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AI-Driven Carbon Monitoring: Enhancing Environmental Accountability Through Intelligent Systems

Dr. Poonam[1]
[1]Assistant Professor,
School of Commerce & Business Management,
Geeta University, Panipat, Haryana, India.
Dr. Nidhi Gehlawat[2]
[2]Assistant Professor,
School of Commerce & Business Management, Geeta University,
Panipat, Haryana, India.
Tanu[3]
[3]University School of Management, Kurukshetra University,
Kurukshetra, Haryana, India

Abstract
The escalating urgency of climate change demands more accurate and timely methods for carbon footprint monitoring. This study investigates the transformative role of Artificial Intelligence (AI) in enhancing environmental accountability through intelligent carbon tracking systems. Leveraging machine learning, natural language processing, and IoT integration, AI-driven solutions offer superior accuracy, real-time responsiveness, and predictive capabilities compared to traditional carbon accounting methods. A mixed-methods analysis across 60 organizations revealed that firms employing AI-based monitoring achieved an average 22.9% reduction in carbon emissions over five years, significantly outperforming those using conventional approaches. The findings emphasize AI's potential to operationalize real-time environmental accountability while highlighting challenges related to data quality, algorithmic transparency, and ethical deployment. This research contributes to the growing discourse on digital solutions for climate resilience and offers strategic insights for policymakers, sustainability leaders, and technologists committed to achieving net-zero goals.

Keywords: Artificial Intelligence (AI), Carbon Emissions Monitoring, Environmental Accountability, ESG Reporting, Predictive Analytics

1. Introduction

The intensifying impacts of climate change have spurred global efforts to reduce greenhouse gas (GHG) emissions and achieve carbon neutrality. Accurate and timely tracking of carbon footprints—defined as the total emissions of CO_2 and other GHGs associated with human activities—is critical for assessing environmental performance and informing sustainable policy and business decisions (Wiedmann & Minx, 2008). Traditional carbon accounting methods, however, are often limited by fragmented data, manual reporting processes, and lack of real-time feedback (Sullivan & Gouldson, 2017). These limitations hinder the capacity of both public and private sectors to measure, manage, and mitigate emissions effectively.

Recent advancements in Artificial Intelligence (AI) offer a transformative opportunity to address these challenges. AI systems, particularly those leveraging machine learning, computer vision, and natural language processing, can process vast volumes of environmental data, identify patterns, and generate actionable insights with unprecedented speed and precision (Rolnick et al., 2019). By automating emissions monitoring and prediction, AI enhances transparency, accountability, and responsiveness in climate action strategies (Vinuesa et al., 2020).

AI-driven carbon monitoring systems can integrate diverse data sources—ranging from satellite imagery and IoT sensors to corporate sustainability reports—to create dynamic, real-time assessments of carbon emissions (Chicco & Tolone, 2020; Lal et al., 2020). For example, deep learning algorithms are being used to estimate urban CO_2 emissions from remote sensing data (Liu et al., 2022), while natural language processing tools can extract emissions disclosures from corporate filings and sustainability reports (Zhang et al., 2021).

Moreover, AI can facilitate predictive modeling of future emissions under different scenarios, enabling organizations and governments to evaluate the long-term impacts of their environmental policies (Creutzig et al., 2022). In industry, AI-powered systems are helping companies monitor supply chain emissions, optimize energy consumption, and comply with ESG (Environmental, Social, and Governance) standards (GeSI, 2019; McKinsey, 2022).

Despite its potential, the use of AI in carbon monitoring raises critical questions regarding data quality, algorithmic transparency, and environmental justice. There is a growing need for robust governance frameworks to ensure ethical, equitable, and sustainable deployment of AI technologies in environmental contexts (Floridi et al., 2018; Mittelstadt et al., 2016).

This paper explores the intersection of AI and carbon footprint tracking, focusing on the technological capabilities, current applications, and challenges of AI-driven carbon monitoring systems. By examining how intelligent systems enhance environmental accountability, the research contributes to the growing discourse on digital solutions for climate resilience.

2. Literature Review

Environmental accountability has become a critical concern in global sustainability discourse, especially as corporations and governments commit to net-zero targets (UNFCCC, 2021). Traditional carbon tracking methods—such as periodic manual reporting and basic sensor-based measurements—have been found to suffer from data lag, inaccuracies, and limited scalability (Kumar et al., 2019). Artificial Intelligence (AI) offers a transformative alternative, with potential to automate, scale, and optimize emissions tracking processes across various sectors (Rolnick et al., 2019; Zhang et al., 2020). Accurate carbon emissions estimation is foundational to effective climate action. Traditional inventory methods rely heavily on activity data and static emission factors, which are often outdated or generalized, leading to substantial estimation errors (Grote et al., 2021). By contrast, AI leverages historical and real-time data to generate dynamic emissions estimates using predictive modeling.

Li et al. (2022) developed a machine learning model to estimate industrial CO_2 emissions with over 95% accuracy, outperforming traditional inventory models by accounting for variables such as process heat levels, fuel mix, and weather conditions. Similarly, Han et al. (2021) used artificial neural networks to predict building energy emissions, demonstrating significant improvements over conventional spreadsheet-based methods. Studies comparing AI to traditional models in the energy sector found that supervised learning algorithms like Random Forests and XGBoost produce more granular and timely emission profiles (Chen et al., 2020; Chatterjee & Huang, 2021). The ability of AI to assimilate unstructured data (e.g., satellite images, energy logs, weather data) further enhances model precision (Peters et al., 2020).

H1a: AI Systems Provide Higher Accuracy in Carbon Emissions Estimation Than Manual or Sensor-Based Methods

Real-time carbon tracking is essential for adaptive environmental management, but legacy monitoring systems typically operate on fixed intervals or require manual data entry, creating latency in response (Yassine et al., 2020). Integrating AI with IoT (Internet of Things) sensors and remote sensing technologies enables autonomous, real-time monitoring of emissions in energy, transport, agriculture, and manufacturing sectors. Mohammadi et al. (2018) describe how AI algorithms combined with smart meters in industrial facilities continuously optimize energy use and calculate carbon emissions. Remote sensing data analyzed using AI—especially convolutional neural networks (CNNs)—has been used for land use carbon estimation and detecting methane leaks from satellite imagery with high precision (Cusworth et al., 2019; Varon et al., 2021). In logistics, AI-powered telematics systems analyze vehicle fuel usage and routing to quantify and reduce CO_2 output (Mehmood et al., 2021). These systems outperform legacy GPS-based emissions calculators by integrating vehicle health, load, and road condition data into emissions models in real-time.

H1b: Integration of AI with IoT and Remote Sensing Leads to More Effective Real-Time Carbon Footprint Tracking

Transparency in emissions reporting is crucial for stakeholders, regulators, and ESG investors. However, many sustainability reports are qualitative and lack standardization, making analysis difficult (Berg et al., 2019). Natural Language Processing (NLP), a subfield of AI, enables automated extraction, classification, and sentiment analysis of environmental disclosures from corporate reports, news, and social media. Wang & Li (2022) developed an NLP model to assess ESG-related language in annual reports, revealing inconsistencies in how firms report emissions-related risks. Their model improved reporting transparency by classifying vague statements and highlighting omissions. Similarly, Kotsiantis et al. (2020) applied NLP to news data to cross-validate self-reported carbon data, uncovering discrepancies in reported vs. actual emissions.

Moreover, NLP-based tools like ClimateBERT (Webersinke et al., 2021) are being used by financial analysts to evaluate climate-related disclosures under frameworks such as TCFD and CDP, enhancing standardization and cross-sector comparison.

H1c: NLP-Based AI Tools Enhance the Transparency of Emissions Reporting Through Automated Disclosure Analysis

Environmental, Social, and Governance (ESG) metrics increasingly drive investor and consumer decisions. A growing body of research shows that companies adopting AI-driven environmental technologies tend to demonstrate superior ESG performance and market valuation (Eccles et al., 2020; García et al., 2021). PwC (2021) found that AI adoption in sustainability strategies correlates with better performance in Scope 1 and 2 emissions reduction. Additionally, companies deploying AI-powered emissions management systems often score higher on third-party ESG indices due to improved data quality and responsiveness (BlackRock, 2020).

Sustainable finance platforms like Arabesque S-Ray and MSCI ESG Ratings have integrated AI to assess corporate ESG performance. Companies leveraging AI tools for emissions reduction and disclosure were more likely to receive favorable ratings and qualify for green financing (O'Connor et al., 2022).

H1d: Organizational Adoption of AI for Carbon Monitoring is Positively Correlated With Improved ESG Performance Metrics

3. Research Methodology

This study adopts a **mixed-methods research design** combining quantitative analysis and qualitative insights to evaluate the effectiveness of AI-driven carbon monitoring systems in enhancing environmental accountability. The methodology is structured around a comparative framework analyzing traditional carbon tracking approaches versus AI-enabled solutions across a sample of organizations varying in size, industry, and geographic location.
Quantitative data was drawn from firm-level ESG disclosures collected via the Carbon Disclosure Project (CDP) database and manually verified for consistency using the S&P Global ESG portal for 60 companies.
The qualitative phase consisted of semi-structured interviews with 25 experts, including AI developers, sustainability consultants, and corporate ESG strategists, to contextualize the quantitative findings. Thematic analysis was used to identify recurring patterns and challenges in AI implementation, with coding performed in NVivo 12 following the Braun and Clarke (2006) methodology. Particular attention was given to identifying how AI algorithms are used in real-world carbon tracking scenarios, such as energy consumption forecasting, satellite-based emission analysis, and automated NLP-based ESG reporting (Lang et al., 2019; Wang & Li, 2022).
This research applies the **technology-organization-environment (TOE) framework** to assess adoption factors, aligning with prior studies on green technology integration (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011). This framework evaluates how technological readiness, organizational capabilities, and external pressures (e.g., regulatory and market forces) influence the uptake of AI for carbon monitoring. The TOE lens enables a holistic interpretation of the structural and institutional conditions that shape AI's role in driving environmental accountability.
This comprehensive methodology allows for a rigorous analysis of AI's empirical impact on carbon accountability, supporting robust hypothesis testing while also capturing the lived realities of AI deployment in sustainability contexts.

4. Data Analysis

This study analyzes the impact of AI-driven carbon monitoring on environmental accountability across a sample of 60 organizations from the manufacturing, transportation, and technology sectors over a period of 5 years (2019–2023). The analysis utilizes:

- Carbon emission reports (Scope 1 and 2) from the Carbon Disclosure Project (CDP)
- AI tool adoption data from corporate ESG disclosures
- Third-party AI system audits from IBM's AI & Sustainability Index (2023)
- Environmental performance scores from Refinitiv and MSCI ESG Ratings

To measure AI adoption and emission reduction trends Organizations were grouped into two cohorts: Group A includes 30 organizations using AI-driven carbon monitoring systems (e.g., IBM Envizi, Microsoft Cloud for Sustainability, Salesforce Net Zero Cloud) and Group B includes other 30 organizations using traditional monitoring methods (manual reports, periodic audits)

Table 1: Average Annual Carbon Emissions (2019–2023)

Year	*Group A (AI-based)*	*Group B (Traditional)*
2019	252,000 tCO_2e	257,500 tCO_2e
2020	243,500 tCO_2e	254,000 tCO_2e
2021	229,000 tCO_2e	248,750 tCO_2e
2022	212,500 tCO_2e	244,300 tCO_2e
2023	194,000 tCO_2e	241,800 tCO_2e

Group A achieved an average **22.9% emissions reduction** over five years, compared to **6.1%** in Group B. The sharper decline in Group A suggests a positive correlation between AI adoption and proactive emissions management. This is consistent with findings from Li et al. (2022), who demonstrated that AI-enabled predictive analytics can optimize energy usage patterns, resulting in faster emissions decline.
One of AI's key advantages is enhanced **monitoring granularity**. The following table captures the frequency of emissions tracking and reporting:

Table 2: Monitoring and Reporting Frequency

Metric	*Group A (AI-based)*	*Group B (Traditional)*
Average reporting interval	7 days	90 days
Real-time dashboard availability	93%	10%
Predictive emission alerts	87%	3%

Group A organizations were significantly more responsive to carbon anomalies due to real-time dashboards and automated alerts. This supports previous research by González-Rivero et al. (2021), which found that AI systems reduce emissions lag by up to 65% through immediate data analysis.

To assess the broader impact on environmental accountability, the study tracked ESG environmental scores pre- and post-AI adoption.

Table 3: Average ESG Environmental Scores (Refinitiv Scale: 0–100)

Sector	*Pre-AI Adoption (2019)*	*Post-AI Adoption (2023)*	*% Increase*
Manufacturing	53.2	74.5	40.0%
Transport	50.1	68.4	36.5%
Technology	60.4	80.7	33.6%

Environmental scores saw a **33–40% improvement**, highlighting that AI systems not only reduce carbon but also improve stakeholder transparency, auditability, and compliance—a finding echoed by Wang & Li (2022) in their analysis of ESG disclosures using NLP-based AI tools.

4.1 Regression Analysis: AI Monitoring vs Emission Reduction

We conducted a linear regression to explore the relationship between the **extent of AI tool integration** and **emission reduction rate**.

Variable	*Coefficient (β)*	*p-value*	*R^2*
AI system maturity score (0–10)	-2.84	< 0.001	0.76

There is a strong negative correlation between AI system maturity and emissions, with each unit increase in AI integration leading to a **2.84% additional reduction** in carbon emissions annually. The findings are in line with Klein et al. (2021), who demonstrated that AI tool maturity, especially predictive AI, is a key factor in emission abatement strategies.

4.2 Sentiment and Disclosure Analysis (NLP-Based)

Using NLP analysis on over 10,000 sustainability reports (2018–2023), AI-based firms displayed more consistent usage of **carbon transparency terms** (e.g., "real-time tracking," "automated audit," "carbon offset verification") than non-AI firms.

Table 4: Carbon Disclosure Sentiment Score (NLP-Based)

Metric	*Group A (AI-Based)*	*Group B (Traditional)*

Sentiment score (0–1)	0.82	0.54
Keyword frequency index	47.3	21.6
Tone consistency (year over year)	93%	61%

This aligns with Berg et al. (2019), who found that AI-enhanced disclosure tools produce more consistent, high-quality ESG documentation.

Summary of Key Findings

Analytical Focus	***Result Highlights***
Emissions Reduction	22.9% vs 6.1% over 5 years (AI vs Traditional)
Reporting Responsiveness	Real-time (AI) vs Quarterly (Traditional)
ESG Environmental Score Increase	Up to 40% in AI-enabled sectors
Regression Analysis	AI integration strongly predicts emissions drop
NLP Sentiment Analysis	AI-enabled firms show clearer, more consistent reporting

This data-driven analysis supports the core hypothesis: **AI-driven carbon monitoring significantly enhances environmental accountability**, as seen in lower emissions, improved transparency, and stronger ESG performance. These results corroborate earlier theoretical frameworks and real-world applications across sectors.

5. Conclusion

This study has critically examined the transformative role of Artificial Intelligence (AI) in carbon footprint monitoring and environmental accountability. By integrating data analytics, machine learning, natural language processing (NLP), and Internet of Things (IoT) frameworks, AI enables a paradigm shift from periodic, reactive emissions reporting to a real-time, predictive, and actionable sustainability strategy (Rolnick et al., 2019; Yassine et al., 2020). The empirical findings of this research affirm the theoretical promise of AI, revealing clear advantages over traditional monitoring systems across several performance metrics.

One of the most significant contributions of AI lies in its ability to **bridge the data gap**. Traditional carbon accounting methods often suffer from inaccuracies, delays, and subjectivity (Cheng et al., 2021). In contrast, AI-driven systems can analyze large, diverse data sources—from energy consumption logs to satellite imagery and textual emissions reports—with higher speed and precision (Lang et al., 2019; Wang & Li, 2022). This not only improves internal corporate ESG reporting but also empowers external stakeholders—such as regulators and investors—with verifiable, real-time environmental insights (Berg et al., 2019; Floridi et al., 2018).

Furthermore, the integration of AI in carbon monitoring aligns well with global sustainability and regulatory frameworks, such as the **European Green Deal** and the **Carbon Disclosure Project (CDP)**, both of which emphasize transparency, traceability, and innovation in emissions management (European Commission, 2020). As nations and corporations commit to net-zero targets, AI will likely become a key enabler of **climate accountability infrastructure**.

However, the deployment of AI in environmental domains is not without challenges. The **energy intensity** of large-scale AI model training can paradoxically contribute to emissions, raising ethical concerns about sustainable AI development (Strubell et al., 2019). Moreover, the success of AI systems depends on **high-quality, standardized data**, which remains a significant barrier, especially in developing regions or decentralized industries (Klein et al., 2021). There is also a growing need for **transparent AI governance** to mitigate algorithmic bias and ensure ethical deployment in carbon tracking initiatives (O'Neil, 2016; Andersson & Lönnqvist, 2020).

From a governance perspective, **AI-enabled firms exhibit superior reporting responsiveness**, shifting from **quarterly disclosures to real-time updates**, a capability that aligns with the increasing regulatory demand for transparency and timeliness in sustainability reporting (Floridi et al., 2018; European Commission, 2020). This responsiveness is further validated by NLP-based sentiment analysis, which reveals that **AI-enabled companies produce clearer, more consistent carbon disclosures**, reducing greenwashing risks and strengthening stakeholder trust (Wang & Li, 2022; Berg et al., 2019).

In conclusion, AI-driven carbon monitoring systems represent a **transformative shift** in how environmental accountability is operationalized across sectors. While still maturing, these technologies offer powerful tools for aligning organizational behavior with sustainability goals. To realize their full potential, it is imperative to invest in robust data infrastructures, foster interdisciplinary collaboration, and develop regulatory frameworks that ensure ethical and transparent use of AI. As climate concerns intensify globally, AI's integration into carbon tracking systems will be not just a technological advantage—but a moral and strategic imperative.

6. Managerial Implications

The integration of AI-driven carbon monitoring systems into organizational practice carries substantial implications for corporate leadership, sustainability strategists, and environmental compliance officers. Managers are increasingly under pressure to operationalize environmental accountability, not only due to regulatory mandates but also in response to growing stakeholder demand for transparency, efficiency, and ethical governance (Eccles & Klimenko, 2019).

First, **real-time emissions tracking powered by AI** enables more agile and proactive environmental decision-making. Unlike traditional carbon accounting, which often relies on retrospective and static data, AI facilitates near-instantaneous detection of carbon-intensive operations. This empowers managers to implement corrective measures swiftly, optimize energy consumption, and reduce environmental impact in a cost-effective manner (Ghahramani et al., 2020; Yassine et al., 2020). The strategic deployment of machine learning models trained on historical energy usage, weather patterns, and production cycles can also assist managers in forecasting carbon peaks and mitigating them before regulatory thresholds are breached (Li et al., 2022).

Second, **AI systems enhance environmental reporting accuracy**, thereby reducing the reputational and financial risks associated with greenwashing and non-compliance. Automated Natural Language Processing (NLP) tools can analyze large volumes of internal and public data—from sustainability reports to operational logs—to detect inconsistencies or omissions in disclosed emissions figures (Wang & Li, 2022). For managers responsible for ESG disclosures, this creates opportunities to generate more transparent and auditable environmental reports, aligning with international frameworks such as the Task Force on Climate-related Financial Disclosures (TCFD) and the Global Reporting Initiative (GRI) (Berg et al., 2019; Deloitte, 2021).

Third, **the integration of AI with IoT and edge computing infrastructure** supports scalable and site-specific carbon monitoring. For operations managers in manufacturing, logistics, or construction industries, embedding AI sensors across facilities or fleets provides granular visibility into emissions sources (Mohammadi et al., 2018). This supports data-driven environmental performance management, enabling localized interventions such as retrofitting equipment or re-routing supply chains for carbon efficiency (Cheng et al., 2021).

From a **governance standpoint**, AI-driven carbon tools can also support board-level decision-making and risk oversight. Boards and executive committees can leverage AI-powered dashboards to monitor key emissions metrics across the organization, ensuring that sustainability strategies are not siloed but embedded into core business objectives (Eccles et al., 2020). Furthermore, firms using AI to improve environmental accountability are more likely to gain access to green financing, ESG index inclusion, and investor confidence—benefits that directly support long-term strategic positioning (BlackRock, 2021).

In conclusion, the managerial adoption of AI-driven carbon monitoring systems can significantly enhance environmental accountability, operational efficiency, and regulatory compliance. However, this transformation requires more than technological procurement—it demands visionary leadership, interdisciplinary collaboration, and a strong commitment to ethical innovation. Organizations that embrace this paradigm shift are better positioned to navigate the sustainability transition and create long-term value for both stakeholders and the planet.

7. Societal Implications

The integration of artificial intelligence (AI) in carbon monitoring systems carries profound societal implications that extend far beyond the technical and environmental realms. As climate change becomes an increasingly urgent global concern, the application of intelligent systems to track and mitigate carbon emissions introduces transformative possibilities for how societies understand, manage, and respond to ecological challenges. However, the deployment of AI in this domain also raises critical questions regarding equity, ethics, access, labor markets, and governance.

At the forefront, AI-driven carbon monitoring has the potential to democratize access to environmental accountability. By enabling real-time, data-rich analysis of emissions, AI tools empower citizens, civil society organizations, and journalists to hold governments and corporations accountable for their environmental impact. Enhanced transparency can reduce greenwashing—the practice of misleading stakeholders about environmental practices—and promote a culture of ecological responsibility across industries. Moreover, such systems can help policymakers design more effective climate regulations based on dynamic, empirical insights, rather than delayed or incomplete data reporting.

In the social sphere, AI systems can contribute to a more informed and engaged public. When deployed through open-access platforms or community-based applications, AI-powered dashboards and carbon tracking tools can increase public awareness of carbon footprints at the individual, local, and national levels. This can encourage behavioral changes such as energy conservation, green consumer choices, and support for sustainable urban planning. Additionally, AI can play a key role in environmental justice by identifying pollution hotspots and emission patterns that disproportionately affect marginalized or vulnerable communities. Such insights can inform equitable policy interventions that prioritize those most impacted by environmental degradation.

However, the societal benefits of AI in carbon monitoring are not evenly distributed. One of the most pressing concerns is the digital divide. Many low-income countries and rural regions lack the technological infrastructure, skilled workforce, and financial resources needed to develop or implement AI systems. This may exacerbate global inequalities in environmental governance, as wealthy nations and corporations gain disproportionate control over data and monitoring capabilities. Ensuring inclusivity in AI deployment—through capacity-building, open-source platforms, and international cooperation—is therefore essential to avoid widening the global sustainability gap.

Finally, the energy consumption of AI systems themselves raises a paradoxical challenge. Large-scale AI models require significant computational resources, which may contribute to emissions unless powered by renewable energy sources. The societal legitimacy of AI in climate governance depends on addressing this issue through innovations in green AI—such as energy-efficient algorithms, sustainable hardware, and transparent carbon accounting of digital infrastructures.

In conclusion, while AI-driven carbon monitoring holds immense promise for enhancing environmental accountability, its societal implications are complex and multifaceted. These systems can catalyze positive change only if their deployment is guided by principles of equity, inclusivity, transparency, and sustainability. A multidisciplinary and participatory approach is essential to ensure that intelligent systems not only measure our impact on the planet but also help shape a more just and resilient future for all.

8. Scope for Future Research

While the current research underscores the transformative potential of artificial intelligence in enhancing environmental accountability through improved carbon monitoring, several areas remain ripe for further exploration. One significant direction for future research involves the **development of standardized AI frameworks** for carbon accounting that are interoperable across industries and geographies. The current lack of uniformity in emissions data formats and ESG reporting practices hinders the scalability and comparability of AI-driven monitoring systems.

Another critical area for investigation is the **ethical and environmental sustainability of AI itself**. As large-scale AI models consume considerable energy during training and deployment, researchers must examine methods for building "green AI" systems with lower carbon footprints. Moreover, **longitudinal studies** that assess the real-world impact of AI-based carbon monitoring systems on corporate behavior and emissions reduction are currently limited. The role of **AI in climate finance and carbon markets** is another emerging frontier. AI could be used to optimize carbon credit pricing, detect greenwashing in environmental claims, and assess climate-related financial risks. Future studies might explore how predictive analytics and AI-assisted auditing can enhance the transparency and efficiency of carbon trading systems.

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Authors:-

1st Author: Dr. Poonam is an Assistant professor in School of Commerce and Business Management at Geeta University, Naultha. Her research focuses on marketing and finance, with a particular interest in brand equity. She has published in reputed Journals and presented in international conferences. Dr. Poonam holds a Ph.D from Kurukshetra University Kurukshetra and had received Junior research fellowship from UGC.

2nd Author: Dr. Nidhi Gehlawat, an accomplished Academician and Professional in Management and Human Resources, holds a Ph.D. in Human Resource Management from Maharishi Markandeshwar (Deemed to be University), along with an MBA in Finance and HR, BBA from Maharishi Dayanand University, and a PGDIBO from IGNOU. Currently serving as an Assistant Professor at the School of Commerce & Business Management, Geeta University, Panipat, Haryana, India. She brings rich teaching and industry experience to her role. Her professional journey includes roles as an Admission Counselor and Linguistic Teacher (2020–2022) and as a Human Resource Executive at Fortune Makers, New Delhi, in 2019. Proficient in American and British English, as well as Hindi, Dr. Gehlawat has also contributed to academic research, publishing papers in national and international journals, reflecting her dedication to advancing knowledge in her field.

3rd Author: Tanu is a Ph.D Scholar at University School of Management, Kurukshetra University. She has a specialization in Digital and Social Media Marketing of Higher Education Institutes. She has presented Five research papers at national and international conferences and has been published in a reputed journal.