy, R., Memon, M. A., Chuah, F., & Ting, H. (2020). Multigroup Analysis using SmartPLS: Step-by-Step Guidelines for Business Research. *Asian Journal of Business Research, 10*(3). https://doi.org/10.14707/ajbr.200087

Chhabra, M., Dana, L.-P., Malik, S., & Chaudhary, N. S. (2021). Entrepreneurship education and training in Indian higher education institutions: A suggested framework. *Education + Training, 63*(7/8), 1154-1174. https://doi.org/10.1108/et-10-2020-0310

Cui, J., & Bell, R. (2022). Behavioural entrepreneurial mindset: How entrepreneurial education activity impacts entrepreneurial intention and behaviour. *The International Journal of Management Education, 20*(2), 100639. https://doi.org/10.1016/j.ijme.2022.100639

Donaldson, C., Liñán, F., & Alegre, J. (2021). Entrepreneurial intentions: Moving the field forwards. *The Journal of Entrepreneurship, 30*(1), 30-55. https://doi.org/10.1177/0971355720974801

Fayolle, A., & Gailly, B. (2015). The impact of entrepreneurship education on entrepreneurial attitudes and intention: Hysteresis and persistence. *Journal of Small Business Management, 53*(1), 75-93. https://doi.org/10.1111/jsbm.12065

Fayolle, A., Gailly, B., & Lassas-Clerc, N. (2006). Assessing the impact of entrepreneurship education programmes: A new methodology. *Journal of European Industrial Training, 30*(9), 701-720. https://doi.org/10.1108/03090590610715022

GEM (Global Entrepreneurship Monitor) (2026). Global Entrepreneurship Monitor 2025/2026 Global Report:From Uncertainty To Opportunity. London: GEM. https://gemconsortium.org/report/gem-20252026-global-report-from-uncertainty-to-opportunity-3

Georgescu, M.-A., & Herman, E. (2020). The impact of the family background on students' entrepreneurial intentions: An empirical analysis. *Sustainability, 12*(11), 4775. https://doi.org/10.3390/su12114775

Gupta, N., & Matharu, M. (2022). Examining the enablers of sustainable entrepreneurship - an interpretive structural modelling technique. *Journal of Entrepreneurship in Emerging Economies, 14*(5), 701-726. https://doi.org/10.1108/jeee-10-2021-0416

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/ebr-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review, 33*(3), 405-431. https://doi.org/10.1108/imr-09-2014-0304

Heuer, A., & Liñán, F. (2013). Testing alternative measures of subjective norms in entrepreneurial intention models. *International Journal of Entrepreneurship and Small Business, 19*(1), 35. https://doi.org/10.1504/ijesb.2013.054310

Jena, R. K. (2020). Measuring the impact of business management Student's attitude towards entrepreneurship education on entrepreneurial intention: A case study. Computers in Human Behavior, 107, 106275. https://doi.org/10.1016/j.chb.2020.106275

Kaur, M., & Chawla, S. (2024). What is the link between entrepreneurial knowledge, business planning and entrepreneurial intentions? An empirical study on Indian Higher Education Institutions. *Journal of Entrepreneurship and Public Policy, 13*(3), 391-413. https://doi.org/10.1108/jepp-09-2023-0096

Krueger, N. F., JR, Reilly, M. D., & Carsrud, A. L. (2000). Competing models of entrepreneurial intentions. *Journal of Business Venturing, 15*(5-6), 411-432. https://doi.org/10.1016/s0883-9026(98)00033-0

Kumar, S., Paray, Z. A., & Dwivedi, A. K. (2020). Student's entrepreneurial orientation and intentions. *Higher Education, Skills and Work-Based Learning, 11*(1), 78-91. https://doi.org/10.1108/heswbl-01-2019-0009

Landström, H., Harirchi, G., & Åström, F. (2012). Entrepreneurship: Exploring the knowledge base. *Research Policy, 41*(7), 1154-1181. https://doi.org/10.1016/j.respol.2012.03.009

Liñán, F., & Chen, Y. (2009). Development and Cross-cultural application of a specific instrument to measure entrepreneurial intentions. *Entrepreneurship Theory and Practice, 33*(3), 593-617. https://doi.org/10.1111/j.1540-6520.2009.00318.x

Liñán, F., & Fayolle, A. (2015). A systematic literature review on entrepreneurial intentions: Citation, thematic analyses, and research agenda. *International Entrepreneurship and Management Journal, 11*(4), 907-933. https://doi.org/10.1007/s11365-015-0356-5

Liñán, F., Rodríguez-Cohard, J. C., & Rueda-Cantuche, J. M. (2011). Factors affecting entrepreneurial intention levels: A role for education. *International Entrepreneurship and Management Journal, 7*(2), 195-218. https://doi.org/10.1007/s11365-010-0154-z

Loi, M., Castriotta, M., Barbosa, S. D., Di Guardo, M. C., & Fayolle, A. (2023). Entrepreneurial intention studies: A hybrid bibliometric method to identify new directions for theory and research. *European Management Review, 21*(3), 581-604. https://doi.org/10.1111/emre.12599

Maheshwari, G., Kha, K. L., & Arokiasamy, A. R. A. (2023). Factors affecting students' entrepreneurial intentions: A systematic review (2005-2022) for future directions in theory and practice. *Management Review Quarterly, 73*(4), 1903-1970. https://doi.org/10.1007/s11301-022-00289-2

McClelland, D. C. (1961). The Achieving Society. Princeton, NJ: Van Nostrand. http://dx.doi.org/10.1037/14359-000

Mishra, A., & Singh, P. (2022). Attitude, subjective norms, and perceived behavioural control as predictors of entrepreneurial intentions among engineering students. *Prabandhan: Indian Journal of Management, 15*(5), 43. https://doi.org/10.17010/pijom/2022/v15i5/169580

Moriano, J. A., Gorgievski, M., Laguna, M., Stephan, U., & Zarafshani, K. (2012). A cross-cultural approach to understanding entrepreneurial intention. *Journal of Career Development, 39*(2), 162-185. https://doi.org/10.1177/0894845310384481

Nabi, G., Walmsley, A., Liñán, F., Akhtar, I., & Neame, C. (2018). Does entrepreneurship education in the first year of higher education develop entrepreneurial intentions? The role of learning and inspiration. *Studies in Higher Education, 43*(3), 452-467. https://doi.org/10.1080/03075079.2016.1177716

Nájera-Sánchez, J.-J., Pérez-Pérez, C., & González-Torres, T. (2022). Exploring the knowledge structure of entrepreneurship education and entrepreneurial intention. *International Entrepreneurship and Management Journal, 19*(2), 563-597. https://doi.org/10.1007/s11365-022-00814-5

Neck, H. M., & Greene, P. G. (2011). Entrepreneurship education: Known worlds and new frontiers. *IEEE Engineering Management Review, 40*(2), 9-21. https://doi.org/10.1109/emr.2012.6210514

Nguyen, C. (2018). Demographic factors, family background and prior self-employment on entrepreneurial intention - Vietnamese business students are different: Why? *Journal of Global Entrepreneurship Research, 8*(1). https://doi.org/10.1186/s40497-018-0097-3

Nguyen, C. Q., Nguyen, A. M. T., & Ba Le, L. (2022). Using partial least squares structural equation modeling (PLS-SEM) to assess the effects of entrepreneurial education on engineering students's entrepreneurial intention. *Cogent Education, 9*(1). https://doi.org/10.1080/2331186x.2022.2122330

Olarewaju, A. D., Gonzalez-Tamayo, L. A., Maheshwari, G., & Ortiz-Riaga, M. C. (2022). Student entrepreneurial intentions in emerging economies: Institutional influences and individual motivations. *Journal of Small Business and Enterprise Development, 30*(3), 475-500. https://doi.org/10.1108/jsbed-05-2022-0230

Pandit, D., Joshi, M. P., & Tiwari, S. R. (2018). Examining entrepreneurial intention in higher education: An exploratory study of college students in India. *The Journal of Entrepreneurship, 27*(1), 25-46. https://doi.org/10.1177/0971355717738595

Paray, Z. A., & Kumar, S. (2020). Does entrepreneurship education influence entrepreneurial intention among students in HEI's? *Journal of International Education in Business, 13*(1), 55-72. https://doi.org/10.1108/jieb-02-2019-0009

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

Rauch, A., & Hulsink, W. (2015). Putting entrepreneurship education where the intention to act lies: An investigation into the impact of entrepreneurship education on entrepreneurial behavior. *Academy of Management Learning & Education, 14*(2), 187-204. https://doi.org/10.5465/amle.2012.0293

Roy, R., & Das, N. (2022). Exploring entrepreneurial intention among engineering students in India: A multiple basket approach. *International Journal of Technology and Design Education, 32*(1), 555-584. https://doi.org/10.1007/s10798-020-09596-9

Sarasvathy, S. D., Dew, N., Velamuri, S. R., & Venkataraman, S. (2010). Three views of entrepreneurial opportunity. *In Handbook of Entrepreneurship Research* (pp. 77-96). Springer New York. https://doi.org/10.1007/978-1-4419-1191-9_4

Saxena, K. (2021). Refuelling entrepreneurship education in India. *In India Higher Education Report 2020* (pp. 268-289). Routledge India. https://doi.org/10.4324/9781003158349-20

Schlaegel, C., & Koenig, M. (2014). Determinants of entrepreneurial intent: A meta-analytic test and integration of competing models. *Academy of Management Proceedings, 2012*(1), 10945. https://doi.org/10.5465/ambpp.2012.10945abstract

Seth, K. P., Clear, F., Khan, T., & Ananthan, S. S. (2018). The role of entrepreneurship education and its characteristics in influencing the entrepreneurial intention: A study based on India and the UK. In Entrepreneurial Universities. Edward Elgar Publishing. https://doi.org/10.4337/9781786432469.00014

Shapero, A. (1984). The entrepreneurial event. In C. A. Kent (Ed.), The environment for entrepreneurship. Lexington, Mass.: Lexington Books.

Smith, R. M., Sardeshmukh, S. R., & Combs, G. M. (2016). Understanding gender, creativity, and entrepreneurial intentions. *Education + Training, 58*(3), 263-282. https://doi.org/10.1108/et-06-2015-0044

Souitaris, V., Zerbinati, S., & Al-Laham, A. (2007). Do entrepreneurship programmes raise entrepreneurial intention of science and engineering students? The effect of learning, inspiration and resources. *Journal of Business Venturing, 22*(4), 566-591. https://doi.org/10.1016/j.jbusvent.2006.05.002

Srivastava, S., & Misra, R. (2017). Exploring antecedents of entrepreneurial intentions of young women in India. *Journal of Entrepreneurship in Emerging Economies, 9*(2), 181-206. https://doi.org/10.1108/jeee-04-2016-0012

Tiwari, P., Bhat, A. K., Tikoria, J., & Saha, K. (2020). Exploring the factors responsible in predicting entrepreneurial intention among nascent entrepreneurs. *South Asian Journal of Business Studies, 9*(1), 1-18. https://doi.org/10.1108/sajbs-05-2018-0054

Trivedi, R. H. (2017). Entrepreneurial-intention constraint model: A comparative analysis among post-graduate management students in India, Singapore and Malaysia. *International Entrepreneurship and Management Journal, 13*(4), 1239-1261. https://doi.org/10.1007/s11365-017-0449-4

Vasumathi, A., Mary, T. S., Mamilla, R., & Thangaiah, I. S. S. (2023). An impact of demographic profile of undergraduate students on the entrepreneurial knowledge and intention in Tamil Nadu, India. *International Journal of Knowledge and Learning, 16*(4), 341-353. https://doi.org/10.1504/ijkl.2023.134096

Wilson, F., Kickul, J., & Marlino, D. (2007). Gender, entrepreneurial self-efficacy, and entrepreneurial career intentions: Implications for entrepreneurship education. *Entrepreneurship Theory and Practice, 31*(3), 387-406. https://doi.org/10.1111/j.1540-6520.2007.00179.x

Zahra, S. A., & Wright, M. (2015). Understanding the social role of entrepreneurship. *Journal of Management Studies, 53*(4), 610-629. https://doi.org/10.1111/joms.12149

Zhao, H., Seibert, S. E., & Hills, G. E. (2005). The mediating role of self-efficacy in the development of entrepreneurial intentions. *Journal of Applied Psychology, 90*(6), 1265-1272. https://doi.org/10.1037/0021-9010.90.6.1265

The Impact of the Behavioural Factors on the Impulsive Food and Grocery Purchasing Activities of the Shoppers: An Empirical Research of the Organized Retail Formats of Kolkata

Arindam Roy[1] and Gairik Das[2]

ABSTRACT

The study attempts to identify some of the behavioural elements responsible for impulsive buying activities by the shoppers while buying different food and grocery products in different organized retail formats of Kolkata city. Further the study intends to examine the impact of the major behavioural related factors for purchasing different food and grocery products impulsively. This study was conducted using the primary data collected by distributing structured questionnaires among the respondents visiting organized retail format of Kolkata city. Data were analyzed by using appropriate statistical tools. The results shows that impulsive purchasing of food and grocery products was associated with the three behavioural factors such as shoppers' self control failure, shoppers' emotional state and shoppers' impulsive buying tendency. The research categorizes shoppers' self control failure, shopper's emotional state and shoppers' impulsive buying tendency as three latent predictors which positively and significantly influence impulsive purchasing activities while performing Structural Equation Modeling.

Keywords: *self-control failure, impulsive buying tendency, behavioural factors, organized retail food and grocery outlets, survey*

1. Introduction

Impulsiveness is a customer trait that shows his tendency to buy immediately, kinetically, unreflectively and spontaneous. Consumers who do impulse buy experience an instantaneous desire that overpowers their feelings. The primary characteristic of impulse buying is to purchase the product in the spur of the moment when exposed to some stimulus without evaluating consequences of buying it.

Consumer emotional states significantly influence impulse buying. It is the emotional stability which regulates the impulse behaviour of a person in all situations. People lose self-control and allow themselves to make impulse buying because they thought such buy will make them feel happier. Thus, there is a relationship between behavioural traits and impulsive buying activities.

For the past decade needs and wants and the shopping pattern of the Indian consumers has been changed radically and impulsive buying behaviour has also become very conspicuous phenomenon in the Indian retail markets. Construction of newer, bigger and technologically sophisticated shopping malls, supermarkets and hypermarkets in India changed the shopping expectation and buying behaviour of Indian consumers. Shopping has now become an enjoyable experience for middle class Indian consumers.

However, very few researches have been undertaken on the Indian consumers to assess the behavioural factors that might elicit such activities.

[1]Assistant Professor, Kingston School of Management Science, West Bengal
[2]Professor, IISWBM, Kolkata

Thus, in this research the researchers aim to find how some of the select behavioural factors encouraging the consumers to indulge into the impulsive purchase activities and to test the impact of those tempting factors on the impulsive buying behaviour of Indian retail consumers.

2. Objective of the Study

In this study the main objectives are as follows :

1. To identify the major behavioural factors influencing consumers' impulsive food and grocery purchasing activities in organized retail formats in Kolkata.
2. To find the impacts of the major behavioural factors influencing consumers' impulsive food and grocery purchasing activities in organized retail formats in Kolkata.

3. Review of Literature

Behavioural factors of impulse purchasing represent the individual's inner cues and features that propel the consumers to participate in impulse buying. In this study we reviewed the past literatures to find the behavioural factors that affect impulse purchase behaviour, as discussed below.

3.1 Self- control failure

Willpower is the resolve to resist a certain want, and self-control is a manifestation of this quality. It is the ability of an individual to control his/her feelings as well as behaviour when the individual come across any kind of enticements and impulses. Recent advances in research in socio-consumer psychology have recommended that self-control is a key component in the decision making. A purchasing impulse has a tendency to upset the consumer's behavioral pattern Rook (1987). The individual is more probable to feel out-of-control when purchasing impulsively rather than buying judiciously. Baumeister (2002) explained connection between self-control failure and impulsive purchasing. Relationship between impulse purchasing propensities and the common personality traits such as absence of self-control, anxiety response, and immersion have also been indicated by Youn & Faber, (2000).

Self-control might also be considered as a resource. A "limited resource" model of self-control has been advocated by certain researchers, who view self-control as a limited resource (Baumeister et Al., 2018). People have larger impulsive purchase demands when their resources for self-control are depleted, which may result in an increase in impulsive purchasing activities (Zhang & Shrum, 2009). One way to describe impulsive purchase is as a struggle involving the need to buy and the ability to avoid it (Hoch & Loewenstein, 1991). Impulsive purchases may happen more often when a person's self-control reserves are depleted and willpower is weak (Vohs & Faber, 2007). Previous research (Rook & Fisher, 1995; Dholakia et al., 2006; Sengupta & Zhou, 2007; Sultan et al., 2012) has usually demonstrated that self-control has a large direct influence on impulsive purchase activity.

3.2 Mood

An important factor in a customer's impulsivity is their emotional state; occasionally, people act irrationally while trying to escape an unpleasant mood (Elliott, 1994). Customers felt better after making impulsive purchases, according to research by Rook (1987) and Gardner and Rook (1988). When shoppers make impulsive purchases, they are able to overcome unpleasant mood like sadness, annoyance, or boredom and experience a sense of improvement (Gardner & Rook, 1988). When shoppers were asked to describe their mood just before making an impulse purchase, Rook and Gardner (1993) found that the most common answers they received were "pleasure," "carefree," and "excited." Sometimes, they have a tendency to do it to make themselves feel better (Mick & Demoss, 1990). Research by Spies et al. (1997) probed into the relationship between shopping environment and mood state. The research revealed that customers would feel happier at a store with a pleasant atmosphere than one with a bad one. A study by Youn and Faber (2000) revealed that impulsive purchasing is influenced by a few internal and exterior stimuli. Positive and negative emotional states of the respondents are examples of internal cues. Internal cues were the emotions, moods, and self-perceptions of the consumer. Hausman Angela (2000) found a correlation between the impulse purchases made by individual customers and their needs to satisfy hedonic wants, such as those for novelty, fun, and surprise. It was recommended by Sneath et al. (2009) that a depressed customer make impulsive purchases to improve his mood. This study has similarities to those of Verplaken and Herabadi (2001), who found that persons who wish to get away from low self-esteem, unpleasant emotions and moods, and negative psychological evaluations are more prone to make impulsive purchases in order to accomplish so. Consumers are driven to make impulsive purchases since they will feel good about themselves immediately (Hausman, 2000; Verplanken et al., 2005). Customers' impulsiveness is determined by their personal condition or mood, according to Beatty and Ferrell (1998). He tries to treat himself generously when he is feeling good, which makes him more impulsive.

3.3 Emotions

According to research studies by Rook and Gardner (1993), Beatty and Ferrell (1998), Youn and Faber (2000), and Hausman (2000), emotions play a major role in impulse purchase. Consumers buy products for non-economic motives including enjoyment, dreams, socializing, and emotional fulfillment. These factors will encourage consumers to overlook the drawbacks and unfavorable effects of making an impulsive purchase (Hausman, 2000). Customers' in-store purchase intentions and spending patterns are primarily determined by their emotions, according to research by Babin and Babin (2001). Customers' emotions are influenced by the store's environment, which can cause them to make impulsive purchases, according to Xu (2007). Impulsive purchases are caused by self-generated autistic stimuli such as the customer's thoughts and feelings, according to Hirschman (1992). According to Heilman et al. (2002), coupons given at the store have an impact on customers' moods, emotions, and psychological processing. According to Chang et al (2011), impulse purchases are most likely to come from customers who feel positively about the retail atmosphere. Consumers who frequently make impulsive purchases see themselves as emotionally invested more so than those who do not (Weinberg and Wolfgang, 1982). According to Hoch & Loewenstein (1991); Thompson et al. (1990), consumers with a propensity for making impulsive purchases struggle to reveal their opinions, become emotionally drawn to the product, and show an interest in satisfying their needs right away. When it comes to the potential drawbacks and adverse effects of their actions, they pay the least attention (Hoch & Loewenstein, 1991; Rook, 1987; O'Guinn & Faber, 1989).

3.4 Impulse Buying Tendency

The "degree to which an individual is likely to make unintended, immediate, and unreflective purchases" refers to the inclination toward impulse buying (Jones et al., 2003). It is a very consistent and stable feature (Parsad et al., 2017) that can be used to predict impulse purchase activity (Ahn & Kwon, 2022; Stancu & Lähteenmäki, 2022). In particular, it encourages consumers to buy a variety of goods at the same time for non-utilitarian purposes (Dawson & Kim, 2009). Impulsive purchase behavior is more common in people with high levels of impulsive buying inclination than it is in people with lower levels of this trait (Jones et al., 2003; Chih et al., 2012).

Researchers identified impulsive purchasing as a personality feature of consumers. The fundamental premise of the study is that consumers vary in their inclination to purchase impulsively. IBT, according to Rook (1987), will ascertain a person's inclination to make impulsive purchases. Furthermore, Beatty and Ferrell's (1998) study looked at the idea that buying impulsivity is a unique personality feature that reflects a person's propensity to contemplate and act in a unique, recognizable manner. Extremely impulsive consumers are more likely to react to spontaneous purchasing stimuli and to be receptive to novel purchasing concepts. They are also more likely to be activated by being physically close to a desired product and to be driven primarily by the product's emotional appeal as well as the need for instant gratification (Rook and Fisher 1995). As a result, individuals are more likely to react favorably to their purchasing urges and to experience them more frequently and powerfully than other customers. According to Foroughi et al. (2011), there is a strong and positive correlation between IBT and having fun when shopping, perusing the aisles, and making impulsive purchases. Customers with a higher IBT are prone to be influenced by marketing stimuli, such as commercials, visual components, or promotional gifts; as a result, they are more likely to browse in-store and give in to impulsive buying inclinations more frequently (Youn & Faber, 2000). Thus, an analysis of the influence of impulse buying inclination on impulse buying has been conducted.

4. Research Methodology

The positivist philosophical approach was used in this study. In addition to the respondents' personal biases, the external settings also had an impact on the collected data.

5. Hypothesis Formulation

According to Saratakos (1991), a hypothesis is "a tentative explanation of the research problem, a possible outcome of the research, or an educated guess about the research outcome." The following assumptions are put forth in light of the previously mentioned conceptual framework and literature review:

5.1 Research Hypotheses

H_1: Shoppers' self-control failure (SSF) has a positive significant impact on Shoppers' Impulsive Purchasing Activity (SIPA) in organized food and grocery retail stores of Kolkata city.

H_2: Shoppers' Impulsive Buying Tendency (SIBT) has a positive significant impact on Shoppers' Impulsive Purchasing Activity (SIPA) in organized food and grocery retail stores of Kolkata city.

H_3: Shoppers' Emotional State (SES) has a positive significant impact on Shoppers' Impulsive Purchasing Activity (SIPA) in organized food and grocery retail stores of Kolkata city.

5.2 Research Tools and Techniques

Surveys are employed as a research method in this work. In Kolkata, a survey was conducted with male and female participants of various ages who purchase food and groceries from various organized retail establishments.

A questionnaire was prepared to collect the data from the customers. The questionnaire's formation has been made easier by the data acquired from the literature study and secondary sources. There are two components to the survey questionnaire. The primary purpose of the first section was to gather consumer demographic data. The second section of the questionnaire consists of several statements designed to pinpoint the behavioural aspect related problems causing the respondents' impulsive purchasing behaviour. The respondents' answers are gathered using a five-point Likert scale. Two hundred and sixteen (216) customers correctly completed the questionnaire and returned it filled out. Therefore, our analysis will be based on the 216 completely filled up customer response.

5.3 Sampling Technique

In this study, the stratified random sampling approach is used. The populations under investigation in this study are the customers who frequently purchases from Kolkata's organized retail spaces. The demographic characteristics separate the city's consumer base into many strata. The consumers' shopping times were taken into account when sampling them.

6. Data Analysis and Findings

After gathering a significant amount of consumer data, the data was coded and altered to make analysis of the data easier. The coded data was analyzed using several statistical methods to verify the conjectures that were developed. Analysis was carried out using the SPSS program. The gathered data was first analyzed using frequency analysis. Next, the reliability of the questionnaire was analyzed using the Chronbach alpha value. After that, an exploratory factor analysis was conducted to find the underlying latent constructs influencing impulsive food and grocery buying behaviour of the consumers. Thereafter, a confirmatory factor analysis was carried out the to test the relationship between the underlying constructs and also to confirm whether the data fits a pre-defined model, evaluates construct validity, and determines if observed variables properly measure underlying factors. After CFA, structural equation modeling was performed to test the hypotheses.

6.1 General Sample Descriptions

In order to accomplish the objectives of the study, primary data were presented in tabular form for general sample description (Table 1)

Table 1. General Sample Description

Sl No	Demographic Variable	Levels	Number	Percentage
	Age (in Years)	18-28	60	27.8
		29-39	68	31.5
		40-49	43	19.9
		50-59	27	12.5
		60 and Above	18	8.3
	Gender	Male	103	47.7
		Female	113	52.3
	Marital Status	Single	77	35.6
		Married	70	32.4
		Separated	18	8.3
		Divorced	36	16.7
		Widowed	15	6.9
	Educational Qualification	Up to class 8	21	9.7
		Secondary	25	11.6
		Higher Secondary	40	18.5
		Graduate	66	30.6
		Post Graduate and Above	64	29.6
	Employment Status	Managerial	43	19.9
		Professional	52	24.1
		Clerical	39	18.1

	Self Employed	34	15.7
	Others	48	22.2
Monthly Household Income (in Rs.)	20000 - 30000	33	15.3
	30001 -40000	39	18.1
	40001 -50000	63	29.2
	50001 - 60000	39	18.1
	60001 and Above	42	19.4

Source: Authors' own Compilation

6.2 Testing the Reliability of the Questionnaire

Cronbach's alpha tests how closely related a set of objects are to one another, or how internally consistent they are. Most studies in social sciences considers alpha values of Cronbach's at least 0.6.

Table 2. Cronbach's Alpha

Cronbach's Alpha	Number of Items
.877	17

Source: Authors' own Compilation

The seventeen items' alpha coefficient is 0.877, which suggests that their level of internal consistency is acceptable.

6.3 Exploratory Factor Analysis

Two hundred and twelve respondent responses were used in this study to carry out the exploratory factor analysis. In order to facilitate easy interpretation of the results, the analysis is made simpler by reducing the number of variables. The statements in the second section of the questionnaire were categorized under distinct headings using the Exploratory Factor Analysis (EFA) applied to all of the items. Factors were produced by employing Varimax rotation method and applying Principal Component Analysis (PCA).

K.M.O. Test of sample sufficiency:

From Table 3, it may be inferred that the sample size is sufficient for factor analysis because the K.M.O. statistic value of 0.826 is significantly greater than the least requisite value 0.5.

Bartlett's Test of Sphericity:

From Table 3, it can be seen that 0.000 (< 0.05) is the level of significance for the Bartlett's Test of Sphericity. Consequently, it is possible to reject the Null Hypothesis and it can be inferred that factor analysis can be used for further analysis as the correlation matrix is considerably different from a unit matrix.

Table 3. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.826
Bartlett's Test of Sphericity	Approx. Chi-Square	919.390
	df	78
	Sig.	.000
Source: Authors' own Compilation		

Table 4 presents the total variances explained, and Figure 1 shows the Scree plot. From Table 4, it can be found that the model's 58.649% of the variance can be explained by three factors. However, the scree-plot (Figure 1) demonstrates that only three components with eigenvalues greater than one must be kept.

Table 4. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	4.386	33.735	33.735	4.386	33.735	33.735	2.691	20.698	20.698
2	1.839	14.148	47.884	1.839	14.148	47.884	2.614	20.110	40.808
3	1.399	10.765	58.649	1.399	10.765	58.649	2.319	17.841	58.649
4	.832	6.402	65.051						
5	.774	5.951	71.002						
6	.674	5.186	76.188						
7	.638	4.907	81.095						
8	.517	3.979	85.073						
9	.492	3.784	88.857						
10	.442	3.396	92.253						
11	.384	2.957	95.210						
12	.377	2.898	98.108						
13	.246	1.892	100.000						
Extraction Method: Principal Component Analysis									
Source: Authors' own Compilation									

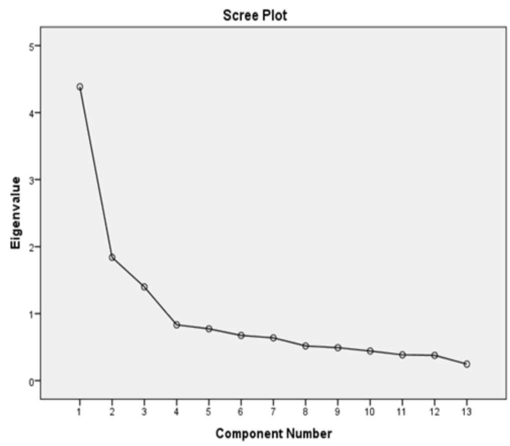

Figure 1. Scree Plot

Source: Authors' own simulation.

In the Scree plot, the component number is plotted against the eigenvalue. From Figure 1, it can be seen that the line appears to be nearly flat after the third component, indicating that each subsequent component is only contributing a decreasing percentage of the variation in total. Only principal components with eigenvalues larger than 1 are taken into account in this case.

Rotated Component Matrix

To obtain a rotated component matrix that groups all twelve elements into three components, the Varimax rotation method is applied. All the items with a factor score of more than 0.5 which is the accepted criterion for analysis (Hair et al., 2006), were taken into considered for the analysis.

Component -

In Table 5, the primary components are extracted and are listed in the columns under the Component heading. The components that have an eigenvalue larger than one are the three that were extracted, as can be seen from Table 5. In this case, data reduction is accomplished through the use of component scores.

From total 5 items the comonent1 is constructed, from total 4 items the component 2 is constructed and from total 4 items the component 3 is constructed.

Table 5. Rotated Component Matrix

Statements	Component		
	1	2	3
I purchase the grocery product if I feel it will suit my lifestyle	.750		
I make unplanned purchase during festive season because it changes my mood	.743		
I seek variety of grocery products in every purchase I do	.705		
I purchase grocery products depending on how I feel at that moment	.662		
When I feel emotionally low, I often buy more than needed to lift myself	.652		
I often purchase grocery products unexpectedly		.875	
It is mouthwatering to buy an attractive grocery product		.822	
I do not contemplate much about price while purchasing grocery products		.786	
Smell of the ready to eat food and grocery products entice me to purchase it		.533	
I often buy grocery products which I did not plan			.802
I often end up spending more than initially intended to expend			.782
Sometimes I feel like shopping grocery products on the spur of the moment			.696
Freshness of the food and grocery products tempts me to purchase the product			.628
Extraction Method: Principal Component Analysis.			
Rotation Method: Varimax with Kaiser Normalization.			
Source: Authors' own Compilation			

Behavioural aspects related items are categorized into the following factors:

- **Factor 1:** i) Purchasing during festive season, ii) Purchasing depending on momentary feeling, iii) Variety seeking behaviour, iv) Purchasing complemented by lifestyle, v) Purchasing when emotionally low
- **Factor 1** ------------------------- Shoppers' Emotional State (SES)
- **Factor 2:** i) Unexpected purchasing, ii) Mouthwatering purchasing, iii) Purchasing without contemplating about price, iv) Purchasing due to enticing smell
- **Factor 2:** ------------------------ Shoppers' Self-control Failure (SSF)
- **Factor 3:** i) Purchasing because of product freshness, ii) Spending more than intended, iii) Shopping on the spur of the moment, iv) Unplanned purchasing
- **Factor 3:** -------------------- Shoppers' Impulsive Buying Tendency (SIBT)

6.4 Measurement Model

Measurement models are collections of observed data that illustrate how constructs or latent variables are quantified and operationalized. They are a type of arrangement of measurement theory. According to Hair & Anderson (2010), Confirmatory Factor Analysis (CFA) let the researchers decide on the relationship between variable before proceeding for further analysis. After deleting the variables with low loadings, the main solution-found using EFA-was applied to CFA. Four first-order constructs were found in the confirmatory factor analysis model, and a minimum was attained. Every study parameter was realistic, with standard errors falling within reasonable bounds (Table 6). The Table 7 shows that all goodness-of-fit indices were higher than the suggested cutoff points (Browne and Cudeck 1993; Bagozzi and Yi 1988). The study model was thus validated.

Table 6. Regression Weights; (Default model)

Relationship			Estimate	S.E.	C.R.	P
B8	<---	SIBT	1.000			
B7	<---	SIBT	.735	.102	7.230	
B6	<---	SIBT	.975	.119	8.182	***
B5	<---	SIBT	.746	.110	6.791	***
B13	<---	SES	1.000			
B12	<---	SES	1.783	.304	5.871	
B11	<---	SES	1.636	.285	5.750	***
B10	<---	SES	1.446	.271	5.330	***
B9	<---	SES	1.670	.296	5.646	***
B3	<---	SSF	1.000			
B4	<---	SSF	.758	.091	8.295	***

B2	<---	SSF	1.064	.101	10.512	***
B1	<---	SSF	1.140	.102	11.148	***
CBB1	<---	SIPA	1.000			
CBB2	<---	SIPA	.929	.096	9.660	***
CBB3	<---	SIPA	.881	.097	9.062	***
CBB4	<---	SIPA	.973	.099	9.825	***

Table 7. Model fit Indices for Measurement Model

Sl No.	Goodness of Fit Index	Obtained Value	Acceptable Threshold Value	Interpretation
1	CMIN	218.810		
2	DF (Degrees of Freedom)	113		
3	CMIN/DF	1.936	Good if <3	Excellent
4	GFI (Goodness of Fit Index)	.897	Range 0 -1, good if more towards 1	Acceptable
5	IFI (Incremental Fit Index)	.921	Good if ≥0.90	Excellent
6	TLI (Tucker-Lewis Index)	.903	Good if ≥ 0.90	Excellent
7	CFI (Comparative fit Index)	.919	Good if ≥0.90	Excellent
8	RMSEA (Root Mean Square Error of Approximation)	.066	Good if < 0.08	Excellent
9	PClose	.024	Good if > 0.05	Acceptable

Source: Authors' own Compilation   Source: Hair et al, (2010)

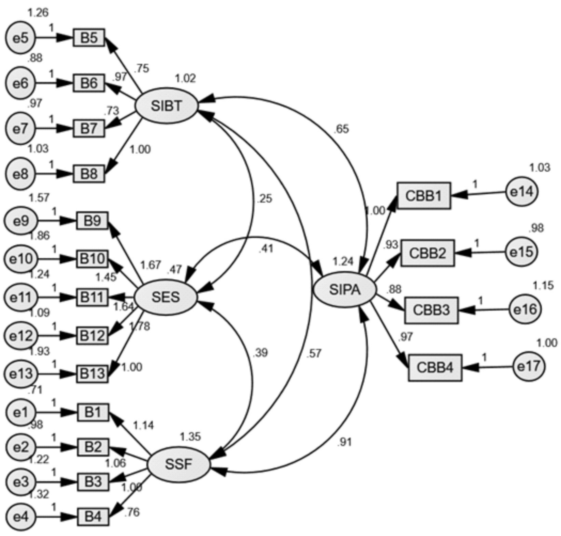

Figure 2. Confirmatory Factor Analysis (Standardized Estimates)

Convergent and Discriminant Validity

The Construct Validity of measurement constructs must be ensured. Construct Validity is ensured with the help of Convergent and Discriminant Validity (Hair et al., 2010). In the present research, Convergent Validity was checked by reviewing Average Variance Extracted (AVE) and Composite Reliability (CR) as suggested by Hair et al., (2010).

Table 8 makes it abundantly clear that all the Composite Reliability values are higher than the necessary 0.70 threshold. In addition, the Average Variances Extracted (AVEs) in the case of all the study constructs were all above the 0.50 level (Bagozzi and Yi 1988; Fomell and Larcker 1981) except for SIBT, thus indicating high levels of convergence among the indicators in measuring their respective constructs.

Table 8. Convergent and Discriminant Validity

	CR	AVE	MSV	SIBT	SES	SSF	SIPA
SIBT	0.745	0.425	0.328	0.652			
SES	0.776	0.514	0.291	0.364***	0.717		
SSF	0.830	0.554	0.497	0.487***	0.488***	0.744	
SIPA	0.810	0.516	0.497	0.573***	0.540***	0.705***	0.718
Diagonal elements measure the square root values of AVE							
* p < 0.050 , ** p < 0.010, *** p < 0.001							
Source: Authors' own Compilation							

To evaluate Discriminant Validity, the method recommended by Hair et al. (2010) and Fomell and Larcker (1981) was used. In accordance with the protocol, the square root of the AVE must be more than the correlation among the constructs and the AVE must be larger than the maximum shared variance (MSV). Table 8's lower half entries correspond to the correlation coefficients, whereas the diagonal elements are the square roots of AVE. Thus Table 8 shows that for the present investigation all of the AVEs are significantly higher than MSVs. Additionally, the study constructs' inter-correlations are less than the square root of AVE. Thus, the Discriminant Validity test was passed by the constructs.

6.5 Structural Equation Model

After the evaluation of the measurement model's validity, the structural model was tested by doing a SEM analysis. After identifying the structural model, a minimum was attained. Every study parameter was realistic, and the standard errors were within reasonable bounds. The Table 9 shows that every Model-fit index was higher than the suggested threshold values (Browne and Cudeck 1993; Bagozzi and Yi 1988). The structural model was therefore validated. Following the approval of the overall model fit, structural equation modeling was used to test the hypotheses (Table 10). All of the predicted standardized path coefficients in a SEM analysis have to be significant for the model to be considered fit overall.

Table 9. Model fit Indices for Structural Model

Sl No.	Goodness of Fit Index	Obtained Value	Acceptable Threshold Value	Interpretation
1	CMIN	218.810		
2	DF (Degrees of Freedom)	113		

3	CMIN/DF	1.936	Good if <3	Excellent
4	GFI (Goodness of Fit Index)	.897	Range 0 -1, good if more towards 1	Acceptable
5	IFI (Incremental Fit Index)	.921	Good if ≥0.90	Excellent
6	TLI (Tucker-Lewis Index)	.903	Good if ≥ 0.90	Excellent
7	CFI (Comparative fit Index)	.919	Good if ≥0.90	Excellent
8	RMSEA (Root Mean Square Error of Approximation)	.066	Good if < 0.08	Excellent
9	PClose	.024	Good if > 0.05	Acceptable
Source: Authors' own Compilation			Source: Hair et al, (2010)	

Table 10. Summary of Path Analysis

Relationships			Standardized Estimates	Unstandardized Estimates	S.E.	C.R.	p-value
SIPA	<---	SIBT	.266	.293	.094	3.123	.002
SIPA	<---	SES	.213	.345	.139	2.481	.013
SIPA	<---	SSF	.471	.452	.090	5.034	***
Source: Authors' own Compilation							

It is evident from the results of the first order Structural Equation Model, that

i) Shoppers' Self-control Failure (SSF) had positive significant impact on Impulsive Purchasing Activity of the shoppers (**β** = 0.452, p < 0.001); and

ii) Shoppers' Impulsive Buying Tendency (SIBT) has a positive significant impact on the Impulsive Purchasing Activity of the shoppers (**β** = 0.293, p = 0.002)

iii) Shoppers' Emotional State (SES) has a positive significant impact on the Impulsive Purchasing Activity of the shoppers (**β** = 0.345, p = 0.013).

Thus, in this structural model, all of the proposed relationships are tested to be significant.

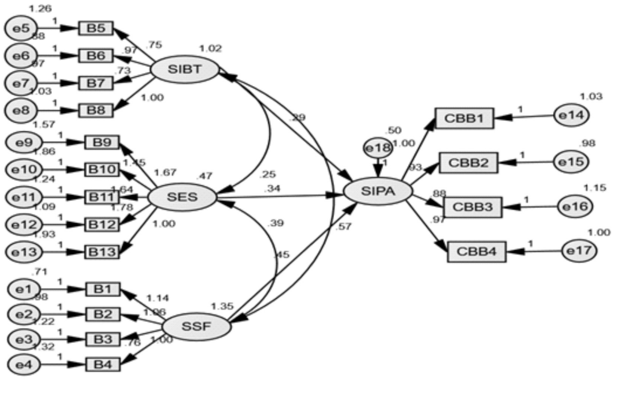

Figure 3. Structural Equation Model

7. Conclusion

According to EFA, three behavioral aspects stand out as being significant when it comes to buyers' impulsive purchasing behavior. Factor 1 may be referred to as the Shoppers' Emotional State (SES) with five variables loaded to it. In a similar vein, Factor 2, which has a loading of three variables, may be referred to as Shoppers' Self-control Failure (SSF). With four variables fed onto it, Shoppers' Impulsive Buying Tendency (SIBT) finally surfaced as factor 3.

An instrument's validation process requires the use of Confirmatory Factor Analysis. The resulting model is tested after each variable is limited to load onto a single factor. The previously provided model fit indications point to a strong model fit. The constructs revealed in EFA are validated by the confirmatory factor analysis results along with the variables loaded under each of the constructs. A structural model has been suggested and analysis has been done in light of the satisfactory findings of the validity and reliability tests.

From the results of SEM, it is found that all the major Model fit indicators are within acceptable limits and it is also found that all of the three latent variables that have been identified with the help of exploratory factor analysis, namely - Impulsive Buying Tendency (SIBT), Shoppers' Emotional State (SES) and Shoppers' Self-control Failure (SSF) have significant impact on shoppers impulsive buying activities.

8. Managerial Implications

This study can be helpful to marketers and retailers in understanding the importance of behavioural aspects and consequently the buying behavior of an individual. Behavioural characteristics of the shoppers are the essential characteristic which influences socialization, attitude, and impulsive buying activities of the individual.

Consumers that have higher IBTs are more likely to be swayed by marketing stimuli like ads, graphic elements, freebies, and so forth. Thus, when it comes to customers making impulsive purchases, store atmosphere is crucial.

Window displays, promotional signage, floor merchandising need to used creatively as a method of exhibiting store products as they are responsible for forming a crucial first imprint of the store in the mind of the consumers, thereby increasing the probability of impulse purchasing. Arrangements for soothing in-store background music and attractive lighting inside the store have to be made by the floor managers. Also, the hygiene of the store needs to be maintained properly.

Different non product attributes also influence the consumers to purchase impulsively. Thus, the product managers need to give proper importance on packaging of the product. The aesthetics and colour schemes of the packages should be done in such a way to attract the consumers.

The pricing of the products impacts impulsive buying behaviour. Retail brand managers must be very careful while formulating their pricing strategies. Penetration pricing, economic pricing and value based pricing methods need to be applied appropriately depending on the nature of the products. Also discounts on product prices should also be given on different festivals in order to increase the usage of the products. Managers need to explore different types of discounts schemes such as - buy one get one free, price bundling, seasonal discounts, referral discounts etc. in order to enhance the likelihood of impulse buying tendency of the consumers.

9. Limitations and Avenues for Future Research

The purpose of this study was to evaluate how the shoppers' behaviors affected their propensity for impulsive purchases. In light of this, there is room for additional methodological part improvements. The influence on impulsive shopping behaviors may vary depending on the location, culture, and socioeconomic background. These characteristics can be used as moderating factors in further research to gain really helpful insights. The state capital of West Bengal, Kolkata, served as the site for this investigation. As a result, care must be taken while extrapolating the findings to the whole Indian market. Furthermore, since Indian consumers can now easily access the internet, longitudinal studies have a lot of potential because internet usage will eventually influence attitudes and preferences.

Declarations

Conflict of Interest: All authors declare that they have no conflicts of interest.

Informed Consent: Our research involved human participants and the authors have taken the consent of all the participants

References

Ahn, J., & Kwon, J. (2022). The role of trait and emotion in cruise customers' impulsive buying behavior: an empirical study. *Journal of Strategic Marketing, 30*(3), 320-333.

Babin, B. J., & Babin, L. (2001). Seeking something different? A model of schema typicality, consumer affect, purchase intentions and perceived shopping value. *Journal of Business research, 54*(2), 89-96.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the academy of marketing science, 16,* 74-94.

Baumeister, R. F. (2002). Yielding to temptation: Self-control failure, impulsive purchasing, and consumer behavior. *Journal of consumer Research, 28*(4), 670-676.

Baumeister, R. F., & Heatherton, T. F. (1996). Self-regulation failure: An overview. Psychological inquiry, 1-15.

Baumeister, R. F., Bratslavsky, E., Muraven, M., & Tice, D. M. (2018). Ego depletion: Is the active self a limited resource?. *In Self-regulation and self-control* (pp. 16-44). Routledge.

Beatty, S. E., & Ferrell, M. E. (1998). Impulse buying: Modeling its precursors. *Journal of retailing, 74*(2), 169-191.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen and J. S. Long (Eds.), Testing structural equation models (pp. 136-162).

Chang, H. J., Eckman, M., & Yan, R. N. (2011). Application of the Stimulus-Organism-Response model to the retail environment: the role of hedonic motivation in impulse buying behavior. *The International review of retail, distribution and consumer research, 21*(3), 233-249.

Chih, W. H., Wu, C. H. J., & Li, H. J. (2012). The antecedents of consumer online buying impulsiveness on a travel website: Individual internal factor perspectives. *Journal of Travel & Tourism Marketing, 29*(5), 430-443.

Dawson, S., & Kim, M. (2009). External and internal trigger cues of impulse buying online. Direct Marketing: *An International Journal, 3*(1), 20-34.

Dawson, S., & Kim, M. (2009). External and internal trigger cues of impulse buying online. Direct Marketing: *An International Journal, 3*(1), 20-34.

Dholakia, U. M., Gopinath, M., Bagozzi, R. P., & Nataraajan, R. (2006). The role of regulatory focus in the experience and self-control of desire for temptations. *Journal of Consumer Psychology, 16*(2), 163-175.

Dittmar, H., & Bond, R. (2010). I want it and I want it now: Using a temporal discounting paradigm to examine predictors of consumer impulsivity. *British Journal of Psychology, 101*(4), 751-776.

Elliott, R. (1994). Addictive consumption: Function and fragmentation in postmodernity. *Journal of consumer policy, 17*(2), 159-179.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research, 18*(1), 39-50.

Foroughi, A., Buang, N., & Sherilou, M. (2011, October). Exploring impulse buying behavior among iranian tourists in Malaysia (case study). In 2nd International Conference on Business and Economic Research (2nd ICBER 2011) Penang.

Gronemus, J. Q., Hair, P. S., Crawford, K. B., Nyalwidhe, J. O., Cunnion, K. M., & Krishna, N. K. (2010). Potent inhibition of the classical pathway of complement by a novel C1q-binding peptide derived from the human astrovirus coat protein. *Molecular immunology, 48*(1-3), 305-313.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Advanced diagnostics for multiple regression: A supplement to multivariate data analysis. Advanced Diagnostics for Multiple Regression: A Supplement to Multivariate Data Analysis.

Hausman, A. (2000). A multi?method investigation of consumer motivations in impulse buying behavior. *Journal of consumer marketing, 17*(5), 403-426.

Heilman, C. M., Nakamoto, K., & Rao, A. G. (2002). Pleasant surprises: Consumer response to unexpected in-store coupons. *Journal of Marketing Research, 39*(2), 242-252.

Hirschman, E. C. (1992). The consciousness of addiction: Toward a general theory of compulsive consumption. *Journal of Consumer Research, 19*(2), 155-179.

Hoch, S. J., & Loewenstein, G. F. (1991). Time-inconsistent preferences and consumer self-control. *Journal of consumer research, 17*(4), 492-507.

Jones, M. A., Reynolds, K. E., Weun, S., & Beatty, S. E. (2003). The product-specific nature of impulse buying tendency. *Journal of business research, 56*(7), 505-511.

Mick, D. G., & DeMoss, M. (1990). Self-gifts: Phenomenological insights from four contexts. *Journal of Consumer Research, 17*(3), 322-332.

O'Guinn, T. C., & Faber, R. J. (1989). Compulsive buying: A phenomenological exploration. *Journal of consumer research, 16*(2), 147-157.

Parsad, C., Prashar, S., & Tata, V. S. (2017). Understanding nature of store ambiance and individual impulse buying tendency on impulsive purchasing behaviour: an emerging market perspective. *Decision, 44*(4), 297-311.

Piron, F. (1991). Defining impulse purchasing. ACR North American Advances.

Rook, D. W. (1987). The buying impulse. *Journal of consumer research, 14*(2), 189-199.

Rook, D. W., & Fisher, R. J. (1995). Normative influences on impulsive buying behavior. *Journal of consumer research, 22*(3), 305-313.

Rook, D. W., & Gardner, M. P. (1993). In the mood: Impulse buying's affective antecedents. *Research in consumer behavior, 6*(7), 1-28.

Sengupta, J., & Zhou, R. (2007). Understanding impulsive eaters' choice behaviors: The motivational influences of regulatory focus. *Journal of Marketing Research, 44*(2), 297-308.

Sharma, P., Sivakumaran, B., & Marshall, R. (2010). Impulse buying and variety seeking: A trait-correlates perspective. *Journal of Business research, 63*(3), 276-283.

Sneath, J. Z., Lacey, R., & Kennett-Hensel, P. A. (2009). Coping with a natural disaster: Losses, emotions, and impulsive and compulsive buying. *Marketing letters, 20*, 45-60.

Spies, K., Hesse, F., & Loesch, K. (1997). Store atmosphere, mood and purchasing behavior. *International Journal of Research in Marketing, 14*(1), 1-17.

Stancu, V., & Lähteenmäki, L. (2022). Consumer-related antecedents of food provisioning behaviors that promote food waste. *Food Policy, 108*, 102236.

Sultan, A. J., Joireman, J., & Sprott, D. E. (2012). Building consumer self-control: The effect of self-control exercises on impulse buying urges. *Marketing Letters, 23*, 61-72.

Thompson, L. (1990). Negotiation behavior and outcomes: Empirical evidence and theoretical issues. *Psychological bulletin, 108*(3), 515.

Verplanken, B., & Herabadi, A. (2001). Individual differences in impulse buying tendency: Feeling and no thinking. *European Journal of personality, 15*(1_suppl), S71-S83.

Verplanken, B., Herabadi, A. G., Perry, J. A., & Silvera, D. H. (2005). Consumer style and health: The role of impulsive buying in unhealthy eating. *Psychology & Health, 20*(4), 429-441.

Vohs, K. D., & Faber, R. J. (2007). Spent resources: Self-regulatory resource availability affects impulse buying. *Journal of consumer research, 33*(4), 537-547.

Weinberg, P., & Gottwald, W. (1982). Impulsive consumer buying as a result of emotions. *Journal of Business research, 10*(1), 43-57.

Xu, Y. (2007). Impact of store environment on adult generation Y consumers' impulse buying. *Journal of Shopping Center Research, 14*(1), 39-56.

Youn, S., & Faber, R. J. (2000). Impulse buying: its relation to personality traits and cues. ACR North American Advances.

Yu, C., & Bastin, M. (2010). Hedonic shopping value and impulse buying behavior in transitional economies: A symbiosis in the Mainland China marketplace. *Journal of Brand Management, 18*, 105-114.

Zhang, Y., & Shrum, L. J. (2009). The influence of self-construal on impulsive consumption. *Journal of consumer research, 35*(5), 838-850.

GST and the Banking Sector: A Critical Review of Existing Literature

Sutrishna Sarkar[1] and Tanima Ray[2]

ABSTRACT

The Goods and Services Tax (GST), one of independent India's most ambitious fiscal reforms, has redefined the landscape of indirect taxation. While conceptualized as a "One Nation, One Tax" policy, its implementation has had profound ramifications across sectors, most notably in banking-a vital service backbone of the Indian economy. This article synthesizes a decade of academic and industry research on GST's impact on the Indian banking sector, providing a nuanced examination of compliance burdens, registration issues, input tax credit (ITC) mechanisms, operational challenges, digital reform, inter-branch complexities, customer service implications, and profitability. The review spans studies from the inception of GST in 2015 to the transformative reforms of 2024, drawing on peer-reviewed literature, policy documents, and sector analyses. Important research gaps are noted, and forward-looking future recommendations are put forth academic inquiries and policy fine-tuning, with particular attention to comparative dynamics with NBFCs, technological integration, and regulatory evolution. Throughout, this paper highlights the evolving nature of GST's impact as India moves toward continued economic formalization, digital compliance, and a more streamlined tax regime.

Keywords: *Indian Banking Sector, Compliance Burden, Service Tax, Input Tax Credit (ITC), Multistage Registration, Place of Supply Rules, Regulatory Impact, Inter Branch Transaction, Public Vs Private Banks, Empirical Analysis.*

1. Introduction

The rollout of the Goods and Services Tax (GST) in July 2017 marked a watershed moment in India's fiscal history. By replacing a patchwork of central and state levies with a unified, destination-based tax, GST sought to dismantle the inefficiencies of the earlier regime and create a seamless national market. While the reform promised transparency and efficiency, its real-world application revealed a complex set of challenges-particularly for service-heavy industries such as banking.

The banking sector, contributing nearly 7.7% to India's GDP, occupies a unique position at the crossroads of financial intermediation and regulatory compliance. With its extensive branch networks, diverse service portfolios, and reliance on both digital and physical infrastructure, banks became one of the most visible testing grounds for GST's impact. The transition from a 15% service tax to an 18% GST not only altered cost structures but also reshaped compliance obligations, inter-branch taxation, and customer-facing processes.

For scholars, regulators, and practitioners alike, the banking sector's experience under GST offers valuable insights into how large service industries adapt to sweeping fiscal reforms. This study therefore undertakes a critical review of existing literature, tracing the evolution of GST's impact on banking from its inception to

[1]SACT - I, Seth Anandram Jaipuria College, Kolkata, West Bengal
[2]Professor and Head- MBA Dept. IISWBM, Kolkata

recent reforms. By synthesizing recurring themes, highlighting contradictions, and identifying gaps, the paper aims to provide a roadmap for future inquiry into taxation, technology, and sectoral competitiveness.

2. Objectives

- To critically examine the operational, financial, and regulatory implications of GST implementation within the Indian banking sector, as reported across existing literature.
- To synthesize recurring patterns, thematic consistencies, and conflicting findings among scholarly studies on GST's impact on banking services.
- To identify unresolved issues and underexplored areas in current research, thereby proposing informed directions for future scholarly inquiry.

3. Rationale for the Study

In line with these objectives, the report identifies important research needs in addition to summarizing previous findings. These include the limited empirical analysis of long term effects on customer service and profitability, insufficient comparative perspectives across public and private banks and NBFCs, unresolved taxation ambiguities, and the underexplored role of technology in compliance. Identifying these gaps ensures that the objectives of examining implications, synthesizing patterns, and proposing future directions are meaningfully addressed.

4. Methodology

This article employs a qualitative meta-analysis of 25+ studies, including descriptive, exploratory, and empirical research. Sources include journal articles, case studies, and government reports. Comparative tables and thematic coding were used to extract patterns across time and geography.

4.1 Data Sources

Peer-reviewed journals and online repositories (e.g., IJRPR, IJCRT, IJRTE, AIJRA).

Official publications and technical guides by bodies such as the ICAI.

Major financial news portals and banking sector reports.

Web sources for ongoing reforms, practical case studies, and sector-specific analyses.

Analytical focus is maintained on banking sector-specific developments, though relevant NBFC and pan-service sector impacts are briefly integrated for comparative context.

5. Phases of Research in GST-Banking Studies

Research on GST's implications on banking has been catetorised in three broad phases :

a) Early explorations (2015-2017): Initial studies, such as Jain (2015), welcomed the input tax credit mechanism but cautioned against the heavy compliance burden and the need for meticulous record-keeping. Kotnal (2017) further emphasized operational hurdles, particularly multi-state registration and place-of-supply rules, which complicated banking transactions.

b) Descriptive analyses (2018-2019): Scholars during this period shifted focus to administrative and customer-facing consequences. Revathi et al. (2018) and Kaur et al. (2018) noted rising service costs and mounting compliance strain. Comparative insights from Murphy (2017-18) on Australia revealed that GST-style levies could even harm economic performance. Meanwhile, Meena (2018) and Kamruddin & Misab (2018) highlighted IT system disruptions and procedural inefficiencies, while Paul et al. (2019) and Rathod & Anjesh (2019) documented customer dissatisfaction with higher tax rates.

c) Empirical and regional studies (2020-2024): More recent work has adopted data-driven approaches. Dhingra (2021) demonstrated statistically that GST raised customer costs and compliance inefficiencies. Regional case studies by Shetty et al. (2022) and Prija & Asha (2022) used chi-square and Garrett ranking techniques to capture localized effects. When comparing public and private banks using profitability ratios, Nagaprakash & Saranya (2023) found different financial results. Although their study was restricted to Hyderabad, Sravani & Poornachandrika (2024) most recently used regression and correlation analysis to find a substantial association between GST reforms and consumer satisfaction.

When taken as a whole, these stages show a path from theoretical optimism to real-world difficulties and ultimately to complex empirical discoveries. GST has unquestionably simplified India's tax system, but its effects on banking are still complex.

6. Literature Survey

6.1 Impact on Banking Sector

Jain, S. (2015) his study was among the first attempts to comprehend how GST might change banking and other financial services in India. She investigated fee-based and fund-based services using secondary data and a descriptive methodology. The study revealed a stark contradiction: although the input tax credit (ITC) provision was perceived as a beneficial innovation that might lessen cascading taxes, the need to keep different sets of records and the growing costs associated with compliance were recognized as major disadvantages. Despite being mostly explanatory, her work laid the groundwork for later conversations on striking a balance between administrative load and efficiency.

Dr. Kotnal, J. (2017) in his article, "Banking Sector in India; A More Focused Area Under GST", offered a qualitative exploration of GST's operational and compliance challenges. Drawing on the Model GST Law and practical examples, he analyzed key variables such as tax rates, place-of-supply rules, multi-state registration, and the classification of taxable versus exempt transactions. His findings pointed to increased compliance costs, restructuring of accounting systems, and taxation of inter-branch transactions as major hurdles. Importantly, Kotnal noted the absence of empirical data on long-term impacts like customer service delivery and profitability, identifying a critical research gap that future scholars would need to address.

Revathi, R. et al. (2018) they conducted a descriptive study based on secondary sources, focusing on how GST affected banking operations. They examined factors such as deposit growth, registration procedures, interstate branch transactions, and charges on banking activities. Their findings revealed that administrative requirements had become more complex and burdensome, service costs were rising, and inter-state transactions were now subject to GST. The study underscored how compliance under the new regime was becoming increasingly hectic for banks.

Kaur, B. et al. (2018) their team analyzed GST's structure and its implications for the banking sector. Their descriptive research, based on government papers, books, and journals, highlighted both benefits and challenges. On the positive side, GST was seen as promoting transparency, reducing tax evasion, and enabling ITC claims. On the negative side, however, the requirement to register and maintain records for numerous branches created significant operational strain. Their work reflected the mixed reality of GST: a reform that promised efficiency but demanded heavy administrative effort.

Murphy, C. (2017-2018) his study provided an international perspective by examining GST's impact on Australian banking. Using explanatory methods supported by tables, charts, and the CGETAX model, he assessed different tax reform options. His findings showed that while an economic rents tax caused minimal harm, full GST taxation imposed moderate harm, and the major bank levy resulted in considerable economic damage. This comparative analysis highlighted how similar reforms could have varying consequences depending on the context, offering lessons for India's banking sector.

Meena G. (2018) her exploratory research focused on the operational challenges GST created for Indian banks. Without relying on test statistics, she examined issues in administration, accounts, and registration. Her conclusions emphasized that banks would face significant problems in handling business transactions, customer profiles, and IT systems. The study argued that GST compliance required banks to overhaul both front-end and back-end operations, making IT systems more vigilant and adaptive. Meena's work highlighted the scale of transformation needed for banks to align with GST requirements.

Kamruddin, S. & Misab, P.T (2018) they approached GST as both a disruptive challenge and a potential driver of reform. Their descriptive study noted that banks, given their diverse operations and large scale, would face compliance difficulties under the new regime. Yet, they also argued that GST could eventually streamline taxation and make processes faster and more complete. The authors emphasized that banks would need to reevaluate their operations, transactions, and compliance systems, facing obstacles but also opportunities for exponential growth.

Savithri, B. & Harini, V. (2018) Savithri and Harini examined GST's impact on banking through a descriptive and exploratory lens. Their study acknowledged that the reform simplified India's indirect tax system and offered benefits such as unified taxation and easier ITC claims. However, they also pointed out that the increase in service tax rates made customers uncomfortable. Their analysis reflected the dual nature of GST: while it eliminated inefficiencies of the old system, it introduced new costs that directly affected customer satisfaction.

Kulkarni, P.G. & Baskaran, S. (2018) Kulkarni and Baskaran studied administrative and service-related issues under GST, relying on secondary data. They concluded that financial transactions became slightly more expensive for customers, while banks faced higher compliance costs due to branch registration and inter-branch taxation. Despite these challenges, they argued that GST was a necessary reform aimed at simplifying India's tax system and promoting growth. The modest cost increase, they suggested, should be seen as a trade-off for long-term efficiency and sustainability.

Azhagan, C.T. & Kanmani, A. (2019) their descriptive study emphasized the scale of restructuring required in banking after GST's implementation. They argued that transactions, operations, registration, accounting, and compliance all needed to be redesigned to fit the new framework. While acknowledging that financial services became slightly more expensive, they framed this as a necessary price for a more efficient future. Their work reinforced the idea that GST was not just a tax reform but a structural transformation for the banking sector.

Paul, P. et al. (2019) they examined GST's impact on the Indian banking sector with the aim of quantifying changes, identifying challenges, and weighing the benefits against the drawbacks. Their exploratory study relied on secondary data rather than statistical testing. They found that while GST introduced additional costs-particularly through interstate taxation and mandatory registration-it also promised long-term improvements by unifying the tax system and reducing inefficiencies. The authors concluded that although banks faced short-term discomfort, the reform was designed to eliminate inconsistencies and strengthen the overall taxation framework.

Rathod, V.G. & Anjesh, H.L. (2019) they adopted a descriptive approach, drawing on books, journals, and prior studies to analyze GST's effects on banking. They argued that GST was a difficult but necessary reform aimed at promoting sustainable banking. Their findings emphasized that while GST addressed many shortcomings of the previous tax system, its introduction created widespread challenges across industries. In banking specifically, the increase in service tax to 18% raised costs for customers, making them less comfortable with financial services. The study highlighted both the systemic importance of GST and its immediate strain on end users.

Puri, L.D. (2020) the way that GST changed banking services was the main focus of this descriptive and explanatory study. He came to the conclusion that while GST decreased inefficiencies, it also increased customer expenses based on secondary evidence. Mandatory registration requirements resulted in increased costs for banks in particular. His findings supported the notion that the Goods and Services Tax (GST) was a dual-purpose legislation that increased operational responsibilities while streamlined taxation.

Dr. Dhingra, G. (2021) his study, "A Study on Goods & Service Tax & Its Impact on Indian Banking Sector", combined qualitative and quantitative methods to provide a comprehensive view. By comparing pre- and post-GST periods, he showed how the increase in tax rates from 15% to 18% affected consumer expenses and banking service usage. His analysis covered transactions, loans, insurance premiums, compliance duties, and operational costs. While acknowledging that GST streamlined taxation, Dhingra highlighted inefficiencies in compliance, particularly due to state-wise registrations and inter-branch taxation. He also identified a research gap: the lack of long-term studies on customer retention and banks' ability to adapt to evolving GST rules.

Shetty, S.K. et al. (2022) they conducted an empirical study in Mangalore City, combining surveys of 55 respondents with secondary data. They analyzed administrative variables such as transparency, double taxation, service improvisation, GSTN portal satisfaction, manpower issues, and documentation. Using chi-square tests, t-tests, and ANOVA, they found that GST had limited impact on profitability but significantly affected inter-state branch transactions. Their research also revealed that the GST system required more manpower and financial resources to function effectively, underscoring the operational strain on banks.

Prija, P.J. & Asha, P. (2022) they carried out a case study in Nagercoil Town, focusing on the challenges banks faced after GST's introduction. Their descriptive research used secondary sources and convenience sampling of 140 respondents. Employing Garrett ranking and weighted averages, they concluded that GST posed serious difficulties for sustainable banking. While the reform applied uniformly across goods and services, its implementation was described as "dangerous and difficult," reflecting the heavy compliance burden and operational disruptions experienced by banks in the region.

Abhirami, K.S. et al. (2023) they investigated GST's effects in Kerala's Thrikkakra region. Using questionnaires with 50 employees and secondary sources, they adopted a descriptive and explanatory approach. Their findings showed that inter-state branch transactions were now taxable, creating new challenges. However, they also noted that GST generated significant revenue for the banking industry. Over time, banks adapted to the changes, and operations began to run more smoothly. The study highlighted the sector's resilience and gradual adjustment to the new tax regime.

Nagaprakash, T. & Saranya, A. (2023) they compared public and private banks using profitability ratios to assess GST's impact. Their descriptive study relied on secondary data and correlation analysis, covering five years before and after GST's introduction. Ratios such as ROA, ROE, NIM, NPM, and ER were used to measure performance. They found that public sector banks needed proactive strategies to improve efficiency and profitability compared to private banks. The authors recommended cost management and operational optimization to enhance competitiveness in the post-GST era.

Sravani, V.S. & Poornachandrika, T.S. (2024) they conducted a mixed-methods study in Hyderabad, focusing on banking operations, employee perceptions, and customer satisfaction. Using interviews, questionnaires, and statistical tools like chi-square, regression, and correlation analysis, they found strong links between GST reforms and customer satisfaction ($R^2 = 0.859$, $r = 0.904$). Their study revealed that GST improved transparency and ITC benefits but also increased compliance costs and complicated inter-branch transactions. While the findings were significant, the authors acknowledged the limitation of studying only one city, suggesting the need for broader regional and international comparisons.

Jain, D. [CA] Chartered Accountant Jain provided a descriptive analysis of GST's implications for banking, comparing the new regime with the earlier service tax system. He discussed taxation changes, compliance obligations, and the impact on services such as interest income, brokerage, account maintenance, and forex transactions. Key findings included the shift from centralized to state-wise registration, the potential taxation of interest income, and the liability of RBI services under GST. While banks faced heavier compliance burdens, they also benefited from ITC claims on assets like computers and imported ATMs. Jain identified several research gaps, including ambiguity around interest income taxation, the need for empirical validation of compliance costs versus ITC benefits, and the absence of comparative international studies.

6.2 Impact on other Service Sector

Giddaiah, R. [2017] In his article "Impact of GST on the Financial Sector in India - A Review", Giddaiah explored how GST reshaped the banking and financial services industry. His qualitative, descriptive study focused on compliance requirements, taxation changes, and operational restructuring. He highlighted that state-wise registrations and taxation of inter-branch services significantly increased compliance costs for banks. Revised tax rates also raised the cost of banking services, placing a heavier burden on customers. On the positive side, input tax credit (ITC) provided some relief by offsetting part of these expenses. However, the study left several questions unanswered: it did not examine long-term implications for financial inclusion, shifts in consumer behavior, or changes in competitiveness within the banking industry. The absence of quantitative analysis further limited the ability to measure GST's financial impact empirically, pointing to the need for deeper, data-driven research.

Samudre, M.M. & Gramopadhye, R.V. [2018] Samudre and Gramopadhye's paper "Impact of GST on Service Sector of India" analyzed GST's broader effects across multiple service industries. Using secondary sources such as journals, newspapers, and magazines, they adopted an explanatory approach without statistical testing. Their findings showed that GST raised the service tax rate from 15% to 18%, increasing costs for both consumers and businesses. While healthcare services were exempt and IT services minimally affected, other areas like CBLO (Collateralized Borrowing and Lending Obligation) faced notable cost implications. The authors argued that GST could positively influence GDP growth and employment in the long run, but they also emphasized challenges such as multi-state registration and compliance obligations. They identified important research gaps, including the absence of longitudinal studies, limited quantitative validation, and insufficient focus on micro-level differences between small and large enterprises. These gaps highlight the need for more nuanced investigations into GST's sectoral impact.

Kumar, R. [2022] Kumar's article in the Journal of Critical Reviews, "Goods and Services Tax Impact in Service Sector", offered an exploratory analysis of GST's structure and implications. Drawing on government reports and scholarly articles, he examined GST rates, ITC mechanisms, and sector-specific impacts across industries such as railways, aviation, banking, media, and tourism. His findings suggested that GST simplified India's indirect tax system and improved credit flow through ITC, but higher tax rates increased service costs. The study also noted revenue losses in major service sectors during the COVID-19 pandemic. Kumar highlighted India's adoption of a dual GST model, similar to Canada's, but pointed out gaps such as the lack of centralized registration for service providers, limited empirical validation, and insufficient sector-specific quantitative analysis. He recommended more data-driven studies to capture GST's nuanced effects on India's service economy.

Varalakshmi, P. [2022] Varalakshmi's case study "Impact of Goods and Services Tax (GST) on Hotel Industry - A Case Study of Chittoor District in Andhra Pradesh" examined GST's effects on the hospitality sector. She examined policy papers, compared the pre- and post-GST tax regimes using descriptive and historical methodologies, and used statistical tools like growth rate analysis, ANOVA, and chi-square testing. According to her research, GST increased compliance, decreased cascading levies, and rationalized the tax system. Remarkably, 71.98% of hoteliers said that GST was superior to the old system. The Chittoor hotel industry benefited from the reform, which also increased tourism and occupancy rates. The study did, however, admit many shortcomings, including the lack of long-term profitability assessments, the inability to compare results with other districts, and the restricted assessment of stakeholder awareness of GST. These gaps point to the necessity for more comprehensive and comparative studies.

Idicula, R. [2023] In "Impact of GST on the Hospitality Sector in Kerala", Idicula conducted a descriptive and analytical study using multi-stage sampling across 303 hotels and surveys of 262 customers. Statistical tools such as ANOVA, t-tests, and chi-square tests were applied to examine variables including service metrics, refund issues, compliance costs, pricing, and customer perceptions. The findings revealed that GST enhanced transparency but raised operational costs, leading to dissatisfaction among hotel owners, particularly due to refund delays. Customer responses varied by hotel category: demand fell in premium hotels, remained steady in budget segments, and dissatisfaction was highest among five-star properties due to higher GST rates. The study identified several limitations, including lack of data beyond 2021, limited regional comparisons, absence of psychographic segmentation, and insufficient causal analysis of demand elasticity. These gaps highlight the need for more nuanced and qualitative research into how GST affects hospitality demand and service adaptation.

Deeksha, G. [2024] Deeksha's study "Analysis & Impact of GST in the BFSI Sector" investigated GST's effects on banking, financial services, and insurance. She investigated compliance changes, financial restructuring, pricing tactics, and technology adoption using a mixed-method approach that incorporated surveys with secondary data. According to her research, GST significantly influenced pricing and finance strategies, promoted more investment in digital infrastructure, and changed compliance procedures. She did point out some significant study gaps, though, including a lack of empirical data on long-term performance, a lack of investigation of sectoral adaptations, and a lack of examination of post-GST technology developments. The study came to the conclusion that although GST had changed the BFSI industry, further in-depth, data-driven research was required to fully comprehend its long-term effects.

7. Sectoral Reflections on GST Implementation

The literature review uncovers a number of common themes which demonstrate the strengths and weaknesses of GST reforms in the banking sector. Introduction of GST was a game changer in India's tax system. The benefit of Input Tax Credit (ITC) was well accepted as a positive step in the direction of reducing cascading taxes. However, this benefit was nullified by the hike in the service tax from 15% to 18% which directly increased the cost of banking services and added to the financial burden on consumers.

GST was also rolled out as a measure to simplify tax administration with the imposition of a common set of rules and procedures. This gave a sense of structure but in reality, things were far more intricate. Multi-state registration was an issue for banks, the compliance cost, and filing multiple returns. These challenges made the demands and resource needs of day-to-day activities even greater, particularly for institutions with extensive branch networks.

The other big theme was technological change necessitated by the implementation of GST. This reform forced banks to implement digital infrastructure and systemic modernization, impacting the processing and reporting of taxes. This transition did not come without huge IT upgrades and complex data management systems, however. For many institutions the transition was difficult, as they had to cope with the extra demands of having to acquire sophisticated technology and adapt constantly.

Inter-branch transactions also came to the fore with the advent of GST. They were a source of new revenue on one side, and created a new level of complexity on the other side by introducing some transactions that would now be subject to taxes. This was on top of the administrative burden and confusion over compliance, thus adding to the complexity of the banking environment.

The picture with regards to the customer experience before the GST was mixed. In some instances, there was an increase in transparency and satisfaction, but in others service charges were higher and thus caused dissatisfaction. The system garnered mixed feedback from consumers, from positive reaction for the clarity it offers to resentment over the additional costs.

Finally, comparative analysis showed differences in the adaptation of Public and Private Banks in the post-GST era. Private banks were better equipped to adjust and remain profitable with their higher cost-control mechanisms. However, the efficiency and cost management problem of the public sector banks and lack of competitiveness in the new regime were a concern.

Overall, the changes to the GST were complex but also clear. They facilitated digital transformation and pieced together an Indian tax regime that was outdated, costly, cumbersome, and not always successful with the sectors. In the literature, the implementation of the GST is often portrayed as a tax reform that will make taxation easier and create new challenges for banks and their customers.

8. Research Gap

The expanding body of research on GST and the banking sector still has some significant holes. First, there aren't enough thorough studies using panel data at the branch level to properly illustrate the complex cost-benefit ramifications of passing the GST. Second, research on the disparate impacts of GST on different bank types is lacking, particularly when it comes to illustrating how rural cooperative banks might encounter distinct challenges than commercial banks with an urban concentration. Third, there are still few comprehensive empirical studies on the impact of GST on data privacy, IT security, and technology adoption, despite the fact that it has accelerated the digital transformation of banking. Fourth, there is a lack of long-term studies that monitor the behavioral effects on consumers, especially how perceptions of transparency and fairness shift among urban, rural, digital-native, and senior citizen populations. Finally, given the rapid expansion of cross-border digital banking and FinTech services, more research into the implications of GST for these emerging models is important in order to understand the regulatory, operational, and customer-level effects of GST.

9. Discussion

The majority of scholarly research uses industry surveys, qualitative reviews, or secondary data. Sector-wide empirical data is still difficult to get, and just a few studies use sophisticated econometric assessments of banking performance before and after the GST. Procedural insights can be found in technical guides from ICAI, CA forums, and Government white papers. Recent years have seen an increase in survey-based and case study research, which is encouraging for future investigations.

There are several key ideas that stand out over the 10-year period of implementation of the GST. In the beginning, it was a jolt, and the banks and consumers would have to cope with added costs, headaches, and uncertainty in their operations. However, eventually, this short-term complication was overcome by long-term benefits. The sector began to work towards greater efficiency, and staff throughout institutions became more digitally literate, while transparency increased. An overarching pattern in literature is that the "shock to adaptation" curve came to represent the transitional nature of the process which led to systemic improvement.

Another major theme is the role of compliance in driving digital transformation. The necessity of meeting GST's stringent requirements pushed banks to adopt new technologies, automate compliance processes, and invest in digital infrastructure. This trend became especially pronounced after 2020, when the pandemic accelerated the pace of digitalization across the financial sector.

Yet today, the administration and law remain impediments. Nevertheless, banks grapple with issues of input tax credit allocation and applicability of GST, despite the rise in the number of regulatory clarifications. The Goods and Services Tax Appellate Tribunal (GSTAT), set up in 2025, is expected to speed up the dispute resolution process but its effectiveness will depend on its capacity to manage the volume of cases and on its consistency of delivering decisions.

Some problems with the inverted duty structure have also been experienced. It is difficult for banks to cope with working capital management and to timely receive ITC refunds where raw material/ services tax rates are higher than the final product tax rates. This is particularly relevant for organisations expanding to offer more fee-based services. These pressures are expected to be reduced by the 2025 reforms, but careful monitoring of the implementation of the changes will be essential.

Finally, a large consensus in favour of rationalising the four-tiered GST regime to a two-tiered one and excluding essential services such as insurance. This is considered as steps towards making the financial system more cost effective, inclusive and retail credit. These are macroeconomic effects of GST reforms for which there are a lot of changes.

10. Findings

The dramatic increase in compliance costs is one of the most recurring conclusions in the literature. With the scrapping of centralized registration, every bank branch was made a separate taxable entity, which meant an individual GST registration was filed in each operating state. Large banks with extensive networks were hardest hit as they had to deal with multiple returns and submit ITC claims in multiple jurisdictions. As a result, there were significant administrative overheads, a greater need for labor, and higher IT costs. Now the state is responsible for adjudication, making litigation more complex and returns delayed.

The input tax credit concept though intended to reduce the inefficiencies has resulted in mixed effects in banking industry. The benefit is smaller than that of other sectors as only 50% of the credits can be recovered with the other 50% offset. In the case of centrally purchased services such as technology and consultancy, it has been difficult to allocate the shared credits, while banks often find it difficult to claim ITC on charges that do not follow the normal invoicing process. Despite the developments in the technology of computerized reconciliation, underclaimed GST continues to have a negative impact on profitability and restrict investment opportunities.

The most visible effect of the imposition of GST on the customers is an increase in the price of services. Normal bank services like ATM withdrawals, lockers, cash handling, penalty fees etc. will be charged 18% service tax now as against 15% earlier. Previous surveys showed some dissatisfaction and confusion, but more recent surveys indicate awareness has grown, largely due to clear invoicing and electronic disclosures. Those who are cost sensitive will benefit from the rationalization of GST rates in 2025, which reduced the tax on some financial services and exempted certain financial products, enhancing their perceptions of fairness and fostering inclusion.

Within the framework of GST, the interbranch transactions have also become more complex. Taxable services, like Internal Services (IT Support, Management etc.), will now require a break-out of services provided and an invoice. These transactions have been difficult to reconcile, and since there are different interpretations from jurisdiction to jurisdiction, a significant liability remains that may lead to litigation. ICAI and GST Council have issued guidance in the form of practice notes but there is significant stress in the minds of branch managers on compliance issues.

Digital compliance is no longer a requirement, it's an opportunity. Since 2020, banks have made substantial investments in automated GST analytics, e-filing and e-invoicing. Banks, especially the larger ones, are testing AI-based monitoring systems, while public sector and mid-sized banks are simply working to align their systems with regulations. New legislation will speed up refunds and make compliance easier-promises that encourage more digitalization-but which require continued investment and support.

Bank profitability trends showed signs of stabilization by 2023 following the first decline experienced after the introduction of the GST, due largely to the positive effects of tax reform, improved ITC reconciliation, and greater efficiency resulting from the digitization of compliance. Further improvement in bank performance was achieved through increased loan demand. The 2025 forecast for lending was slightly negative due to new reforms, while there are positive indicators for profitability in the service sector.

Moreover, there has been a direct relationship between the credit expansion and GST reforms, which has resulted in increased demand for loans through consumer finance, housing, and automotive finance due to the reduction of taxes on necessities and durable goods. Significant increases in credit demand of 8% to 10% are anticipated by banks such as SBI and Indian Overseas Bank across both urban and rural markets resulting from lower insurance premiums and increased consumer confidence, which together will serve as a stimulus for increased financial expansion due to GST.

11. Conclusion

In the last decade, the Indian banking sector has seen substantial evolution due to the introduction of GST. Banks have progressed in the right direction through multiple reform efforts, digital technology improvements and rationalized rate setting, although the initial years faced obstacles such as operational issues, higher levels of compliance and consumer reluctance to embrace change. While banks incurred more in compliance costs than their nonbank counterparts, they have also led the way in terms of improvements to digitalization and regulatory compliance throughout the sector.

2025 and beyond: As GST 2.0 cements streamlined rates, technology-driven compliance, and greater legal clarity, prospects for banking sector efficiency, profitability, and customer inclusion look increasingly robust. However, problems with ITC implementation, branch-level management, and conflict resolution require continued policy focus and academic engagement. Future studies on micro-level effects, rural bank adaptation, IT security, behavioral economics, and cross-border digital banking would be essential to sustaining the positive momentum of GST-driven change in Indian banking.

References

Abhirami, K. S., et al. (2023). Impact of GST on banking sector with reference to Thrikkakra region. India. Retrieved from IJRPR Journal

Azhagan, C. T., & Kanmani, A. (2019). Banking sector in India - A more focused area after GST. India. Retrieved from IJRTE Journal

Central Board of Indirect Taxes and Customs (CBIC). (n.d.). GST Laws & Rules. *Retrieved September 22*, 2025, from https://cbic-gst.gov.in

Deeksha, G. (2024). Analysis & impact of GST in the BFSI sector. India. Retrieved from IJRPR Journal

Dhingra, G. (2021). A study on Goods & Service Tax & its impact on Indian banking sector. India. Retrieved from IJRPR Journal

Giddaiah, R. (2017). Impact of GST on the financial sector in India - A review. India. Retrieved from Academia.edu

Idicula, R. (2023). Impact of GST on the hospitality sector in Kerala. India. Retrieved from IJRPR Journal

Jain, D. (n.d.). GST impact on banking sector. India. Retrieved from TaxGuru

Jain, S. (2015). Impact of Goods and Services Tax (GST) on Indian economy (With special reference to banking and financial sector). India. Retrieved from ResearchGate

Kamruddin, S., & Misab, P. T. (2018). Impact of GST on banking sector: An overview. India. Retrieved from IJRPR Journal

Kaur, B., et al. (2018). Impact of Goods & Services Tax on Indian banking sector. India. Retrieved from IJCRT Journal

Kulkarni, P. G., & Baskaran, S. (2018). Impact of GST on banks - Issues and challenges. India. Retrieved from IJCRT Journal

Kumar, R. (2022). Goods and services tax impact in service sector. Journal of Critical Reviews, 9(3), 45-52. https://doi.org/10.31838/jcr.09.03.45

Kotnal, J. (2017). Banking sector in India: A more focused area under GST. India. Retrieved from Academia.edu

Meena, G. (2018). Impact of GST on banking sector. India. Retrieved from IJIRT Journal

Ministry of Finance, Government of India. (n.d.). GST Revenue and Sectoral Impact Reports. Retrieved September 22, 2025, from https://finmin.nic.in

Murphy, C. (2017-2018). GST and how to tax Australian banking. Economic Papers: *A Journal of Applied Economics and Policy, 36*(4), 369-384. https://doi.org/10.1111/1467-8462.12295

Nagaprakash, T., & Saranya, A. (2023). Examining the effects of GST on Indian banks: A comparative analysis of public and private sectors using profitability ratios. *International Journal of Research Publication and Reviews, 4*(5), 112-120. Retrieved from IJRPR Journal

Paul, P., Sandhu, V., & Atwal, H. (2019). Implications of GST on Indian banking sector. *International Journal of Recent Technology and Engineering, 8*(3S3), 1072-1076. https://doi.org/10.35940/ijrte.C1072.1183S319

Prija, P. J., & Asha, P. (2022). Indian banking sector - Issues and challenges on GST in Nagercoil Town. India. Retrieved from Academia.edu

Puri, L. D. (2020). A study of GST implications on Indian banking sector. India. Retrieved from ResearchGate

Rathod, V. G., & Anjesh, H. L. (2019). GST and Indian banking sector - Issues and challenges. India. Retrieved from IJCRT Journal

Reserve Bank of India (RBI). (n.d.). Annual Reports and Banking Statistics. Retrieved September 22, 2025, from https://rbi.org.in

Revathi, R., Madhushree, L. M., & Aithal, P. S. (2018). Case study on impact of Goods and Service Tax in the banking sector. India. Retrieved from IJRTE Journal

Samudre, M. M., & Gramopadhye, R. V. (2018). Impact of GST on service sector of India. India. Retrieved from IJRTE Journal

Savithri, B., & Harini, V. (2018). GST: Its impact on banking sector. India. Retrieved from AIJRA Journal

Shetty, S. K., Spulb?r, C., Bir?u, R., & Ninulescu, P. V. (2022). Investigating the impact of GST on the banking sector with reference to selected banks in India. *Journal of Risk and Financial Management, 15*(6), 275. https://doi.org/10.3390/jrfm15060275

Sravani, V. S., & Poornachandrika, T. S. (2024). A study on impact of GST on banking industry. *International Journal of Research Publication and Reviews, 5*(6), 144-149. https://doi.org/10.55248/gengpi.5.0624.1402

Varalakshmi, P. (2022). Impact of Goods and Services Tax (GST) on hotel industry - A case study of Chittoor District in Andhra Pradesh. India. Retrieved from Academia.edu

Artificial Intelligence Applications for Sustainable Energy Management: A Review

Dipanjan Bose[1]

ABSTRACT

The ongoing evolution of power systems, driven by the large-scale adoption of renewable energy resources, distributed generation technologies, and increasing electrification, has created a growing need for advanced and intelligent energy management strategies (EMS). Artificial Intelligence (AI) has appeared as an intriguing strategy to tackle these challenges by enabling data-driven analysis, predictive modelling and intelligent control of energy systems. This paper reveals a strategic review of AI-based approaches for sustainable energy management within modern smart grid infrastructures. Various AI methodologies, including machine learning, deep learning, and reinforcement learning, are examined with respect to their applications in load demand forecasting, renewable energy prediction, demand-side management, microgrid control, and battery energy storage optimization. A comparative assessment of recent studies demonstrates the significant advantages of AI-driven techniques in enhancing grid flexibility, improving operational efficiency, and facilitating higher penetration of renewable energy sources. In addition, the review highlights the importance of supporting technologies such as big data analytics, Internet of Things (IoT) platforms, and cloud computing in enabling intelligent energy management frameworks. Key challenges associated with AI deployment in energy systems, including data quality limitations, cybersecurity concerns, model transparency, and computational requirements, are also discussed. Finally, future research opportunities are outlined to aid in the growth of robust, intelligent, and sustainable energy infrastructures. Overall, the findings indicate that AI-powered energy management systems have considerable potential to improve forecasting performance, enhance system reliability, and optimize operational efficiency in next-generation smart grids.

Keywords: *Artificial Intelligence; Smart Grid; Energy Management Systems (EMS); Renewable Energy Integration; Load Forecasting; Demand Response; Energy Storage Optimization*

1. Introduction

The global energy sector is undergoing a significant transition toward sustainable and low-carbon energy systems. Increasing penetration of renewable energy resources, rapid growth of distributed energy generation, and electrification of transportation have transformed the operational structure of modern power grids. Smart grid technologies have emerged as a key solution for managing these complex energy systems by enabling advanced monitoring, communication, and control capabilities. Nevertheless, since renewable energy sources like solar and wind are sporadic and fluctuating, integrating them creates substantial amounts of uncertainty. Traditional energy management approaches based on deterministic optimization methods often struggle to effectively manage this complexity. Artificial Intelligence (AI) has come up as a promising technology for addressing the threat associated with modern energy systems. AI techniques enable power systems to process large volumes of operational data generated by smart meters, sensors, and distributed energy resources, thereby supporting intelligent decision-making and real-time system optimization. Machine learning algorithms are widely used for load forecasting, renewable energy prediction, and fault detection in power systems.

[1]Assistant Professor, Department of Energy Management, IISWBM, Kolkata

Deep learning models have demonstrated superior performance in capturing nonlinear patterns in energy consumption and generation data. Reinforcement learning techniques further enable autonomous decision-making in dynamic environments such as microgrids and demand response systems.

Figure 1. illustrates the hierarchical classification of AI techniques including machine learning (ML), deep learning (DL), and reinforcement learning (RL), Deep Reinforcement Learning (DRL) which form the foundation of modern AI-driven energy management solutions. Machine learning techniques enable predictive modeling, while deep learning architectures facilitate complex pattern recognition. Reinforcement learning algorithms, on the other hand, enable autonomous decision-making through interaction with dynamic environments.

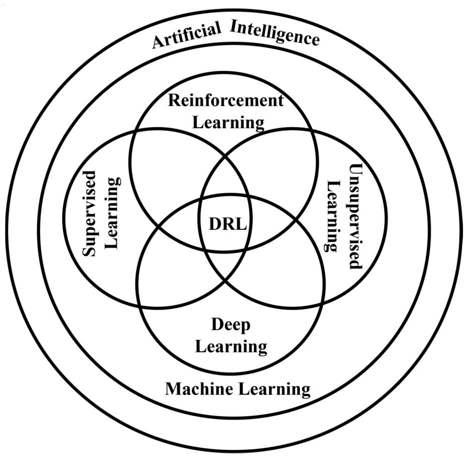

Figure 1. Classification of Artificial Intelligence Technologies

In recent years, AI-based energy management systems have gained increasing attention due to their capacity to boost renewable energy integration, optimise energy scheduling, and increase system resilience. These systems intends advanced analysis and predictive modeling to enable intelligent control of generation, transmission, distribution, and demand-side resources. Additionally, emerging digital technologies like IoT, cloud computing, and big data analytics have further accelerated the evolution of AI-driven smart energy infrastructures.

This paper provides a comprehensive review of Artificial Intelligence applications in sustainable energy management. The main objectives of this study are to examine recent advancements in AI-based energy management systems, analyze the importance of ML techniques in smart grid operations, and identify emerging challenges and research opportunities in AI-enabled energy systems. Through a systematic analysis of recent literature, this work highlights the potential of AI technologies to transform modern energy systems into intelligent, adaptive, and sustainable infrastructures.

2. Literature Review

AI has gained significant attention in recent years as a powerful tool for addressing the growing complexity of modern energy systems. Uncertainty, variability, and large-scale system management have become major challenges as a result of the integration of dispersed generation, smart grid technology, and renewable energy resources. Conventional optimisation and control techniques often struggle to manage these complexities effectively. It reveals, AI-based approaches such as machine learning, deep learning, and reinforcement learning have been increasingly adopted for sustainable energy management. Recent studies have demonstrated the growing importance of AI techniques in sustainable energy management. Several research works, presented in Table 1, have focused on load forecasting, renewable energy prediction, and intelligent energy dispatch strategies.

Table 1. Comparative analysis of different AI techniques applied to energy management

Ref	Author / Year	AI Technique	Application Area	Key Contribution
[1]	Zhao et al., 2020	Machine Learning	Renewable energy forecasting	Demonstrated improved solar and wind forecasting accuracy using AI-based models
[2]	Liu et al., 2019	AI optimisation	Renewable integration	Case studies showing improved grid stability with AI-based control
[3]	Vázquez-Canteli & Nagy, 2019	Reinforcement Learning	Demand response	RL-based energy management reduced electricity cost in smart buildings
[4]	Mostafa et al., 2022	Machine Learning	Smart grid energy management	Applied big data analytics for renewable integration in smart grids
[5]	Zhou et al., 2021	Deep Learning	Load forecasting	LSTM models improved electricity demand prediction accuracy
[6]	Li et al., 2020	Deep Learning	Power system fault detection	Deep learning models improved detection accuracy for grid faults
[7]	Rahman et al., 2020	AI optimisation	Microgrid control	AI improved operational efficiency of microgrid energy systems
[8]	Kusiak, 2019	Machine Learning	Wind energy optimisation	AI models enhanced wind turbine performance prediction
[9]	Chen et al., 2024	Deep Reinforcement Learning	Microgrid dispatch	Proposed hierarchical DRL model for optimal energy scheduling
[10]	Jayaraj et al., 2024	Reinforcement Learning	Islanded microgrid control	RL improved dynamic control of microgrid operation
[11]	Alam et al., 2025	Machine Learning	Smart grid optimisation	AI-enabled monitoring and optimisation of grid operations
[12]	Xu et al., 2025	Reinforcement Learning	Smart grid control	Reviewed RL techniques for power flow optimisation and load scheduling
[13]	Banad et al., 2025	AI/ML hybrid models	Smart grid management	Integration of IoT, ML and digital twin technologies for energy systems
[14]	Singh et al., 2025	Multi-Agent DRL	Demand response	Blockchain-enabled RL framework for real-time energy trading
[15]	Waghmare et al., 2025	Reinforcement Learning	Microgrid optimisation	RL control methods for micro-grid energy systems
[16]	Ahmadi et al., 2026	AI-based optimisation	Smart grid resilience	Review of AI methods for real-time grid management and fault detection
[17]	Safari et al., 2024	Machine Learning	Energy management systems	AI improved system reliability and predictive maintenance
[18]	Bouquet et al., 2024	Deep Learning	Solar energy forecasting	AI models improved solar energy prediction for smart grid planning
[19]	Chowdhury et al., 2025	AI optimisation	Urban energy systems	AI strategies for energy uses & forecasting and optimisation
[20]	Khan et al., 2025	AI optimisation	Renewable energy systems	AI improves efficiency of energy use and system sustainability
[21]	Balamurugan et al., 2025	AI techniques	Smart grid operations	AI improves reliability and automation in power systems
[22]	Kouihi et al., 2025	AI-based energy management	Smart grid optimisation	AI improves energy distribution efficiency
[23]	Antonesi et al., 2025	Transformer models	Energy forecasting	Advanced AI models for complex energy system modelling
[24]	Madani et al., 2025	Large Language Models	Smart grid management	LLM integration for adaptive grid decision-making
[25]	Pirie et al., 2024	Machine Learning	Mini-grid energy management	AI models improve renewable energy management in rural grids

Machine learning approaches are increasingly being utilized in renewable energy forecasting and the optimisation of energy systems. Reliable prediction of solar irradiance and wind power output is particularly important for maintaining grid reliability and ensuring efficient energy scheduling. Numerous studies have shown that machine learning models provide more accurate forecasting performance than conventional statistical techniques, primarily due to their ability to capture complex and nonlinear relationships within energy datasets [26]. However, despite the rapid progress in AI-enabled energy management solutions, several challenges still limit their widespread deployment. Key concerns include the limited availability and quality of training data, potential cybersecurity vulnerabilities associated with digitalized power infrastructures, the lack of transparency in complex AI models, and the high computational requirements needed for training advanced algorithms. Furthermore, integrating AI algorithms with existing power system infrastructures requires careful consideration to ensure reliability and secure operation. Nevertheless, ongoing advancements in AI technologies and data analytics continue to expand the potential of intelligent energy management systems. Overall, the literature indicates that AI-driven energy management systems significantly enhance forecasting accuracy, operational efficiency, and system reliability in modern power grids. However, further research is required to develop scalable, secure, and explainable AI models capable of supporting large-scale sustainable energy systems.

3. Artificial Intelligence Techniques in Energy Management

Artificial intelligence encompasses a broad set of computational techniques designed to imitate human cognitive processes including learning and thinking, and decision-making. In the purview of energy management, AI algorithms enable intelligent control of energy resources and predictive analytics for system optimization. The methods for machine learning, including support vector machines (SVM), decision trees, and random forests have been widely applied in load forecasting and energy demand prediction. These techniques utilize historical data to develop predictive models capable of estimating future energy consumption patterns.

Table 2 summarizes the key applications of artificial intelligence (AI) techniques in modern energy systems and highlights their impact on improving system efficiency, reliability, and operational performance. The table illustrates how different AI methodologies are applied across several critical domains of energy management. In building energy management, techniques such as RL and neural networks are used to optimize heating, ventilation, and air conditioning (HVAC) operations, leading to lower energy use while keeping occupant's comfort. For renewable energy forecasting, deep learning and time-series models enable accurate prediction of solar and wind power generation by analyzing historical weather and generation data, thereby supporting reliable grid operation. In the area of demand response, reinforcement learning and machine learning algorithms help manage electricity consumption patterns by encouraging consumers to adjust their loads during peak demand periods, which leads to peak load reduction and lower electricity costs.

Table 2. Key AI Applications in Energy Systems

Application Area	AI Techniques Used	Energy System Impact
Building Energy Management	Reinforcement Learning, Neural Networks	Reduced energy consumption and improved HVAC control
Renewable Energy Forecasting	Deep Learning, Time-series models	Improved prediction of solar and wind generation
Demand Response	Reinforcement Learning, Machine Learning	Peak load reduction and electricity cost optimisation
Virtual Power Plants	Multi-Agent Systems, Predictive Analytics	Efficient coordination of distributed resources
Battery Energy Storage	Reinforcement Learning, Optimisation Algorithms	Improved storage scheduling and market participation
Power System Resilience	Machine Learning, Deep Learning	Early fault detection and faster outage recovery

Virtual power plants (VPPs) utilize multi-agent systems and predictive analytics to coordinate distributed energy resources such as solar panels, wind turbines, and storage units, enabling them to operate collectively and efficiently in electricity markets.

Similarly, battery energy storage systems employ reinforcement learning and optimization algorithms to determine optimal charging and discharging schedules, improving energy arbitrage opportunities and participation in energy markets. Finally, power system resilience benefits from machine learning and deep learning techniques that analyze grid data to detect faults, predict equipment failures, and support faster outage recovery. Overall, the applications presented in Table 2 demonstrate the transformative role of AI in enabling intelligent, adaptive, and data-driven management of modern energy systems. Figure 2 represents the taxonomy of artificial intelligence techniques applied in sustainable energy management. AI approaches can be broadly categorised into machine learning, deep learning, and reinforcement learning. These techniques enable several applications in modern power systems, including renewable energy forecasting, microgrid optimisation, smart grid coordination, demand response management, and energy storage control. Reinforcement learning represents another important AI paradigm in energy management. RL-based controllers learn optimal policies through interactions with dynamic environments, enabling autonomous decision-making in energy systems. The integration of these AI techniques into energy management systems has significantly enhanced the efficiency and reliability of smart grid operations.

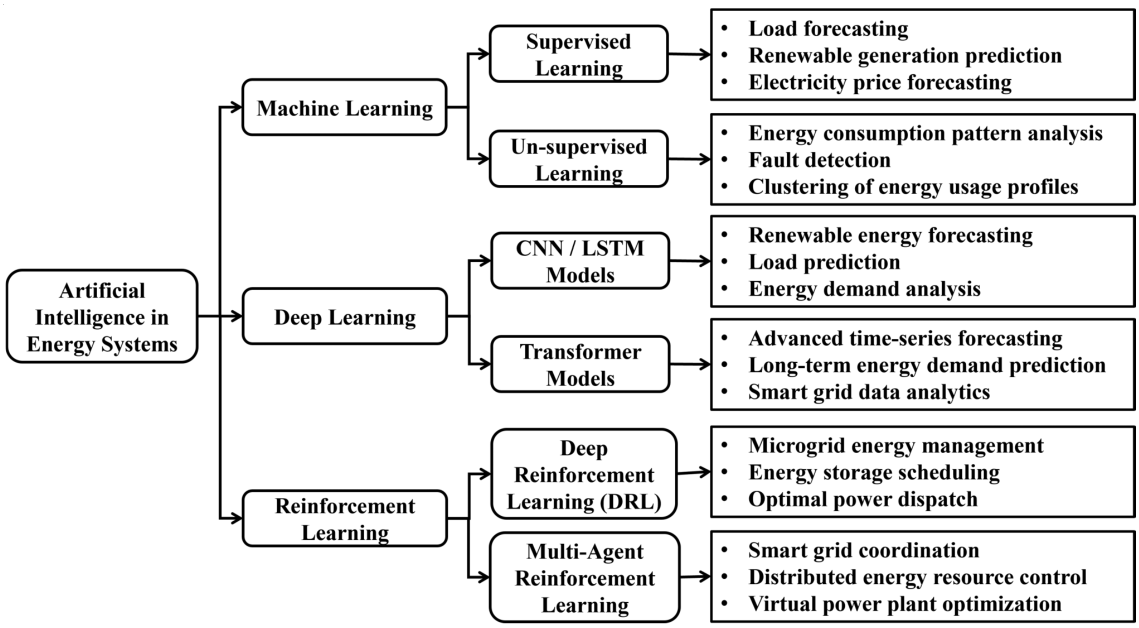

Figure 2. Taxonomy of Artificial Intelligence Methods in Energy Systems

4. EMS Framework and AI applications in Smart Grids

Modern EMS are designed to coordinate multiple components within smart power systems including generation units, storage devices, and consumer loads. Figure3 presents the overall classification of EMS functionalities in smart power systems. On the utility side, EMS frameworks focus on load research, load shaping, and operational monitoring to ensure efficient electricity distribution. AI algorithms assist utilities in analyzing consumption patterns and optimizing load balancing strategies

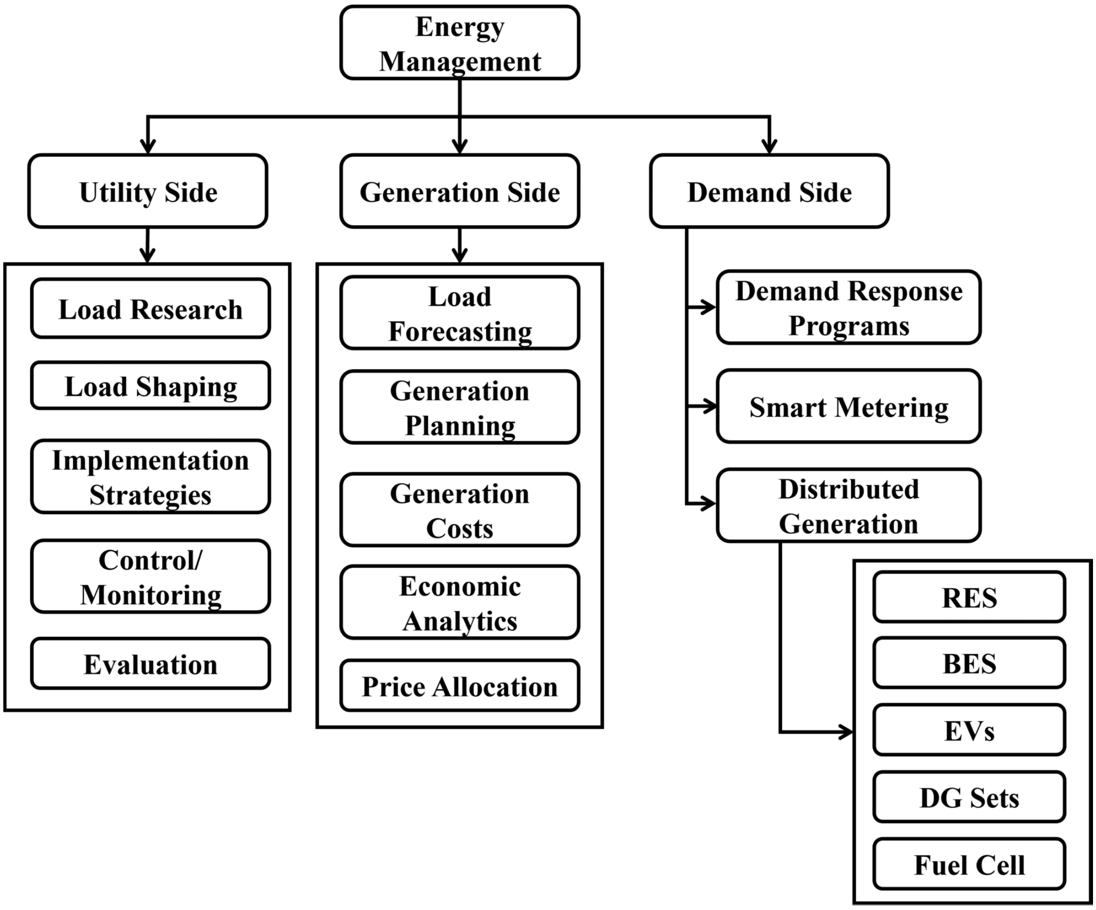

Figure 3. Overall Classifications of Energy Management Systems in Smart Power Systems

The generation side involves generation planning, economic dispatch, and electricity price allocation. AI-based predictive models are used to forecast renewable energy output and optimize generation schedules. The demand side represents a critical component of modern EMS architectures. Demand response programs, smart metering infrastructure, and distributed energy resources are integrated to improve grid flexibility. Technologies such as battery energy storage systems, electric vehicles, and distributed generators enable dynamic energy management strategies. AI-driven EMS platforms facilitate coordination among these components by enabling predictive analytics, automated decision-making, and real-time control mechanisms. AI technologies have been applied across multiple operational layers of smart grid infrastructures. In the generation sector, AI algorithms are used for generator scheduling, renewable resource planning, and efficiency optimization. Machine learning techniques enable accurate forecasting of renewable energy output, which is essential for maintaining grid stability. In transmission systems, AI-driven tools assist in grid planning, loss identification, and fault detection. Advanced anomaly detection algorithms can identify transmission line faults and initiate corrective actions in real time. Energy Management Systems (EMS) play a crucial role in coordinating generation resources, managing electricity demand, and optimizing grid operations. As illustrated in Fig. 3, EMS frameworks typically operate across three key domains: the utility side, generation side, and demand side. AI technologies are increasingly deployed within these domains to support load forecasting, generation planning, smart metering, demand response programs, and distributed generation management. Distribution systems benefit from AI-based monitoring techniques that enable voltage optimization, equipment health monitoring, and fault restoration. These capabilities significantly enhance the reliability of electricity distribution networks. Demand-side management represents another important application area where AI technologies support load forecasting, demand response programs, and dynamic pricing strategies.

5. Machine Learning Workflow in Energy Forecasting

AI-based forecasting models follow a structured development process involving data collection, model training, parameter tuning, and performance evaluation. Figure 4 illustrates the typical workflow of machine learning models used in energy forecasting. Historical datasets are divided into training and testing datasets. Learning algorithms are applied to extract patterns from training data, and model parameters are optimized through tuning procedures.

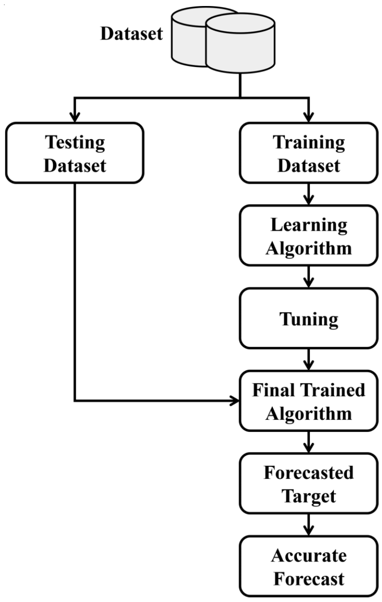

Figure 4. Workflow of forecasting using Artificial Intelligence

The trained models are then used to forecast energy demand or generation output. Performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and prediction accuracy are used to evaluate the performance of forecasting models.

6. AI-Optimised Battery Energy Storage Systems

The integration of green energy sources into conventional electrical systems becomes feasible in a significant way by incorporating energy storage devices. However, efficient management of battery storage requires sophisticated optimisation techniques due to uncertain electricity prices, variable renewable generation, and battery degradation characteristics. Artificial intelligence methods, particularly machine learning and reinforcement learning, have been applied to optimise battery charging and discharging strategies. AI-based control systems can analyse historical market prices, demand patterns, and renewable generation forecasts to determine optimal operating schedules. One key application is energy arbitrage, where batteries store electricity during low-price periods and discharge during high-price periods. AI algorithms improve arbitrage strategies by predicting future price fluctuations more accurately than conventional forecasting methods. AI has also been used to improve battery health management. Machine learning models can estimate battery state-of-charge and state-of-health with higher accuracy, enabling optimal utilisation while preventing degradation. Additionally, AI-driven battery management systems can support grid services, including frequency regulation, peak shaving, and renewable energy smoothing. These services improve overall grid stability while increasing the economic value of energy storage systems.

7. Results and Discussion

The efficacy of various machine learning algorithms used for short-term load forecasting inside the energy management system is assessed in this section. The models were developed using historical electricity demand data, and their forecasting accuracy was assessed using two commonly adopted performance indicators: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

These evaluation metrics measure the difference between the predicted load values produced by the models and the corresponding actual load observations. Figure 5 presents a visual comparison between the measured load values and the forecasted outputs generated by the trained models. The plot indicates that the predicted load trend closely aligns with the actual load variations across the dataset, suggesting that the models are capable of effectively capturing the underlying patterns in electricity demand behavior. Although small deviations can be observed at certain sample points, the overall prediction trend remains consistent with the actual load variations. This indicates that the machine learning models successfully capture the underlying patterns in electricity demand data.

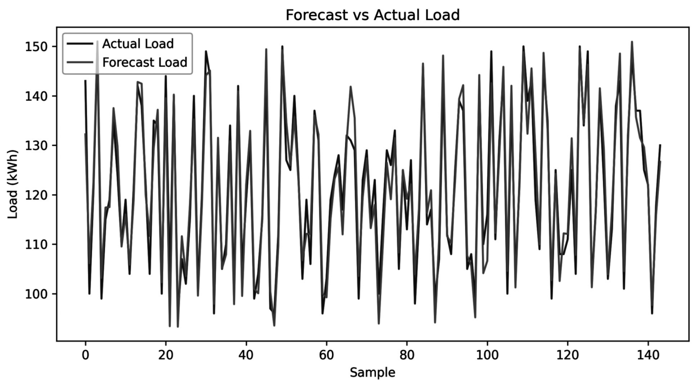

Figure 5. Graphical representation of Forecasted Load vs Actual Load

To quantitatively evaluate the forecasting accuracy, five machine learning models were tested, including Gradient Boosting, Linear Regression, Random Forest, K-Nearest Neighbors (KNN), and Decision Tree algorithms. Table 3 summarizes the performance of these models in terms of MAE and RMSE values. The results indicate that the Gradient Boosting model achieved the best performance, with the lowest MAE value of 2.381952% and RMSE value of 3.028949%. This suggests that Gradient Boosting provides the most accurate predictions among the tested models. The superior performance of this model can be attributed to its ensemble learning approach, which combines multiple weak learners to improve predictive accuracy and reduce model bias. The Linear Regression model also performed well, achieving an MAE of 2.592721% and RMSE of 3.153108%. Despite being a simple statistical model, it demonstrated reasonable forecasting capability for the given dataset. Similarly, the Random Forest model, another ensemble learning method, produced competitive results with an MAE of 2.520256% and RMSE of 3.184522%. This model effectively captures nonlinear relationships within the dataset through multiple decision trees. The K-Nearest Neighbors (KNN) model also produced acceptable results with an MAE of 2.518556% and RMSE of 3.282102%. However, its performance was slightly lower than that of Gradient Boosting and Random Forest due to its dependence on local data patterns and sensitivity to feature scaling. Among the evaluated models, the Decision Tree model exhibited the lowest forecasting accuracy, with an MAE of 3.350278% and RMSE of 4.125928%. This relatively higher error rate may result from the model's tendency to overfit training data, leading to reduced generalization capability when applied to unseen test data.

Table 3. Comparison of error metrices for various machine learning techniques applied

Sl No.	ML Model	MAE (%)	RMSE (%)
1	Gradient Boosting	2.381952	3.028949
2	Linear Regression	2.592721	3.153108
3	Random Forest	2.520256	3.184522
4	KNN	2.518556	3.282102
5	Decision Tree	3.350278	4.125928

Overall, the comparative analysis demonstrates that ensemble learning methods such as Gradient Boosting and Random Forest provide superior performance for load forecasting tasks in energy management systems. These models effectively capture complex nonlinear relationships in electricity demand data, enabling more accurate predictions compared with traditional machine learning algorithms. Accurate load forecasting plays a crucial role in smart grid operation, demand response programs, and optimal energy scheduling, thereby improving the efficiency and reliability of modern energy management systems.

8. Conclusion

Artificial Intelligence has become a key enabling technology for transforming modern power systems into intelligent and sustainable energy networks. This review examined the role of AI techniques including machine learning, deep learning, and reinforcement learning in addressing the challenges associated with renewable energy integration, smart grid management, and energy optimization. The analysis demonstrates that AI-based energy management systems significantly improve forecasting accuracy, operational efficiency, and grid reliability compared with conventional optimization approaches. The study highlighted several important application areas including load forecasting, renewable energy prediction, demand response programs, microgrid optimization, and battery energy storage management. AI-driven predictive analytics and automated control strategies enable efficient coordination of distributed energy resources, which is essential for maintaining stability in modern smart grids. Furthermore, the integration of enabling technologies such as big data analytics, Internet of Things (IoT), and cloud computing has accelerated the development of intelligent energy management platforms. Despite these advancements, several challenges remain in the deployment of AI-based energy management systems. Issues related to data availability, cybersecurity risks, computational complexity, and model interpretability must be addressed to ensure reliable and secure operation of AI-driven smart grids. Future research should focus on developing explainable AI models, hybrid optimization frameworks, and scalable AI architectures capable of supporting large-scale energy systems.

Overall, the continued development of artificial intelligence technologies will play a crucial role in enabling resilient, efficient, and sustainable energy infrastructures that support global decarbonization and energy transition goals.

9. Challenges and Future Research Directions

Despite the promising benefits of AI technologies in energy management, several challenges remain. One major challenge is the availability and quality of energy data required for training AI models. In many regions, energy datasets are incomplete or inconsistent, which limits the effectiveness of data-driven algorithms. Another challenge involves cybersecurity risks associated with AI-enabled smart grid infrastructures. As power systems become increasingly digitized, they become more vulnerable to cyber attacks targeting data integrity and system control mechanisms. Computational complexity also represents a challenge for large-scale AI applications in energy systems. Advanced deep learning models require significant computational resources, which may limit their deployment in real-time grid operations. Future research should focus on developing explainable AI models that improve transparency in decision-making processes. Additionally, hybrid AI frameworks combining optimization techniques with machine learning models may further enhance energy system performance.

References :

Ahmed, R., Sreeram, V., Mishra, Y., & Arif, M. D. (2020). A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization. *Renewable and Sustainable Energy Reviews*, *124*, 109792. https://doi.org/10.1016/j.rser.2020.109792

Arwa, E. O., & Folly, K. A. (2020). Reinforcement Learning Techniques for Optimal Power Control in Grid-Connected Microgrids: A Comprehensive Review. *IEEE Access*, *8*, 208992–209007. https://doi.org/10.1109/ACCESS.2020.3038735

Bose, D., Dolui, C., Das, S., Das, B., Reddy, V. S., & Chanda, C. K. (2024). Power System Resiliency Assessment Aided by Machine Learning Techniques. *2024 IEEE Calcutta Conference (CALCON)*, 1–6. https://doi.org/10.1109/CALCON63337.2024.10914219

Cao, D., Hu, W., Zhao, J., Zhang, G., Zhang, B., Liu, Z., Chen, Z., & Blaabjerg, F. (2020). Reinforcement Learning and Its Applications in Modern Power and Energy Systems: A Review. *Journal of Modern Power Systems and Clean Energy*, *8*(6), 1029–1042. https://doi.org/10.35833/MPCE.2020.000552

Chen, W., Qiu, Y., Feng, Y., Li, Y., & Kusiak, A. (2021). Diagnosis of wind turbine faults with transfer learning algorithms. *Renewable Energy*, *163*, 2053–2067. https://doi.org/10.1016/j.renene.2020.10.121

Fathi, S., Srinivasan, R., Fenner, A., & Fathi, S. (2020). Machine learning applications in urban building energy performance forecasting: A systematic review. *Renewable and Sustainable Energy Reviews*, *133*, 110287. https://doi.org/10.1016/j.rser.2020.110287

Foruzan, E., Soh, L.-K., & Asgarpoor, S. (2018). Reinforcement Learning Approach for Optimal Distributed Energy Management in a Microgrid. *IEEE Transactions on Power Systems*, *33*(5), 5749–5758. https://doi.org/10.1109/TPWRS.2018.2823641

Hua, W., Chen, Y., Qadrdan, M., Jiang, J., Sun, H., & Wu, J. (2022). Applications of blockchain and artificial intelligence technologies for enabling prosumers in smart grids: A review. *Renewable and Sustainable Energy Reviews*, *161*, 112308. https://doi.org/10.1016/j.rser.2022.112308

Hudec, M., & Smutny, Z. (2022). Ambient Intelligence System Enabling People With Blindness to Develop Electrotechnical Components and Their Drivers. *IEEE Access*, *10*, 8539–8565. https://doi.org/10.1109/ACCESS.2022.3144109

Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., & Zhang, Y. (2019). Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network. *IEEE Transactions on Smart Grid*, *10*(1), 841–851. https://doi.org/10.1109/TSG.2017.2753802

Leukel, J., González, J., & Riekert, M. (2021). Adoption of machine learning technology for failure prediction in industrial maintenance: A systematic review. *Journal of Manufacturing Systems*, *61*, 87–96. https://doi.org/10.1016/j.jmsy.2021.08.012

L'Heureux, A., Grolinger, K., & Capretz, M. A. M. (2022). Transformer-Based Model for Electrical Load Forecasting. *Energies*, *15*(14), 4993. https://doi.org/10.3390/en15144993

Lu, R., & Hong, S. H. (2019). Incentive-based demand response for smart grid with reinforcement learning and deep neural network. *Applied Energy*, *236*, 937–949. https://doi.org/10.1016/j.apenergy.2018.12.061

Majumder, S., Dong, L., Doudi, F., Cai, Y., Tian, C., Kalathil, D., Ding, K., Thatte, A. A., Li, N., & Xie, L. (2024). Exploring the capabilities and limitations of large language models in the electric energy sector. *Joule*, *8*(6), 1544–1549. https://doi.org/10.1016/j.joule.2024.05.009

Massaoudi, M., Abu-Rub, H., Refaat, S. S., Chihi, I., & Oueslati, F. S. (2021). Deep Learning in Smart Grid Technology: A Review of Recent Advancements and Future Prospects. *IEEE Access*, *9*, 54558–54578. https://doi.org/10.1109/ACCESS.2021.3071269

Miraftabzadeh, S. M., Longo, M., Foiadelli, F., Pasetti, M., & Igual, R. (2021). Advances in the Application of Machine Learning Techniques for Power System Analytics: A Survey. *Energies*, *14*(16), 4776. https://doi.org/10.3390/en14164776

Mostafa, N., Ramadan, H. S. M., & Elfarouk, O. (2022). Renewable energy management in smart grids by using big data analytics and machine learning. *Machine Learning with Applications*, *9*, 100363. https://doi.org/10.1016/j.mlwa.2022.100363

Pirie, C., Kalutarage, H., Hajar, M. S., Wiratunga, N., Charles, S., Madhushan, G. S., Buddhika, P., Wijesiriwardana, S., Dimantha, A., Hansamal, K., & Pathiranage, S. (2024). *A Survey of AI-Powered Mini-Grid Solutions for a Sustainable Future in Rural Communities*. http://arxiv.org/abs/2407.15865

Ranjbar, H., Hosseini, S. H., & Zareipour, H. (2020). Hurricane Induced Damage Scenario Determination of Transmission Network Components. *2020 IEEE Power & Energy Society General Meeting (PESGM)*, 1–5. https://doi.org/10.1109/PESGM41954.2020.9282011

Shajari, Z., Guerrero, J. M., & Hossein Javidi, M. (2020). Operation Management for Next-Generation of MVDC Shipboard Microgrids. *2020 International Conference on Smart Energy Systems and Technologies (SEST)*, 1–6. https://doi.org/10.1109/SEST48500.2020.9203288

Shams, M. H., Niaz, H., Hashemi, B., Jay Liu, J., Siano, P., & Anvari-Moghaddam, A. (2021). Artificial intelligence-based prediction and analysis of the oversupply of wind and solar energy in power systems. *Energy Conversion and Management*, *250*, 114892. https://doi.org/10.1016/j.enconman.2021.114892

Trivedi, R., & Khadem, S. (2022). Implementation of artificial intelligence techniques in microgrid control environment: Current progress and future scopes. *Energy and AI*, *8*, 100147. https://doi.org/10.1016/j.egyai.2022.100147

Vázquez-Canteli, J. R., & Nagy, Z. (2019). Reinforcement learning for demand response: A review of algorithms and modeling techniques. *Applied Energy*, *235*, 1072–1089. https://doi.org/10.1016/j.apenergy.2018.11.002

Wang, H., Lei, Z., Zhang, X., Zhou, B., & Peng, J. (2019). A review of deep learning for renewable energy forecasting. *Energy Conversion and Management*, *198*, 111799. https://doi.org/10.1016/j.enconman.2019.111799

Zhang, S., Wang, Y., Liu, M., & Bao, Z. (2018). Data-Based Line Trip Fault Prediction in Power Systems Using LSTM Networks and SVM. *IEEE Access*, *6*, 7675–7686. https://doi.org/10.1109/ACCESS.2017.2785763

Zhou, S., Hu, Z., Gu, W., Jiang, M., Chen, M., Hong, Q., & Booth, C. (2020). Combined heat and power system intelligent economic dispatch: A deep reinforcement learning approach. *International Journal of Electrical Power & Energy Systems*, *120*, 106016. https://doi.org/10.1016/j.ijepes.2020.106016

Assessing Regional Disparities in Universal Health Coverage in West Bengal: A District-Level Composite Index Analysis

Jayanta Das[1] and K.M. Agrawal[2]

ABSTRACT

Reducing regional disparities is crucial for achieving Universal Health Coverage in India. The sub-state level variations in service delivery, disease burden and financial protection are not well documented in West Bengal.

The purpose of this study is to create a District-level composite index for comparing the performance of health systems and estimating regional variations in coverage, service capacity, and financial protection by districts in West Bengal.

A composite index was developed based on the indicators at the district level and grouped into four domains: reproductive, maternal, newborn and child health (RMNCH), infectious diseases, non-communicable diseases (NCD) and service capacity and access, as well as financial protection indicators. Indicators were rescaled using the min-max approach with the reverse approach used for negative indicators (e.g. out-of-pocket expenditure). Scores for each district were calculated based on the average values of normalized indicators, and then aggregated into an overall composite score for each district. The composite index values were used to categorize districts on performance.

There were considerable inter-district differences with the composite index ranging from about 0.32 to 0.71. High performing districts were Birbhum, Jalpaiguri, Darjeeling, South 24 Parganas and Cooch Behar while Purba Medinipur, Paschim Barddhman, Hooghly, Purulia and Paschim Medinipur were among the poor performing districts. Disparities in service capacity, the level of RMNCH coverage, NCD management, and financial protection were substantial drivers of disparities at the district level. High OOP and low insurance coverage were identified as a significant aspect of financial protection, contributing to inequality.

There was a significant inter-district variation in composite index scores which ranged from 0.32 to 0.71. The top-performing districts were Birbhum, Jalpaiguri, Darjeeling, South 24 Parganas and Cooch Behar while the worst districts were Purba Medinipur, Paschim Bardhaman, Hooghly, Purulia and Paschim Medinipur. The most heterogeneity was found in the areas of financial protection and service capacity, which are likely to be major contributors to district-level inequality. One of the factors that contribute to inequality is financial protection, specifically linked to high OOP and low insurance coverage. The results for the northern and deltaic districts were better than the western districts.

The outcome shows that there are considerable differences in performance of health systems at the district level across West Bengal. Increasing service capacity, improving RMNCH use, strengthening NCD services, and strengthening financial protection mechanisms is a must to address inequities and accelerate progress towards UHC.

Keywords: *Universal health coverage; Composite index; Health inequality; District-level analysis; West Bengal*

[1]State RMNCHA Coordinator, West Bengal State Technical Support Unit, State Family Welfare Bureau, Swasthya Bhawan, W.B
[2]Director, IISWBM, Kolkata

1. Introduction

Universal health Coverage (UHC) has become a key goal of health systems around the globe and is a critical part of Sustainable Development Goal (SDG) 3.8. UHC aims to provide everyone with access to care they need, including health promotion, disease prevention, treatment, rehabilitation and palliative care, without facing financial hardship. Service coverage and financial risk protection are the two major indicators of progress towards UHC recommended by the World Health Organization (WHO) and the World Bank. While much has been done around the world to incr ease access to basic health care services, progress has been uneven both within and across countries. National averages can mask having very different levels of health service access across the country, including socioeconomic inequalities in health service access, use, quality, and financial protection, resulting in less equitable health outcomes and progress towards UHC.

Significant efforts have been made to enhance the health system in India with several major policy initiatives like the National Health Mission (NHM), Ayushman Bharat, scaling up primary healthcare services programme, and the involvement of public resources in maternal and child health programme. The reforms have resulted in better institutional deliveries, immunisation coverage, control of communicable diseases and some health outcomes. Despite this, there remain deep disparities between states and districts due to variations in socioeconomic conditions, demographic, health systems, work force availability, governance capacity, and financial protection systems. Research using the National Family Health Survey (NFHS), the Health Management Information System (HMIS) and NITI Aayog Health Index has consistently shown that the benefits of health have not been even across the country. Therefore, concluding that the health system is effective based on data from the national or state level level may mask significant local variation that needs to be focused on in policy action.

Assessment at the district level is gaining importance in India's decentralised health system where planning, implementation and resource allocation is done largely at the district level. Globally, districts vary widely in size, populations, disease burden, geographic accessibility, health system infrastructure, health care human resources and socio-economic conditions which all affect health system performance. It helps to recognize these differences in order to identify communities where services are not being delivered, target resources, improve monitoring and oversight, and tailor interventions. These composite indices have become the preferred means of summarising multidimensional health system performance, and are accepted as useful tools to consolidate multiple indicators into a single summary measure that enables comparison between administrative units. The WHO-World Bank monitoring of UHC also calls for multidimensional measurement, with service coverage indicators and financial protection indicators, to get a comprehensive picture of health system performance.

In the last one decade, West Bengal has made significant strides in various health outcomes such as enhancing maternal and child health care services, advancing immunization rates, improving communicable disease control, and increasing access to health services. There is, however, significant disparities in service availability, distribution of health workers, burden of disease, utilization of services and financial risk protection between districts. Focusing on individual programmes, health infrastructure, accessibility or selected health indicators, the previous studies conducted in West Bengal have been mainly of this nature with district performance generally being evaluated through a set of fragmented indicators rather than an integrated UHC framework. Current evidence thus only brings a partial picture of regional inequalities and has limited capacity to account for the synergies between service coverage, health system capacity and financial protection at the district level with regard to health system performance. As a result, there is still a huge gap in evidence on overall assessment of district level achievements on UHC in West Bengal.

To help fill this gap, the current research proposes a district-level composite indicator of health system performance based on indicators linked to WHO-World Bank expanded UHC monitoring framework. The index combines the five critical domains of Reproductive, Maternal, Newborn and Child Health (RMNCH), infectious diseases, non-communicable diseases, service capacity and access, and financial protection to assess health systems in the districts of West Bengal in a multidimensional way. The analysis of regional disparities and ranking of district performance provide evidence-based information to inform planning for equity, optimal resource allocation, and targeted policy interventions. The results will help the pertinent literature on sub-national monitoring of UHC and offer helpful lessons for improving the district health system in West Bengal, and for decentralized health systems in India.

2. Literature Review

2.1 Sub-national inequalities in Universal Health Coverage

There is a large literature documenting that there are often large sub-national variations in health system performance as evidenced at the national and state level. Gwatkin et al. (2007) and Victora et al. (2012) have shown that an increase in the overall level of health services coverage does not need to come at the cost of reducing inequality across clusters of area or socioeconomic characteristics, and in fact, it can be done while maintaining inequalities. Likewise, Balarajan et al. (2011) found income, geography, gender and social disadvantage to be key factors in inequitable access to health services in LMICs. The results underscore the value of exploring the performance of health systems at a subnational level to uncover populations that are still unattained.

2.3 Evidence from India

The health service coverage and financial protection for health services as well as infrastructure varies significantly across districts and states in India, as reflected in several national evaluations. The National Family Health Survey (NFHS-5) results show that there is continuing inequity in access to maternal care at the district level, along with low rates of vaccination, sanitation, and non-communicable diseases (IIPS & ICF, 2021). There is also wide variation in the availability of health infrastructure, rural health workforce and health services across the states and UTs as revealed by the NITI Aayog Health Index and the Rural Health Statistics (NITI Aayog, 2021; MoHFW, 2022). In addition, despite recent policy efforts, OOP spending remains high and constitutes a significant share of financing of health services, as shown by NHA.

2.4 Composite indices for assessing health system performance

The use of composite indices has gained widespread acceptance as a good measure for the performance of multidimensional health systems. The WHO - World Bank monitoring framework for UHC combines indicators of services coverage and financial protection for monitoring progress towards UHC (WHO and World Bank, 2023). Boerma et al. (2014) suggested a common framework for the periodic assessment of UHC at the national and international level and Hogan et al. (2018) calculated the UHC Service Coverage Index based on the availability and utilization of key health services. Global Burden of Disease (GBD) UHC Collaborators went further in the development of the approaches; they came up with a good coverage index to compare health systems across countries and over time. Moreover, Kruk et al. (2018) suggested that in addition to expanding access to services, it was important that health systems would provide quality services that would help achieve health outcomes if UHC were to be realized. This is in line with these methods, as has been found to be the case with composite indices like NITI Aayog Health Index and the Primary Health Care Performance Initiative (PHCPI) that have proven to be useful for monitoring performance, identifying gaps and providing evidence for health planning.

2.5 Evidence from West Bengal

There are also regional differences in access to health care within the state of West Bengal, as evidenced at the district level. There was a marked disparity between different districts in terms of the quality and availability of health care, as the infrastructure and socioeconomic status of the districts varied (Majumder et al., 2023). On a more micro-level, Barman and Roy (2021) showed significant disparities in the availability of health management facilities and services in the Block wise level of Cooch Behar, using composite index approach, and Saha (2025) revealed that there is significant block-wise variation in health infrastructure, health manpower dispersion and utilization of health services in Dakshin Dinajpur district. While these studies offer good information on regional variations, these studies generally examine only one dimension of health care and leave out a fuller measurement of the performance of the health system in the context of UHC.

2.6 Knowledge gap

However, integration of service coverage, health system capacity and financial protection at the district level remains very sparse in West Bengal despite the growing focus on UHC. Previous studies tend to assess individual programmes or infrastructure or selected health indicators and do not apply a multidimensional assessment, using the WHO-World Bank framework of UHC. Given this, the present study constructs a district level composite index using five domains (RMNCH, infectious diseases, non-communicable diseases, service capacity/access, and financial protection) to come up with a comprehensive measure of health system performance and regional inequalities in West Bengal.

3. Methods

3.1 Study design

This study is conducted with a cross sectional analytical design with secondary data at the district level, which are used to analyze the variation in health system performance across West Bengal.

3.2 Data sources

Secondary data were gathered from various sources such as national representative surveys, administrative reports and programme records. The key sources included were the National Family Health Survey (NFHS-5), Rural Health Statistics, Health Management Information System (HMIS) and other relevant government publications. Data at the district level were used for analysis, but only the most up to date and reliable data available were used.

3.3 Indicator selection

A total of sixteen indicators were selected to construct the composite index, guided by the tracer framework outlined in the World Health Organization-World Bank Tracking Universal Health Coverage: 2023 Global Monitoring Report. The selection aimed to capture key dimensions of UHC, including service coverage, health outcomes, system capacity, and financial protection.

Indicators were chosen based on three criteria: (i) relevance to the UHC framework, (ii) availability and consistency of district-level data, and (iii) contextual suitability for West Bengal. The selected indicators were grouped into five domains:

- Reproductive, Maternal, Newborn and Child Health (RMNCH)
- Infectious Diseases (ID)
- Non-Communicable Diseases (NCDs)

- Service Capacity and Access
- Financial Protection

This classification was intended to provide a balanced and multidimensional assessment of district-level health system performance. The domain specific indicators are presented in Table 1

Table 1. The Domain specific Indication

Domain	**Indicator**	**Type**
Reproductive, maternal, new born and child health (RMNCH)	Any modern method	Positive
	4 antenatal care visits	Positive
	Children received 3 doses of Penta or DPT vaccine	Positive
	Children with fever or symptoms of ARI taken to a health facility or health provider	Positive
Infectious diseases (ID)	TB patients put on treatment	Positive
	ART Coverage of HIV PW	Positive
	Improved sanitation facility	Positive
	Improved drinking-water source	Positive
Non-communicable diseases (NCD)	Diabetes among Adults (age 15 years and above)Blood sugar level - high or very high (>140 mg/dl) or taking medicine to control blood sugar level	Negative
	Hypertension among Adults (age 15 years and above)- Elevated blood pressure (Systolic ≥140 mm of Hg and/or Diastolic ≥90 mm of Hg) or taking medicine to control blood pressure	Negative
	Non use of Tobacco among Adults (age 15 years and above)	Positive
Service capacity and access	Funtional Delivery points (Public Health)	Positive
	Hospital bed density (Public Health) (Bed / 10000 population)	Positive
	Health worker density (HW/10000 Pop)	Positive
Financial protection	Average out-of-pocket expenditure per delivery in a public health facility (Rs.)	Negative
	Households with any usual member covered under a health insurance/financing scheme	Positive

3.4 Normalization and Index Construction

Indicators were normalized using min-max scaling:

Positive indicators:

[(X_i - X_{min}) / (X_{max} - X_{min})]

Negative indicators:

[(X_{max} - X_i) / (X_{max} - X_{min})]

Domain scores were calculated as arithmetic means of constituent indicators. The overall composite index was computed as the mean of the domain scores.

3.5 District classification

Based on composite index scores, districts were classified into three categories-high, medium, and low performance. Classification thresholds were determined using a distribution-based approach to facilitate relative comparison across districts.

3.6 Statistical Analysis

To improve analytical rigor, the study assessed:

- Rank-order district comparisons and classification
- Mean, standard deviation, and range of composite index score
- Coefficient of variation (CV) to evaluate relative dispersion
- Domain wise performance
- Regional grouping analysis by administrative division

4. Results

4.1 District-level composite index of health system performance

District-level composite index of health system performance is presented in Table 2.

Table 2. District level Composite Index of Health System Performance

District	Composite Index
Birbhum	0.71
Jalpaiguri	0.69
Darjeeling	0.66
South 24 Parganas	0.65
Coochbehar	0.63
Purba Bardhman	0.57
Maldah	0.57
Bankura	0.57
Uttar Dinajpur	0.56
Dakshin Dinajpur	0.55
Murshidabad	0.54
North 24 Parganas	0.53
Howrah	0.49
Kolkata	0.48
Nadia	0.48
Paschim Medinipur	0.45
Purulia	0.43
Hooghly	0.43
Paschim Bardhaman	0.40
Purba Medinipur	0.32

The composite index indicated significant inter-district variation in overall health system performance throughout West Bengal.

4.2 District classification based on composite index

Districts were classified into three performance categories based on composite index values:

- High-performing districts (≥0.60): Birbhum, Jalpaiguri, Darjeeling, South 24 Parganas, and Cooch Behar
- Moderate-performing districts (0.45-0.59): Majority of districts, showing mixed domain performance
- Low-performing districts (<0.45): Purba Medinipur, Paschim Bardhaman, Hooghly, Purulia, and Paschim Medinipur

This classification highlights a group of districts that require priority attention.

Table 3. Descriptive Statistics of Composite Index

Mean	SD	Min	Max	Range	CV
0.53	0.10	0.32	0.71	0.39	0.19

Table 3 presents the descriptive statistics of the composite index across districts. The composite index scores across districts ranged from 0.32 to 0.71, with a mean of 0.53 and a standard deviation of 0.10, indicating a moderate level of variation in health system performance across the state. The range of 0.39 suggests a substantial gap between the highest- and lowest-performing districts, pointing to notable disparities in service coverage, system capacity, and financial protection. Furthermore, the coefficient of variation (0.19) indicates a moderate level of relative dispersion, suggesting noticeable but not extreme inequality in district-level health system performance. Overall, these findings reflect significant inter-district inequality in health system performance within West Bengal.

4.3 Domain-wise performance

Reproductive, maternal, newborn, and child health (RMNCH)

Districts that achieved higher composite scores demonstrated consistently superior performance in antenatal care utilization, institutional deliveries, and child immunization coverage. In contrast, lower-performing districts showed deficiencies in maternal service utilization and early childhood care indicators.

Infectious diseases

The performance in controlling infectious diseases was relatively consistent across districts, especially regarding tuberculosis treatment and HIV service coverage. However, indicators related to sanitation exhibited greater variability and contributed to the differences observed between districts.

Non-communicable diseases (NCDs)

The NCD sector exhibited significant disparities, especially regarding screening coverage and the management of hypertension and diabetes. Districts that performed poorly in NCDs contributed disproportionately to reduced overall com posite scores.

Service capacity and access

A considerable variation was noted in service capacity indicators, such as the availability of health workforce, access to facilities, and service readiness. Districts with lower composite scores typically had less robust infrastructure and limited human resource availability.

Financial protection

Financial protection surfaced as a crucial differentiating factor. Districts with higher out-of-pocket expenses for delivery care and lower insurance coverage recorded markedly lower composite scores. In contrast, districts with enhanced insurance coverage and reduced financial burden exhibited superior overall performance.

Table 4. Domain wise composite score across districts

Indicators	RMNCHA	ID	NCD	Service capacity and access	Financial indicator
Bankura	0.44	0.74	0.47	0.48	0.70
Purba Medinipur	0.22	0.65	0.24	0.41	0.06
Purulia	0.13	0.50	0.48	0.38	0.66
Paschim Medinipur	0.38	0.70	0.41	0.45	0.31
Birbhum	0.81	0.79	0.67	0.39	0.88
Hooghly	0.46	0.86	0.43	0.25	0.14
Paschim Bardhaman	0.45	0.54	0.64	0.08	0.28
Purba Bardhman	0.58	0.63	0.63	0.22	0.79
Dakshin Dinajpur	0.61	0.72	0.52	0.43	0.49
Maldah	0.47	0.70	0.67	0.41	0.60
Murshidabad	0.61	0.72	0.61	0.30	0.48
Uttar Dinajpur	0.53	0.66	0.87	0.43	0.31
Darjeeling	0.76	0.48	0.85	0.70	0.51
Jalpaiguri	0.78	0.80	0.73	0.45	0.70
Coochbehar	0.50	0.93	0.67	0.37	0.67
Howrah	0.47	0.66	0.69	0.25	0.38
Kolkata	0.35	0.65	0.32	0.67	0.43
Nadia	0.47	0.90	0.44	0.38	0.19
North 24 Parganas	0.59	0.90	0.50	0.15	0.50
South 24 Parganas	0.60	0.85	0.68	0.40	0.71

Domain-wise analysis reveals uneven performance across districts, suggesting that disparities are not uniformly distributed across components of the health system. While the infectious disease domain shows relatively consistent and higher scores across most districts, greater variability is evident in RMNCH and NCD indicators. More pronounced disparities are observed in service capacity and access, with substantial differences in infrastructure and workforce availability across districts. The financial protection domain exhibits the widest variation, with some districts showing very low coverage, indicating that financial risk protection remains a key driver of overall inequality in health system performance.

The regional pattern is very clear from Table 5. There were a number of districts in the northern and delta regions that did very well, and districts in the western belt that did consistently very poorly. This is a sign of geographic variation of access to health facilities, infrastructure and financial protection.

The factors that cause variation will be identified.

The disparities found between districts can be attributed to three main factors:

1. Capability of the health services, including access to health staff and facilities

2. Services provided by RMNCH were utilized

3. Financial cover, particularly out-of-pocket costs and insurance cover

Districts that are underperforming generally display shortcomings in more than one of these areas.

4.4 Regional pattern of inequality

Table 5. Region wise composite index

Sl. No.	Division	Indicators	Composite Index
1	Medinipur	Bankura	0.57
14		Purba Medinipur	0.32
15		Purulia	0.43
20		Paschim Medinipur	0.45
2	Burdwan	Birbhum	0.71
6		Hooghly	0.43
18		Paschim Bardhaman	0.40
19		Purba Bardhman	0.57
3	Malda	Dakshin Dinajpur	0.55
10		Maldah	0.57
11		Murshidabad	0.54
17		Uttar Dinajpur	0.56
4	Jalpaiguri Division	Darjeeling	0.66
7		Jalpaiguri	0.69
8		Coochbehar	0.63
5	Presidency	Howrah	0.49
9		Kolkata	0.48
12		Nadia	0.48
13		North 24 Pgs	0.53
16		South 24 Pgs	0.65

4.5 Summary of findings

To sum up, the composite index shows that there is a considerable difference at the district level in terms of performance of the health systems in West Bengal. While some districts are doing well in multiple areas, a small number of districts still struggle with structural issues in service delivery, infrastructure and financial protection.

The findings provide empirical support to inform targeted district-level planning and allocation of resources to speed up progress in achieving UHC.

5. Discussion

This research takes a closer look at how well the health system is working in different parts of West Bengal, using a set of measures that line up with the idea of universal health coverage. What it found is that there are some big differences in how well the health system is working from one district to another. This means that even if the state as a whole seems to be doing okay, there are still some areas that are being left behind. On average, the health system in West Bengal is doing moderately well, but there's a big range in how well different districts are doing - some are doing really well, while others are struggling. This suggests that the health system is not evenly distributed across the state, and that some areas have better access to healthcare and financial protection than others.

A key insight from the analysis is that disparities are not uniformly distributed across domains. The infectious disease domain appears relatively more consistent across districts, which may reflect the long-standing prioritization of communicable disease control programmes and relatively standardized implementation mechanisms. In contrast, greater variability is observed in RMNCH and NCD indicators, suggesting differential access to maternal health services and uneven preparedness to address the growing burden of chronic diseases. This pattern is broadly consistent with the ongoing epidemiological transition, where health systems often remain more responsive to traditional public health challenges than to emerging non-communicable conditions.

More pronounced disparities are evident in service capacity and financial protection, which appear to act as critical determinants of overall district performance. The wide variation in service capacity indicators-such as workforce density, facility availability, and service readiness-suggests structural imbalances in health system infrastructure across regions. Districts with lower composite scores tend to have weaker health system foundations, limiting their ability to deliver essential services effectively. Similarly, the financial protection domain shows stark inequalities, with some districts experiencing significantly higher out-of-pocket expenditure and lower insurance coverage. This indicates that financial barriers remain a major constraint to equitable healthcare access, despite ongoing policy efforts to expand risk pooling and insurance coverage.

The district ranking further reinforces the presence of systematic disparities rather than random variation. Higher-performing districts such as Birbhum, Jalpaiguri, Darjeeling, and South 24 Parganas demonstrate relatively balanced performance across domains, suggesting more integrated and functional health systems. In contrast, lower-performing districts-including Purba Medinipur, Paschim Bardhaman, Hooghly, and Purulia-consistently lag across multiple dimensions, pointing to overlapping deficits in infrastructure, service utilization, and financial protection. This clustering of disadvantage indicates that underperformance is likely driven by structural constraints rather than isolated programmatic gaps.

The analysis also reveals a distinct regional pattern, with northern and deltaic districts generally performing better than those in the western belt. This geographic gradient may reflect historical differences in infrastructure development, population distribution, and accessibility. Western districts, which often have more challenging terrain and lower levels of socioeconomic development, appear to face compounded constraints in service delivery and health system capacity. Such spatial inequalities highlight the limitations of uniform policy approaches and underscore the need for geographically targeted interventions.

When we look at all the findings together, it's clear that West Bengal's progress towards Universal Health Coverage is not happening evenly. There are still some big differences in how the health system works, and these differences are affecting how well the system performs. While there have been some improvements in certain areas, like controlling infectious diseases, there are still some big gaps in the system's ability to provide services and protect people from financial problems when they get sick. This means that just trying to get more people covered by health services might not be enough - the government also needs to invest in things like buildings, equipment, staff, and ways to help people pay for healthcare so that everyone can get the care they need without going broke.

To improve healthcare, we need to focus on the areas that are struggling the most. This means giving more resources to the districts that are not doing well, making sure they have good primary healthcare, and getting the right people in the right places. We also need to make sure people are protected from high medical costs, so everyone can get the care they need without breaking the bank. One way to do this is by getting more people insured and reducing the amount they have to pay out of their own pockets. By keeping a close eye on how each district is doing and using that information to make decisions, we can make sure our healthcare system is working as well as it can. This will help us plan better and make sure everyone is held accountable for providing good care.

6. Strengths and Limitations

This study contributes to the literature by providing a multidimensional, district-level assessment of health system performance aligned with the UHC framework. By integrating indicators across service coverage, system capacity, and financial protection, it offers a more comprehensive perspective than single-indicator analyses. The use of normalized indicators and a composite index allows for systematic comparison across districts.

However, several limitations should be acknowledged. First, the analysis relies on secondary data sources, which may vary in quality and reference period. Second, the use of equal weighting across domains, while methodologically transparent, may not fully capture the relative importance of different indicators. Third, since this study uses data from only one point in time, it cannot show changes over time or establish cause-and-effect relationships. Finally, although the composite index helps compare districts, it may hide differences within districts and does not fully capture all local factors that influence health system performance.

7. Conclusion

Overall, the study highlights that achieving universal health coverage at the state level requires addressing deeply embedded district-level disparities. To effectively address these discrepancies, it is essential to implement targeted, equity-oriented interventions that strengthen service capacity, enhance financial protection, and improve access to vital health services.

The composite index formulated in this research serves as a valuable instrument for evidence-based planning, prioritization, and tracking progress towards universal health coverage at the district level.

Declarations

- Ethics approval and consent to participate: Not required (secondary data)
- Consent for publication: Not applicable
- Competing interests: None
- Funding: No funding received

References :

Balarajan, Y., Selvaraj, S., & Subramanian, S. V. (2011). *Health care and equity in India. Lancet, 377*(9764), 505-515. https://doi.org/10.1016/S0140-6736(10)61894-6

Barman, B., & Roy, R. (2021). Regional disparities of health care infrastructure in Koch Bihar District, West Bengal India. *Asian Journal of Research in Social Sciences and Humanities, 11*(8), 1-15. https://doi.org/10.5958/2249-7315.2021.00026.5

Gwatkin, D. R., Rutstein, S., Johnson, K., Suliman, E., Wagstaff, A., & Amouzou, A. (2007). Socio-economic differences in health, nutrition, and population within developing Countries: An Overview

Majumder, S., Roy, S., Bose, A., & Chowdhury, I. R. (2023). Understanding regional disparities in healthcare quality and accessibility in West Bengal, India: A multivariate analysis. *Regional Science Policy & Practice, 15*(5), 1086-1114. https://doi.org/10.1111/rsp3.12607

National Family Health Survey (NFHS-5). (n.d.). IIPS.

National Health Accounts Estimates for India (2017-18). Ministry of Health and Family Welfare. (2021). Government of India.

Niti. (2021). Health Index Round IV: Progress on health outcomes. Government of India.

Rural Health Statistics 2021-22. Government of India. (2022).

Saha, A. K. (2025). Disparities in Healthcare Delivery: A Quantitative Analysis of Inequalities in Healthcare Facilities, Workforce and Services in Dakshin Dinajpur District, West Bengal, India. *Int J Recent Sci Res, 16*(03), 157-164.

Socio-Economic Differences in Health, Nutrition, and Population Within Developing Countries: An Overview. (n.d.).

The world health report: Health systems financing-The path to universal coverage. (2010). World Health Organization.

Tracking universal health coverage: 2023 global monitoring report. (2023). o World Health Organization, & World Bank.

Victora, C. G., Barros, A. J. D., Axelson, H., Bhutta, Z. A., Chopra, M., França, G. V. A., Kerber, K., Kirkwood, B. R., Newby, H., Ronsmans, C., & Boerma, J. T. (2012). How changes in coverage affect equity in maternal and child health interventions in 35 Countdown to 2015 countries: an analysis of national surveys. *Lancet, 380*(9848), 1149-1156. https://doi.org/10.1016/S0140-6736(12)61427-5

Wagstaff, A., Flores, G., Hsu, J., Smitz, M.-F., Chepynoga, K., Buisman, L. R., van Wilgenburg, K., & Eozenou, P. (2018). Progress on catastrophic health spending in 133 countries: a retrospective observational study. The Lancet. *Global Health, 6*(2), e169-e179. https://doi.org/10.1016/S2214-109X(17)30429-1

Corporate Environmental Disclosure and Circular Economy Practices: An Evidence from Select Indian Companies

Anandi Sarkar Pyne[1]

ABSTRACT

The research explores the extent to which Indian businesses reveal about their environmental activities while following circular economy principles during their operations. The study draws its foundation from legitimacy theory together with stakeholder and institutional and agency theories to analyse how businesses present their sustainability efforts about resource management and waste disposal and environmental protection in developing market environments. The research depends on existing corporate documentation to build an Environmental Disclosure Index which uses Global Reporting Initiative-based indicators to show vital aspects of circular economy implementation. The study uses Tobit regression analysis because the disclosure index operates within fixed boundaries which determine its range of values. The research team confirmed their data analysis results through diagnostic assessments which proved their data set contained no multicollinearity problems and heteroskedasticity issues before they started their estimation work. The research shows that bigger companies tend to produce more environmental disclosure information because they actively create sustainability reports and circular economy practices. The study results show that companies in India's developing ESG framework use environmental disclosure to achieve better transparency while they build trust with their stakeholders and achieve their sustainability objectives. The research establishes a direct link between disclosure analysis and circular economy elements through its development of an appropriate methodological approach which uses censored regression techniques. The research results provide essential information which helps both government officials and business leaders to create sustainable reporting systems that produce consistent data for all users.

Keywords: *Environmental Disclosure, ESG, Firm Size, India, Sustainability Reporting*

1. Introduction

The growing calls of environmental sustainability have essentially changed the manner in which corporations conduct, report, and are assessed in the international economic system (Chopra et al., 2024; Diwan & Amarayil Sreeraman, 2024; Lukács et al., 2025). The increasing ecological degradation, discharge of climate change and resources wear and tear, has put strain on businesses to forego the past-traditional and profit maximizing model of behavior and embrace more responsible and transparency models (Cunha et al., 2025; Dibra, 2023; KPMG, 2024). In this regard environmental disclosure has become one of the most valuable tools which actually help the companies to control their environmental performance, sustainability and environmental impact, by reporting the same to the stakeholders (Hahn and Kuhnen, 2013; KPMG, 2022). These types of disclosure not only enable to enhance the corporate level of transparency, but also have an impact on the perception of stakeholders, adherence to regulations and value of the firm in the long run (Yuan et al., 2025; Rohendi, 2024; Sari et al., 2025).

The role of the Environmental, Social and Governance (ESG) structures in the environmental reporting process has also greatly been enhanced during the last 10 years, as companies have begun noticing the

[1]Assistant Professor,Amity College of Commerce & Finance, Amity University Kolkata

applicability of the principles and guidelines of the concept of corporate strategy (Saini & Kharb, 2025; TechTarget, 2025; Xiao, 2025). Gradually, investors, regulators, and the civil society are demanding standardized, close and reliable sustainability reports, compelling companies to invest in orchestrated reporting designs like Global Reporting Initiative (GRI) and country-specific systems like Business Responsibility and Sustainability Reporting (BRSR) in India (Bhattacharyya and Cummings, 2021). The recent empirical studies show that the more transparent companies under the criteria of ESG are, the better financial performance, minimized risk exposure, and increased market value (Yadav, Hanief, and Patnaik, 2020; Friede, Busch, and Bassen, 2015). This has caused the fact that environmental disclosure has not been a progressive practice, but has been strategic and regulatory imperative in current corporate governance (Clarkson et al., 2008; KPMG, 2022). Theories that are principally applied in explaining the environmental disclosure are theoretically, legitimacy theory and stakeholder theory (Del Gesso & Lodhi, 2024; Zhang, 2025; Garcia-Sánchez et al., 2025). Legitimacy theory is that firms will disclose information regarding the environment so that they can make their activity match the expectation of the society and be given the right to work (Deegan, 2002). Another practice emphasized in the stakeholder theory is that various stakeholders like the investors, regulators, customers and communities exert pressure on the organizations by enhancing the transparency and accountability of the reporting of practices by the organizations (Freeman, 1984; Hahn and Kuhnen, 2013). All these theoretical models imply that environmental reporting is reactive and proactive in its application in maintaining a firm to deal with the external perceptions and long-term legitimacy (Suchman, 1995; Deegan, 2002).A good amount of empirical data has been conducted on determinants of environmental disclosure, and the firm size is one of the most important determinants (Joshi & Joshi, 2024; Padang & Hernawati, 2024). Larger organizations may tend to be more familiar and have more regulatory scrutiny and, consequently, pressure on their stakeholders, prompting them to disclose the environmental performance of companies in more detail (Kansal, Joshi, and Batra, 2014; Clarkson et al., 2008). Originating research confirms that ESG disclosure is positively linked to a firm size since bigger firms have more financial and organizational resources to adopt ordered sustainability reporting systems (Malarvizhi & Mathew, 2016; Bhattacharyya and Cummings, 2021). There is, however, also recent research that indicates this correlation to be unqualified and subject to variation based upon the nature of the industries and systems of governing and strategic priority (Hahn and Kuhnel, 2013).

Although there has been an increased focus on ESG reporting, a number of challenges have still existed within the disclosure practices on the environment (Chopra et al., 2024; Khamisu & Paluri, 2024; Abramson, 2024). Additional issues relating to sustainability disclosures, such as lack of standardization, inconsistency, reportability, and instances of greenwashing, still have the negative effect of undermining the quality and credibility in sustainability disclosures (Chopra et al., 2024; Delmas and Burbano, 2011; Clarkson et al., 2008). These barriers are particularly significant in the new economies, including India, where policies have only developed, and belligerence units are developing (Kolk and Perego, 2010; KPMG, 2022).

The rest of the paper is arranged in the following way:

Section 2 discusses the pertinent theoretical basis and literature on environmental disclosure and ESG practices. Section 3 presents the objectives of the study. Section 4 works out the research hypothesis on the basis of earlier literature. Section 5 explains the research method, data sources, sample selection and analytical framework. Section 6 outlines the materials and methods to be used in building the Environmental Disclosure Index (EDI) and statistical analysis. Section 7 summarizes the empirical findings with descriptive statistics, ANOVA and Tobit regression test. This comes with the discussion section that interprets the findings based on theoretical and empirical knowledge. Lastly, the conclusion is the final part of the study which brings out the important findings, implications and future research opportunities.

2. Literature Review

Stakeholder and legitimacy theories have widely been applied in researching the environmental disclosure of companies, would answer the question of why firms willingly disclose their green status (Raghuvanshi et al., 2026; Zhang, 2025; Khamisu and Paluri, 2024). According to the legitimacy theory, organisations exchange information about the environment to be aligned to the expectations of society and licence to operate (Deegan, 2002). Previous initial researches believe that disclosure is a strategic instrument of controlling the external perceptions as opposed to an indication of the actual environmental performance (Gray, Kouhy, and Lavers, 1995).

Stakeholder theory also means that investors, regulators and the society pressurize the companies to be more transparent in their sustainability reporting. This fact is reinforced by recent studies that have indicated the increasing importance of ESG responsibility in the corporate governance structures (Hahn and Kuhnen, 2013). Moreover, there has been a reinforcement of institutional pressure in seeking the standardization of environmental disclosures by the development of regulatory frameworks with the view of promoting Business Responsibility and Sustainability Reporting (BRSR) in India (KPMG, 2022).

Agency theory also augments these views by giving the disclosure of environmental information an explanation as a way of mitigating information asymmetry among managers themselves (agents) and the shareholders (principals) (Jensen and Meckling, 1976; Healy and Palepu, 2001). This theory states that managers voluntarily share sustainability and environmental information as a means to signal transparency, help lower agency costs, and develop investor trust (Jensen and Meckling, 1976; Clarkson et al., 2008; Michelon, 2011). Recent news also has indicated that the ESG reporting is capable of minimizing the conflict of interest. and bring about better monitoring of the business by its stakeholders, thus, improving the corporate accountability and governance performance (Frias-Aceituno et al., 2014; Velte, 2017).

2.2 Determinants of Environmental Disclosure (Firm-Level Factors)

Determinants of the environmental disclosure at the firm level have been of particular concern to size and there has been a substantial literature regarding these determinants, profitability and even governance structure (Cormier, Magnan, and Van Velthoven, 2005; Hahn and Kuhnen, 2013). Empirical studies have also repeatedly found out that firm size is a pertinent variable because bigger corporations could report more data regarding the environment owing to the heightened disclosure and pressure on adherence (Kansal, Joshi, and Batra, 2014).

As the recent research points out, ESG reporting has also a positive impact on the value of the firm and financial performance, which implies that sustainability reporting is strategic and compliant (Bhattacharyya and Cummings, 2021; Yadav, Hanief, and Patnaik, 2020). In addition, some aspects of corporate governance such as independence of board have been found to significantly affect the quality and level of environmental disclosure (Malarvizhi and Mathew, 2016).

However, recent studies have revealed that such impact of firm size is not universal and, in all firms, which suggests that the factors behind disclosure practices cannot be explained by the determinant on its own but in a synergistic composition of economic, institutional and strategic factors (Hahn and Kuhnen, 2013).

2.3 Emerging Trends and Challenges in ESG Disclosure

The study of environmental disclosure has changed considerably as more of the issues related to environmental sustainability are being integrated through ESG models and international sustainability frameworks (Kartal et al., 2024; Lukács et al., 2025). Recent analysis points to an increased organization and standardization of

ESG reporting brought about by global reporting standards like GRI and regulatory requirements (KPMG, 2022).

Although such developments have been made, a number of problems still exist such as lack of comparability, inconsistency in reporting and the challenges of greenwashing. Companies tend to selectively disclose information with a bias toward positive aspects, ignoring the negative effects that their activities have on the environment, which calls into question the level of transparency and credibility (Clarkson et al., 2008).

Moreover, a recent literature stresses the role of longitudinal and data-driven methods of examining ESG disclosures. Both quantitative and content analysis have added credibility to the empirical research techniques in that it can be aptly deduced about the disclosure habits over time. (Hahn and Kuhnen, 2013). These are especially pronounced in the emerging markets such as India where reporting practices and the enforcement of regulations are still developing.

Although the literature is expanding, there is a gap in the literature of combining longitudinal content analysis and state of the art statistical approaches, ANOVA and Tobit regression, within the Indian scenario. The current research will fill this gap by offering an in-depth empirical research study carried out over a decade hence adding to the existing literature on the topic of environmental disclosure in emerging markets.

3. Objectives of The Study

The current research is pursued with the following specific aims:

(a) To test the hypothesis that there is a relationship between the size of firms and the environmental disclosure practices of the sampled companies in India.

(b) To examine the inter-firm differences in environmental disclosure practices, with a structured Environmental Disclosure Index (EDI).

4. Methodology

4.1 Hypothesis Development

In the past literature, environmental disclosure has been extensively studied as a role of company-based factors, especially the company size. The bigger companies tend to be more exposed to the public, other regulators, and more stakeholders, which is a motivating factor to engage in more transparent environmental reporting (Kansal et al., 2014). According to the theory of legitimacy, companies that have a greater exposure will report more environmental-related information to retain the societal acceptance and the legitimacy of the corporation (Deegan, 2002).

Moreover, industry distinctiveness, differentiation in the governance system, and strategic interests might lead to differences in disclosure procedures among companies (Hahn & Kühnen, 2013; Dye, 2001). Current research suggests that environmental reporting is not consistent across companies and that it is commonly associated with a firm-level heterogeneity (Hahn and Kuhnen, 2013).

Against this backdrop, the current paper empirically analyses how firm size and environment disclosure are related, and the differences in disclosure of the sample firms amongst them using the scale of quantitative methods, including ANOVA, and Tobit regression analysis.

4.2 Hypothesis Formulation

Due to the theoretical background and the empirical data, the hypotheses are the following:

H_0 (Null Hypothesis): There is no statistically significant relationship between firm size and environmental disclosure.

H_1 (Alternative Hypothesis): There is a statistically significant positive relationship between firm size and environmental disclosure.

4.3 Research Frame

The current study is based on secondary research using published annual reports of a group of selected Indian companies in a ten-year timeframe (2014-2024). The sample includes the five top companies, i.e., Reliance Industries Limited, Nestle India Limited, Oil and Natural Gas Corporation Limited (ONGC), Pidilite Industries Limited and Power Grid Corporation of India Limited. The firms will undergo purposive sampling with the aim of ensuring that they represent different sectors of industries, such as energy, fast-moving consumer goods, chemicals and infrastructure. This sectoral variety allows a detailed analysis of the trends in environmental disclosure behaviour in the presence of different levels of environmental sensitivity, regulatory interest, and pressure on the part of stakeholders (Freeman, 1984; Deegan, 2002). The main source of data are annual reports since they are standardized, comply with the regulations, and cover all financial and non-financial disclosures. They are generally accepted in disclosure-based research studies to be good and verifiable documents that can be used to improve the validity and comparability of empirical results (KPMG, 2022; Velte, 2023). The data set is structured in such a way that it is a balanced panel, i.e. firm level data over the time of study, such that each data point in the dataset is in form of a firm-year combination or integration of financial and disclosure related data (Wooldridge, 2010)

5. Materials and Methods

The research design embraces a quantitative research design to empirically test the relationship that exists between the firm size and environmental disclosure practices using STATA 19 software. Environmental Disclosure Index (EDI) is a dependent variable, which is operationalized through the framework of the structured content analysis that involves sixteen predefined environment disclosure indicators.

These indicators are classified under seven major environmental aspects, viz. materials, energy, water and effluents, biodiversity, emissions, waste management and environmental policies as shown in Table 1. The indicators are constructed according to the framework of the Global Reporting Initiative (GRI) and reinforced by the previous empirical research, which guarantees the validity and completeness of the disclosure index.

Table 1. Environmental Disclosure Index (EDI) Indicator

Dimension	**Indicator**	**Description**
Materials	Material Usage	Materials used by weight or volume
	Recycled Materials	Percentage of recycled input materials used
Energy	Energy Consumption	Total energy consumption within the organization
	Energy Reduction	Measures undertaken to reduce energy consumption
Water and Effluents	Water Withdrawal	Water withdrawal by source
	Water Consumption	Water consumption in water-stressed areas
Biodiversity	Operational Sites	Operations in or near protected areas
	Biodiversity Protection	Measures for preservation of affected species
Emissions	GHG Emissions	Greenhouse gas emissions by type
	Emission Intensity	Intensity of greenhouse gas emissions

Waste	Waste Generation	Total waste generated
Management	Waste Impact	Environmental impact of waste generated
Environmental Policies	Waste Initiatives	Waste management and reduction initiatives
	Compliance	Environmental compliance status
	Supplier Assessment	Environmental screening of suppliers
	Grievance Mechanism	Environmental grievance redressal mechanisms

Source: Developed by the author based on the GRI Framework and prior studies (Chakladar & Gulati, 2015; Brammer & Pavelin, 2006; Ahmad, 2012)

The evaluation of each indicator is done on a structured ordinal scale with "0" being the absence of disclosure, "1" being qualitative disclosure, "2" being quantitative disclosure and "3" being both qualitative and quantitative information. Each firm-year observation has a composite disclosure score computed as an average of the individual scores of indicators, therefore, making it consistent and comparable across firms and time.

The paper uses both quantitative and qualitative statistical methods to undertake the empirical analysis. To analyse the difference in environmental disclosure practices of the sampled firms, the firm-based descriptive statistics will be used to give information regarding the level and the dispersion of the disclosure scores.

In a bid to further determine inter-firm differences, one way analysis of variance (ANOVA) is used to determine whether there is any statistically significant difference between the environmental disclosure practices of the sampled firms.

Since the data are cross-sectional (firms) and time-series (years), we have a panel dataset, then we apply Tobit regression analysis to examine the relationship between firm size and environmental disclosure. The Tobit regression is justified because it is effective in controlling the unobserved heterogeneity among firms and identifies the temporal variation of disclosure behaviour. Further, as the data does not meet the criterion of normality, panel data methods are more robust and reliable estimations, as opposed to conventional regression techniques.

6. Results

6.1 Descriptive Statistics

Table 2 shows the firm-wise average Environmental Disclosure Index (EDI) across the selected companies over the study period.

Table 2. Firm-wise Descriptive Statistics of Environmental Disclosure Index

Firm	Mean EDI	Std. Deviation	Minimum	Maximum
Reliance Industries Limited	0.268	0.0156	0.479	0.541
ONGC	0.252	0.0310	0.270	0.354
Power Grid Corporation of India	0.228	0.0186	0.291	0.354
Nestlé India Limited	0.198	0.0514	0.125	0.270
Pidilite Industries Limited	0.174	0.0484	0.229	0.354

Source: Author's own computation based on data collected from annual reports of selected firms (2014-2024)

Firm- Based Descriptive Statistics reveal that the environment disclosures of the different companies selected vary greatly. The mean Environmental Disclosure Index (EDI) of Reliance industries Limited is the best and it implies that the level of compliance to environmental reporting is relatively high. The low standard deviation indicates that the disclosure practices have not changed much within the study period.

The average level of disclosure by ONGC and Power grid corporation of India is moderate with the variance of the ONGC being relatively higher than that of power grid, meaning that its disclosure practices have been varying over a period of time.

However, both Nestle India Limited and Pidilite Industries Limited show a relatively lower mean disclosure score. The standard deviation values are however higher in both firms indicating a higher level of inconsistency and variation in the practices of the two firms in their environmental disclosure.

The difference between minimum and maximum values between the firms also magnifies the existence of change between temporal variation showing that environmental disclosure practices have changed between the study period (Baltagi, 2008; Clarkson et al., 2008).

In general, the findings indicate that whereas certain companies have stable and more disclosure, others show a more stable and more variable reporting conduct that are relatively lower.

6.2 Firm Size

Table 3 shows the average total assets of firms, firm size among the selected companies.

Table 3. Firm size in crores (₹ Crores)

Firm	Total Assets (Average over Study Period)
Reliance Industries Limited	7,03,396.18
ONGC	2,94,128.56
Power Grid Corporation of India	2,16,350.12
Nestle India Limited	7,912.29
Pidilite Industries Limited	6,074.01

Source: Author's own computation based on secondary data obtained (Moneycontrol)

There is a significant amount of heterogeneity in the amount of business operations of the selected firms in the total firm-specific assets. The highest average asset base (₹7,03,396.18 crores) is observed in Reliance Industries Limited which is far much above the rest of the firms in the sample. This is an indication of its diversified business, capital-intensive nature and market dominance.

Similarly, ONGC and Power grid corporation of India also exhibit quite big asset base, as the companies operate on infrastructure and energy sensitive fields, where capital intensive investments are required. Nevertheless, they are still significantly smaller than Reliance Industries, which means that there are differences even in high-capital industries.

Contrary to this, Nestle India Limited and Pidilite Industries limited do not have much higher asset levels because their operations are characterized by less capital-intensive industries of FMCG and specialty chemicals. The high differences between the maximum and minimum values show that there is a large difference in the size of the firms of the sample.

On the whole, the findings verify the existence of an important cross-sectional dispersion in the size of firms that gives a strong foundation of study on its impact on environmental disclosure practices.

6.3 Firm-wise Environmental Disclosure Analysis

Table 4 shows the average Environmental Disclosure Index (EDI) of the firms.

Table 4. Firm-wise Average Environmental Disclosure Index

Firm	Average EDI
Reliance Industries Limited	0.517
Power Grid Corporation of India	0.333
ONGC	0.307
Pidilite Industries Limited	0.307
Nestle India Limited	0.212

Source: Author's own computation based on data collected from annual reports of selected firms (2014-2024)

The firm-based analysis indicates that there is a significant difference in environmental disclosure of firms. The Reliance Industries Limited has the largest average disclosure score (0.517), which means that they are much more committed to environmental reporting.

Power grid Corporation of India shows moderate disclosure (0.333) whereas ONGC and Pidilite Industries Limited have a similar disclosure performance (0.307). Conversely, Nestle India Limited has the lowest average disclosure score (0.212) implying a comparative poor disclosure of the environment.

These differences suggest that the environmental reporting practices of firms vary significantly across firms, as difference in industry sensitivity, regulatory exposure and strategic priorities.

6.4 ANOVA Results

To test the hypothesis H1 of whether there is significant variation in environmental disclosure among firms, one-way ANOVA test was performed.

Table 5. ANOVA Results

Source of Variation	F-Statistic	p-value
Between Firms	101.52	0.000

Source: Author's own computation

The ANOVA results show that environment disclosure of firms differ significantly ($F = 101.52$, $p < 0.001$). The large F-statistic shows that the difference in the disclosure scores among the firms is not because of the chance variation. This observation indicates that the practice of environmental disclosures is firm specific and heterogeneous and it depends on the industry features, regulatory forces and organizational strategies.

6.5 Tobit Regression Analysis

The estimate of a Tobit regression model was done to measure the effect of the firm size on environmental disclosure.

Table 6. Tobit Regression Results

Variable	Coefficient (β)	Std. Error	t-value	p-value
Company Size (COSZ)	3.11×10^{-7}	2.96×10^{-8}	10.50	0.000
Constant	0.2588	0.0110	23.61	0.000

Source: Author's own work

A Tobit regression model was used to explain the censored nature of the dependent variable, which is environmental disclosure (ED) and is constrained between 0 and 1. This method guarantees the uniform and unbiased estimates of parameters as opposed to the traditional OLS that might not be suitable in the circumstances of limited dependent variables.

The model shows good overall statistical significance, as shown by the likelihood ratio statistic (LR χ 2 = 60.53, $p < 0.01$), which proves the joint explanatory power of the independent variable.

The coefficient of company size (COSZ) is positive and highly statistically significant ($\beta = 3.11 \times 10^{-7}$, t = 10.50, $p < 0.01$). This implies that the larger the firm, the greater the degree of environmental disclosure. The coefficient magnitude is small, but this can be explained by the fact that the monetary scaling of the firm size variable is used; the effect is not insignificant economically.

The constant value is also positive and significant (= 0.2588, $p < 0.01$), which means that there is a minimum level of environmental disclosure even without the change in the size of the firm.

In general, the results are strong empirical evidence of a strong positive correlation between company size and environmental disclosure, which suggests that bigger companies have a higher probability of reporting on sustainability in a comprehensive manner. This could be motivated by increased publicity, regulatory pressure, and availability of resources, which all encourage improved disclosure practices.

6.6 Company-wise Trend Analysis of Environmental Disclosure Scores

The graphical representation shown illustrates the trend of environmental disclosure scores among the chosen companies over the years 2014-2024.

Source: Author's own calculation and compilation

The graphical model illustrates how environmental disclosure scores of the chosen companies have been trending in the year 2014 to 2024. It is noted that during the period, Reliance always has the highest disclosure score, which means a high level of transparency on environmental issues. ONGC and Power grid present average results with certain swings, which are inconsistent disclosure over the years.

Pidilite shows continuous growth of its disclosure score starting from 2017, though, which may indicate a greater emphasis on sustainability reporting. Comparatively, Nestle records relatively lower disclosure, with minor improvements since 2017 but since then, it has been relatively stable.

On the whole, the graph shows considerable differences in the environmental disclosure practices among companies, and firm-specific strategies and responsiveness to the regulatory environment are critical factors in defining the amount of sustainability reporting.

7. Discussion

Empirical results of the research are very supportive of the alternative hypothesis (H 1) that suggests that there is a statistically significant positive correlation between firm size and environmental disclosure. The findings of the Tobit regression model indicate that the size of the company (COSZ) has a positive and highly significant coefficient ($\beta = 3.11 \times 10$ -7, $p < 0.01$) and thus the null hypothesis (H 0) cannot be accepted and the alternative hypothesis (H 1) is accepted.

This finding supports the claim that the size of firms is a decisive factor in environmental disclosure practices of Indian firms. The bigger companies are more likely to report detailed environmental data because they are more visible, have stakeholder pressure, and are subject to regulatory scrutiny. The results are in line with the legitimacy theory, which argues that companies are involved in disclosure practices to ensure that they are socially acceptable, and the stakeholder theory, which argues that external pressures influence corporate transparency.

Moreover, the statistically significant likelihood ratio (LRχ 2 = 60.53, $p < 0.01$) supports the overall explanatory power of the model, which means that firm size has a significant impact on the differences in the level of environmental disclosure. Therefore, the results of hypothesis testing are strong empirical support that environmental disclosure is not arbitrary but is systematically determined by firm-specific attributes, especially size.

The firm level analysis has shown clearly that environmental disclosure practices differ significantly among the sampled firms, and it is possible that reporting behaviour is not uniform across the sample but is determined by firm specific factors.

Reliance Industries Limited stands out as the best company in regard to environmental disclosure as it has the highest EDI score. This high performance could be attributed to its high scale of operation, diversified business operations, and presence in the market that exposes it to more regulatory requirements and expectations of stakeholders. Consequently, the company seems to have more organized and detailed sustainability reporting practices to stay legitimate and build on the trust of stakeholders.

On the other extreme, Nestle India Limited is the least disclosed in terms of environmental disclosure. This comparatively poor performance can be attributed to the variations in the nature of industries since companies in the FMCG industry are usually exposed to relatively less environmental scrutiny compared to companies in the energy or infrastructure industry. Moreover, the reporting policy of the company can be less focused on the disclosures of the environment.

Examples of companies with moderate disclosure include ONGC and Power grid Corporation of India. Although these companies are engaged in the environmentally sensitive sectors where an increase in transparency is anticipated, their disclosure practices are not fully developed but seem to be undergoing evolution. This shows that despite the regulatory and stakeholder pressures; there is still a way to go in ensuring consistency and depth in reporting.

The same is also true of Pidilite Industries Limited that indicates a moderate level of disclosure, though with certain variations over time. This trend indicates that the company might be at the transitional stage, slowly enhancing its sustainability reporting procedures without being completely standardized and consistent.

The implication of these observations is that environmental disclosure not only depends on the size of firms but also on the sectoral exposure and strategic priorities as well as internal governance mechanisms. The disparities among companies emphasize the lack of a standardized reporting system and are indicative of increased standardization of disclosure practices.

Improvement wise, companies that have relatively lower disclosure rates, especially Nestle India Limited and Pidilite Industries Limited, should aim at improving the depth and consistency of their environmental reporting. Implementation of globally recognized standards like GRI, more extensive use of quantitative metrics, and increased compliance with regulatory demands like BRSR can all help to enhance the quality of disclosure to a large extent. Also, more transparent reporting can be further reinforced by incorporating sustainability into the core business strategies and enhancing internal monitoring mechanisms.

The ANOVA results indicate that the difference in the disclosure practices among firms is significant ($p < 0.001$), which means that these differences are not accidental. This supports the claim that firm-level attributes are important in the determination of disclosure behaviour.

In addition, the findings of the Tobit regression analysis are in line with the ANOVA results, and both methods show high statistical significance ($p < 0.01$). Although ANOVA shows that there are differences between firms, the Tobit model shows how and why the relationship between firm size and disclosure is directional and significant. The fact that all these methods have similar levels of significance boosts the strength of the findings and empowers the research with more empirical evidence.

On the whole, despite the fact that some companies show rather developed disclosure practices, the results indicate that environmental reporting in Indian companies is still rather patchy, and much can be done to make it more consistent, comparable, and comprehensive.

8. Conclusion

The current research offers an extensive empirical investigation in the association between firm size and environmental disclosure under the longitudinal framework of a longitudinal period (2014-2024) in the context of Indian firms. Through the use of structured Environmental Disclosure Index (EDI) and descriptive statistics, an ANOVA, and Tobit regression, the study presents a solid analytical design to test the inter-firm variations as well as the major factors of the disclosure practices.

The results indicate that there exists a statistically significant and positive connection between firm size and environmental disclosure thus demonstrating that bigger firms are characterized by high degrees of transparency in reporting such environmental information. This finding

aligns with the theoretical foundations of legitimacy, stakeholder, and agency theories, which all point to the common direction of implying that more visible firms, those with higher regulatory visibility, and those with more stakeholder pressure tend to embrace comprehensive sustainability reporting measures. The null hypothesis rejection and acceptance of the alternative hypothesis also support the position of firm size as a crucial factor of environmental disclosure.

Also, the findings of the ANOVA analysis demonstrate the presence of the significant inter-firm heterogeneity in the disclosure practices, which reveals that environmental reporting is not a consistent process but it is affected by the peculiarities of industry sensitivity, strategic orientation, and governance structure of firms. These findings can also be supported using the graphical and descriptive analyses since they show that a company such as Reliance Industries Limited always upholds higher and more consistent disclosure levels compared to the rest which have moderate or relatively lower and inconsistent reporting patterns.

Practically and in policy terms, the paper points out the necessity of more standardization and enforcement of regulations in the environmental reporting models especially in the emerging economies such as India where ESG practices may not yet be fully developed. Such guidelines used in areas like Business Responsibility and Sustainability Reporting (BRSR) should be reinforced by regulatory agencies to make disclosures uniform, comparable, and credible across the firms.

To corporate managers, the results provide a strategic significance of the harmonization of environmental disclosure in the main business operations not just as a mandatory measure but as a value-added mechanism, which increases the trust of all stakeholders and long-term sustainability. Companies that have lower disclosure rates are urged to use globally accepted standards like the Global Reporting Initiative (GRI), improve both quantitative and prospective disclosures, and consistency of reporting practices over the years.

Moreover, the research adds to the current body of literature by integrating longitudinal content analysis into the sophisticated econometric analysis, and hence, closes one of the research gaps in the Indian ESG. It offers a methodological basis to the subsequent research to investigate further firm-level and institutional factors of environmental disclosure.

In general, the paper concludes that, though there are gradual improvements in the environmental disclosure of companies in India, it is skewed among companies, as bigger companies take the lead in adapting to more transparent and structured sustainability reporting. To establish a more consistent and credible system of environmental disclosure, more regulatory mechanisms and commitments to strategic firm-level commitments are crucial.

References :

Abramson, K. (2024). ESG reporting is already challenging: Don't let (lack of) tech make it harder. Forbes Business Council.

Ahmad, Z. (2012). Corporate environmental disclosure practices in developing countries. Journal of Accounting and Sustainability, 2(1), 1-15.

Baltagi, B. H. (2008). Econometric analysis of panel data (4th ed.) Wiley.

Bhattacharyya, A., & Cummings, L. (2021). Measuring corporate environmental performance: Stakeholder engagement, reporting, and auditing. *Business Strategy and the Environment, 30*(1), 1-13. https://doi.org/10.1002/bse.2610

Brammer, S., & Pavelin, S. (2006). Voluntary environmental disclosures by large UK companies. *Journal of Business Finance & Accounting, 33*(7-8), 1168-1188.

Chakladar, J., & Gulati, P. A. (2015). A study of corporate environmental disclosure practices in India. *IUP Journal of Accounting Research & Audit Practices, 14*(2), 7-25.

Chopra, S. S., Senadheera, S. S., Dissanayake, P. D., Withana, P. A., Chib, R., Rhee, J. H., & Ok, Y. S. (2024). Navigating the challenges of environmental, social, and governance (ESG) reporting: The path to broader sustainable development. *Sustainability, 16*(2), 606.

Clarkson, P. M., Li, Y., Richardson, G. D., & Vasvari, F. P. (2008). Revisiting the relation between environmental performance and environmental disclosure: An empirical analysis. *Accounting, Organizations and Society, 33*(4-5), 303-327. https://doi.org/10.1016/j.aos.2007.05.003

Cormier, D., & Magnan, M. (2003). Environmental reporting management: A continental European perspective. *Journal of Accounting and Public Policy, 22*(1), 43-62.

Cormier, D., Magnan, M., & Van Velthoven, B. (2005). Environmental disclosure quality in large German companies: Economic incentives, public pressures or institutional conditions? *European Accounting Review, 14*(1), 3-39.

Cunha, Í. G. F., Policarpo, R. V. S., de Oliveira, P. C. S., Abdala, E. C., & Rebelatto, D. A. N. (2025). A systematic review of ESG indicators and corporate performance: Proposal for a conceptual framework. *Future Business Journal, 11*, 106.

Deegan, C. (2002). Introduction: The legitimising effect of social and environmental disclosures-A theoretical foundation. *Accounting, Auditing & Accountability Journal, 15*(3), 282-311. https://doi.org/10.1108/09513570210435852

Del Gesso, C., & Lodhi, R. N. (2024). Theories underlying environmental, social and governance (ESG) disclosure: A systematic review of accounting studies. *Journal of Accounting Literature, 47*(2), 433-461.

Delmas, M. A., & Burbano, V. C. (2011). The drivers of greenwashing. *California Management Review, 54*(1), 64-87.

Dibra, S. (2023). The 2023 state of corporate ESG: How companies are embracing ESG for resilience and growth. Thomson Reuters Institute.

Diwan, H., & Amarayil Sreeraman, B. (2024). Sustainability reporting between financial market forces and regulatory mandates: A global bibliometric analysis. *Journal of Risk and Financial Management, 14*(4), 82.

Dye, R. A. (2001). An evaluation of "essays on disclosure" and the disclosure literature in accounting. *Journal of Accounting and Economics, 32*(1-3), 181-235. https://doi.org/10.1016/S0165-4101(01)00024-6

Freeman, R. E. (1984). Strategic management: A stakeholder approach. Pitman.

Frias-Aceituno, J. V., Rodríguez-Ariza, L., & Garcia-Sanchez, I. M. (2014). Explanatory factors of integrated sustainability and financial reporting. *Business Strategy and the Environment, 23*(1), 56-72.

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2,000 empirical studies. *Journal of Sustainable Finance & Investment, 5*(4), 210-233.

García-Sánchez, I. M., Rodríguez-Ariza, L., & Frías-Aceituno, J. V. (2025). Institutional and stakeholder perspectives on ESG disclosure and performance. Review of Managerial Science.

Gray, R., Kouhy, R., & Lavers, S. (1995). Corporate social and environmental reporting: A review of the literature and a longitudinal study of UK disclosure. *Accounting, Auditing & Accountability Journal, 8*(2), 47-77.

Hahn, R., & Kühnen, M. (2013). Determinants of sustainability reporting: A review of results, trends, theory, and opportunities in an expanding field of research. *Journal of Cleaner Production, 59*, 5-21. https://doi.org/10.1016/j.jclepro.2013.07.005

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics, 31*(1-3), 405-440.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behaviour, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305-360.

Joshi, B., & Joshi, H. (2024). Financial determinants of environmental, social, and governance performance: Empirical evidence from India. *Investment Management and Financial Innovations, 21*(1), 13-24.

Kansal, M., Joshi, M., & Batra, G. S. (2014). Determinants of corporate social responsibility disclosures: Evidence from India. *Advances in Accounting, 30*(1), 217-229. https://doi.org/10.1016/j.adiac.2014.03.009

Kartal, M. T., Depren, S. K., Pata, U. K., Taskin, D., & Savl1, T. (2024). Modeling the link between environmental, social, and governance disclosures and scores. *Financial Innovation, 10*(1), 80.

Khamisu, M. S., & Paluri, R. A. (2024). Emerging trends of ESG disclosure research. *Cleaner Production Letters, 7*, 100079.

KPMG. (2022). Survey of sustainability reporting 2022. KPMG International.

KPMG. (2024). Businesses balancing ambition with regulation and evolving roles as sustainability becomes a key focus. KPMG International.

Lukács, B., Rickards, R. C., Molnár, P., Suta, A., & Tóth, Á. (2025). ESG disclosure topics and reporting frameworks: Exploratory research across industries. *Discover Sustainability, 6*, 649.

Malarvizhi, P., & Mathew, M. (2016). Link between corporate environmental disclosure and firm performance: Evidence from India. *Journal of Global Responsibility, 7*(1), 84-108.

Michelon, G. (2011). Sustainability disclosure and reputation: A comparative study. *Corporate Reputation Review, 14*(2), 79-96.

Padang, R. D., & Hernawati, R. I. (2024). Determinants of ESG disclosure in the energy sector. Proceedings of the International Conference on Management, Entrepreneurship, and Business.

Rohendi, H. (2024). ESG disclosure and firm performance: Evidence from emerging markets. Cogent Business & Management.

Saini, M., & Kharb, R. (2025). Strategic enablers of ESG reporting in India. International Journal of Creative Research Thoughts.

Sari, D. P., Fikri, M., Kartika, R., & Tanwattana, N. (2025). Corporate governance, ESG disclosure, and firm value. *Journal of Economics and Management, 3*(2), 42-51.

TechTarget. (2025). ESG strategy and management: Complete guide for businesses.

Velte, P. (2017). Does ESG performance have an impact on financial performance? *Journal of Global Responsibility, 8*(2), 169-178.

Velte, P. (2023). Determinants and consequences of ESG performance. Business Strategy and the Environment.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data (2nd ed.). MIT Press.

Xiao, L. (2025). ESG integration into corporate strategy and value realization. arXiv.

Yadav, P. L., Hanief, S., & Patnaik, S. (2020). Does ESG disclosure influence firm performance? Evidence from India. Journal of Sustainable Finance & Investment.

Yuan, W., et al. (2025). ESG disclosure and firm long-term value: Evidence from emerging markets. Finance Research Letters.

Zhang, Y. (2025). A stakeholder-legitimacy framework for ESG disclosure in banking. SSRN.

SURVEY

(ISSN: 0586-0008)

A Journal of Management and Welfare Studies

Call for Paper and Guidelines for Submission

Editorial Policy:

SURVEY, a Journal of Management and Welfare Studies is published by IISWBM, Kolkata with an endeavor to promote and disseminate knowledge and ideas in the complex multi-disciplinary management field. The Journal encourages theoretical and empirical research papers and articles of relevance to academia and industry/corporate houses. In addition, the Journal invites manuscripts covering application of theory to real life management activities where findings would be of interest to researchers, executives, academicians and management students. SURVEY, a Peer Reviewed Quarterly Journal does not require any publication charges.

The Journal publishes articles in the key functional area of management viz. marketing, finance & accounting, human resource, information technology, transportation & logistics, energy, environment, healthcare & hospital, retail, production & supply chain and other related areas. Articles reflecting diversity, cross-functional nature of management and emerging concerns are also considered for publication.

Guidelines for Authors:

1) Manuscript should normally be of 3,000 to 7,000 words may be of 12-20 typed pages including figures and tables, typed in 1.5 space in 12-point font Times New Roman on A4 size paper in MS-Word format.
2) The manuscript should be arranged in the following order:
   a. Title page containing the title of the paper, author's name, designation, official address, contact phone/fax number, e-mail address and a brief biographical sketch of the author(s).

   b. Abstract of not more than 300 words in italic font type along with the key words.

3) The Papers may contain the following broad headings and structure
   a) Title
   b) Abstract, Keywords
   c) Introduction
   d) Literature Review
   e) Objective
   f) Methodology
   g) Material and methods
   h) Results
   i) Discussion (Results and discussion can be combined in one section)
   j) Conclusion
   k) References in APA 7 style (in case of website reference, specify website detail (URL) including the date of accessing the site.
4) The author(s) should send a declaration stating that the paper is an original work and it has neither been published nor will it be submitted elsewhere till the editorial decision has been communicated.
5) The author(s) should submit a plagiarism report from any Standard Plagiarism check platform and similarity should not exceed 10%.
6) Authors should submit the papers by email only at **editor.survey@iiswbm.edu**
7) The contributions sent for publication will be referred for blind review. Correspondence and proofs for correction, if required, will be sent to the first named author unless otherwise indicated. Corrected proofs should be returned within 15 days.
8) The final decision on the acceptance or otherwise of the paper rests with the Editorial Board and it depends entirely on its standard and relevance. The final draft may be subjected to editorial amendment to suit the Journal's requirements. The decision about acceptance or otherwise of the paper will be conveyed to author by email only within 60 days.
9) Each author will receive a complimentary copy of the journal after publication.
10) The copyrights of the contributions published in the journal lie with the publishers of the journal - IISWBM, Kolkata.

SURVEY

A Journal of Management and Welfare Studies

SUBSCRIPTION FORM

To
The Registrar
Indian Institute of Social Welfare & Business Management
Management House, College Square (West), Kolkata 700 073

Sir,

I/we would like to subscribe your Journal 'SURVEY' for 1/3/5 year(s). A bank draft/cheque bearing no ……………………………… dated ………………………… For Rs. US$ ……………… drawn in favour of "Indian Institute of Social Welfare & Business Management", payable at Kolkata.

Nature of Subscription (Please tick in the appropriate box):

Individual ☐ Institution ☐ Student ☐ Foreign ☐ On Reciprocal of our Journal

Name of Individual/Institution______________________________

Address____________________________________

City____________ State____________ Postal Code____________

Phone No. (R)____________ (O)____________ (Mob) ____________

E-mail id____________________________________

Signature with date

Subscription Rates (Inclusive of Postage)			
Category	**1 Year**	**3 Years**	**5 Years**
Indian (In Rs.)			
Institutions	1500	3600	5400
Individual/Alumni	800	1900	3000
Students	300	600	800
Foreign (in US $)	200	500	750

About IISWBM

The Indian Institute of Social Welfare and Business Management (IISWBM), Kolkata, stands as a pioneering institution in the history of management education in India. Established on 25th April 1953 through a resolution of the University of Calcutta, IISWBM holds the distinction of being India's first institute to offer formal management education. The institution was founded through the collective vision of the Government of West Bengal, the Government of India, the University of Calcutta, and leading industrialists of the country. Dr. Bidhan Chandra Roy, the legendary Chief Minister of West Bengal, served as its Founder-President, while Pandit Jawaharlal Nehru laid the foundation stone of the Institute, making IISWBM an institution deeply rooted in the nation's educational and developmental history.

Over the decades, IISWBM has built a rich legacy of academic excellence, professional integrity, and social responsibility. True to its name, the Institute has consistently emphasized the integration of business management with social welfare, creating managers who are not only professionally competent but also socially conscious and ethically responsible. This unique philosophy continues to distinguish IISWBM among management institutions in India.

The Institute actively collaborates with government bodies, industries, professional organizations, and research institutions to address contemporary socio-economic challenges. Through research, consultancy, management development programmes, and community-oriented initiatives, IISWBM continues to contribute to nation-building and public welfare.

With more than seven decades of legacy, IISWBM continues to nurture future leaders and remains a symbol of academic distinction, innovation, and societal contribution in the field of management education.

Pandit Jawaharlal Nehru laying the Foundation Stone of the Academic Block-1958

Dr. B. C. Roy,
Chief Minister of West Bengal (1948-1962) &
the Founder President Board of Governors

Professor D. K. Sanyal,
the Founder Director

Inauguration of the First Business Management course in India (PGDBM) on 5th July, 1954
(Dr. B. C. Roy addressing the gathering : Dr. J. C. Ghosh,
Vice-chancellor of University of Calcutta, sitting)

Commemoration of 50th Anniversary of Management Education by IISWBM

Indian Institute of Social Welfare and Business Management
Management House, College Square (West)
Kolkata - 700 073, India
www.iiswbm.edu

ISSN: 0586-0008