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AI-Driven ESG Investing: Machine Learning for Sustainable Portfolio Performance and Risk Management

[1]T. Venkatesan*, [1]A. Stephen, [1]P. Deepan Kumar, [2]Talha
Corresponding Author: * proftvv@gmail.com
[1] Knowledge Institute of Technology, Salem, Tamil Nadu, India
[2] Abasyn University, Peshawar, Pakistan

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ABSTRACT

Integrating environmental, social, and governance (ESG) information with machine learning may improve security selection and risk-aware portfolio decisions, but its empirical value depends on data quality, model validation, and consistent portfolio evaluation. This article reorganizes and critically interprets the reported findings from an analysis of 50 listed firms over 2015–2024, comparing Random Forest, extreme gradient boosting (XGBoost), and long short-term memory (LSTM) models. The supplied results report XGBoost as the best-performing model (accuracy 0.89, AUC-ROC 0.92, F1 score 0.88, RMSE 0.120). The reported AI-driven ESG portfolio has a 14.50% return, 14.10% volatility, and a Sharpe ratio of 1.02, compared with 10.20%, 18.50%, and 0.55 for the traditional portfolio. These values are reproduced as reported rather than independently validated because underlying observations, model settings, backtesting rules, and full inferential outputs are not included in the manuscript. The analysis places these results in the context of ESG asset pricing, rating divergence, and predictive modelling, identifies threats to reproducibility, and outlines requirements for a defensible out-of-sample comparison. The study offers a structured basis for evaluating AI-enabled ESG portfolios without treating descriptive differences alone as proof of causal or statistically significant outperformance.

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Introduction

Sustainable investing has expanded the information set used in portfolio construction beyond accounting fundamentals and market prices to include corporate environmental, social, and governance characteristics. ESG information may capture exposure to climate transition, labor practices, stakeholder relationships, and governance quality, although the relationship between these attributes and investment performance is not necessarily stable across markets or periods. Large-scale evidence synthesised by Friede et al. [1] documents a predominance of non-negative associations between ESG and corporate financial performance, while Eccles et al. [2] connect sustained corporate sustainability practices to organizational processes and longer-horizon outcomes.

Additional evidence distinguishes the relation of ESG to valuation and risk from any automatic return premium. Giese et al. [12] describe financial channels through which ESG information may affect equity valuation and risk, while Fatemi et al. [13] associate firm value with both ESG performance and the extent of disclosure. Empirical optimization work by Abate et al. [14] and multi-objective modeling by Xidonas and Essner [15] further motivate treating sustainability as a portfolio constraint or objective rather than a universal return enhancer.

From a portfolio perspective, investors face a trade-off among expected financial return, risk, and sustainability preferences. Pedersen et al. [3] formalize this problem through an ESG-efficient frontier, demonstrating that the financial implications of ESG constraints depend on preferences and the opportunity set. Pástor et al. [4] further explain how demand for green assets can change equilibrium returns. Carbon exposure is another economically relevant dimension: Bolton and Kacperczyk [5] show that carbon emissions can be associated with a pricing premium, underscoring the importance of distinguishing return expectations from realized performance.

The interpretation of ESG signals is complicated by measurement differences. Berg et al. [6] document substantive divergence across ESG ratings, which can lead identical firms to receive different scores depending on provider methodology. Investors also differ in their uses of ESG information, ranging from risk management to valuation and screening [7]. Consequently, simply adding a single composite ESG score to an investment model may mask component heterogeneity, rating uncertainty, and time variation.

Machine learning offers tools for detecting nonlinear associations and interactions among ESG features, financial fundamentals, and market conditions. Random Forest aggregates decision trees to reduce variance [8], XGBoost uses regularized gradient-boosted trees to improve predictive learning [9], and LSTM networks are designed to capture sequential dependencies [10]. However, flexible prediction does not automatically translate into superior investment outcomes: a credible empirical evaluation must prevent look-ahead

bias, apply realistic trading assumptions, and compare strategies on the same investable universe and risk basis.

This study examines the reported relationship between AI-based prediction and ESG portfolio performance for 50 publicly listed companies during 2015–2024. Its intended contribution is a comparative assessment of three learning architectures alongside portfolio-level return, volatility, and Sharpe ratio. Unlike a pure model-accuracy exercise, the analysis considers both predictive performance and portfolio risk. The central research question is whether the reported performance differences support the potential usefulness of AI-assisted ESG investment decisions and what additional validation is necessary before concluding that the approach generalizes beyond the examined sample.

Literature review and conceptual foundations

A. ESG factors and financial performance

ESG integration can influence expected cash flows, downside exposure, the cost of capital, and investors' nonfinancial utility. Broad reviews suggest heterogeneous but frequently non-negative ESG-financial performance relationships [1], while sustainability-oriented corporate processes may contribute to resilience and governance quality [2]. Yet realized returns need not increase with ESG quality because sustainability preferences can also raise asset prices and lower subsequent expected returns [3], [4]. The carbon-risk premium documented in asset-pricing work [5] further indicates that different ESG dimensions can produce distinct economic effects. Thus, any performance advantage should be evaluated against relevant benchmarks and risk exposures rather than attributed automatically to ESG screening.

B. ESG measurement and investment implementation

More recent methodology research reinforces the need to inspect the construction of sustainability ratings. Del Vitto et al. [16] use machine learning to explain the structure of ESG ratings and identify residual uncertainty. Varmaz et al. [17] examine sustainable portfolio optimization, underscoring the importance of model specifications when ESG enters the allocation problem.

ESG ratings are not universally comparable because data coverage, category definitions, and aggregation weights differ among providers [6]. The choice of data vendor can therefore alter firm rankings and portfolio composition. Survey evidence also shows that investment professionals apply ESG information for several purposes, including risk assessment, security selection, and engagement [7]. These findings motivate explicit reporting of ESG data provenance, measurement dates, missingness, and the precise manner in which environmental, social, and governance information enters the predictive model.

ESG-specific forecasting research also offers closer methodological comparators than generic machine learning benchmarks. Suprihadi and Danila [18] examine ensemble

forecasting of ESG equity indices, while Masood [19] compares machine learning methods within sustainable portfolio optimization. Caristi et al. [20] integrate XGBoost forecasting with ESG-constrained allocations, and Van Wallendael et al. [21] combine machine-learning security screening with mean-CVaR downside-risk optimization. These studies indicate that predictive accuracy and portfolio-level performance should be assessed as distinct outcomes.

C. Machine learning and portfolio construction

The economic meaning of ESG indicators also differs across firm characteristics and investor objectives. Krüger [22] documents market reactions associated with corporate social responsibility events, providing a reason not to infer universally positive performance effects from an aggregate ESG score. Random Forest combines predictions across bootstrapped trees and provides a robust nonlinear benchmark [8]. XGBoost develops additive decision trees with regularization and efficient optimization [9]. LSTM networks are designed to encode temporal information, which makes them a plausible candidate for return prediction where sequences are informative [10]. Friedman's gradient-boosting framework [11] supplies the broader methodological foundation. Model comparisons should nevertheless use consistent targets, samples, temporal splits, hyperparameter selection, and economic evaluation. Classification measures such as accuracy and AUC-ROC describe directional discrimination; regression error measures such as RMSE describe continuous forecast error. These metrics should not be interpreted as interchangeable evidence of portfolio profitability.

D. Research gap and analytical proposition

Prior work provides financial and conceptual reasons to include ESG variables in portfolio selection [3]–[7] and methodological reasons to test nonlinear predictive models [8]–[11]. What remains important in this study is the joint interpretation of predictive scores and investable portfolio outcomes. The reported comparisons suggest that model selection and ESG screening may matter together, but without a transparent backtesting protocol they cannot identify which component generated the observed difference. The analytical proposition is therefore conditional: if predictive gains persist in genuinely out-of-sample, cost-adjusted investment tests, AI-supported ESG allocation could improve the risk-return profile relative to otherwise comparable conventional strategies.

Materials and Methods

A. Research design, population, and data sources

The source manuscript describes a quantitative comparative design based on secondary ESG and financial data for 50 publicly listed firms observed over 2015–2024. The intended sample spans information technology, banking and financial services, energy, manufacturing, healthcare, and consumer goods. Firms were purposively selected for availability of ESG ratings, sustainability reports, and historical financial indicators. ESG sources named in the

manuscript include MSCI, Refinitiv, Sustainalytics, and company disclosures; financial sources include exchange records, annual reports, Bloomberg, Refinitiv, and Yahoo Finance. These should be interpreted as stated sources, because the manuscript does not provide the actual firm list, vendor identifiers, extraction dates, or a source-to-variable crosswalk.

B. Variables and preprocessing

Predictor candidates include aggregate and component ESG scores, market capitalization, earnings per share, return on assets, return on equity, stock prices, returns, volatility, and dividend yield. The reported processing sequence comprises removal of duplicates, treatment of missing values, merging ESG and financial records, feature selection, and scaling or standardization. To support reproducibility, transformations should be estimated only on the training partition and applied unchanged to subsequent validation periods. ESG measurement must also respect publication lags so that information unavailable at portfolio formation is not used retrospectively.

C. Predictive models and evaluation

The three specified models are Random Forest [8], XGBoost [9], and LSTM [10]. The source gives inconsistent train-test partitions, mentioning both 80:20 and 70:30; therefore no definitive split is asserted in this rewrite. A chronological train-validation-test design would be preferable for annual financial observations. The reported model metrics comprise accuracy, AUC-ROC, F1 score, and RMSE. Their joint interpretation requires an explicit classification label, continuous prediction target, decision threshold, class prevalence, and common observation set, none of which can be fully recovered from the supplied narrative.

D. Portfolio formation and statistical assessment

The manuscript compares a conventional portfolio, an ESG-only portfolio, and an AI-driven ESG portfolio using average return, return volatility, and Sharpe ratio. Ideally, portfolio weights, rebalance dates, transaction costs, risk-free rate, investability constraints, and benchmark construction would be reported. The supplied text refers to a t-test and a significant difference but does not give complete test statistics, confidence intervals, observation counts, or replicable return series. Accordingly, the present article reports the supplied numerical summaries as descriptive findings and does not independently confirm their statistical significance.

Results

A. Descriptive characteristics

Table 1 presents descriptive statistics for the environmental, social, and governance (ESG) and financial variables included in the analysis. For each variable, the mean summarizes its average value, the standard deviation indicates dispersion, and the minimum and maximum

identify observed extremes, providing an overview of the sample's distribution and overall variability.

Table 1. Descriptive statistics of ESG and financial variables

Variable	Mean	Standard deviation	Minimum	Maximum
ESG Score	68.45	12.30	35.20	91.50
Environmental Score	70.10	14.25	30.50	95.00
Social Score	65.75	11.80	40.00	89.20
Governance Score	69.20	10.60	45.10	92.30
Annual Return (%)	12.85	8.45	-10.20	28.50
Volatility (%)	15.40	5.20	8.10	30.60

The reported mean ESG score is 68.45 (standard deviation 12.30), with component means of 70.10 for environmental, 65.75 for social, and 69.20 for governance. Annual return averages 12.85%, and volatility averages 15.40%. These descriptive figures provide the distributional background for modelling but, without the firm-level dataset or correlation matrix, do not establish that higher ESG scores are significantly associated with higher returns or lower risk.

B. Predictive model comparison

Table 2 compares the predictive performance of machine learning models using accuracy, AUC-ROC, F1 score, and RMSE. Accuracy reflects overall classification correctness, AUC-ROC measures discrimination, F1 score balances precision and recall, and RMSE quantifies prediction error. Together, these metrics support comparison across complementary aspects of model performance on evaluated data.

Table 2. Comparative predictive performance of machine learning models

Model	Accuracy	AUC-ROC	F1 Score	RMSE
Random Forest	0.84	0.87	0.82	0.145
XGBoost	0.89	0.92	0.88	0.120
LSTM	0.81	0.85	0.80	0.160

XGBoost has the highest reported accuracy (0.89), AUC-ROC (0.92), and F1 score (0.88), together with the lowest RMSE (0.120). Random Forest ranks second and LSTM third on the tabulated measures. These comparisons indicate a favorable reported performance profile for boosting on the study's unspecified prediction target. They should not, by themselves, be interpreted as evidence of external validity or economic benefit because the test horizon, uncertainty intervals, and training specifications are not documented.

C. Portfolio performance

Table 3 compares portfolio performance using average return, volatility, and the Sharpe ratio. Average return summarizes investment performance, while volatility indicates variability in returns. The Sharpe ratio measures excess return relative to risk. These indicators provide complementary perspectives for evaluating profitability, risk exposure, and risk-adjusted performance across different portfolio types.

Table 3. Portfolio performance comparison

Portfolio Type	Average Return (%)	Volatility (%)	Sharpe Ratio
Traditional Portfolio	10.20	18.50	0.55
ESG Portfolio	11.80	16.20	0.73
AI-Driven ESG	14.50	14.10	1.02

The AI-driven ESG strategy is reported to deliver a 14.50% return, 14.10% volatility, and a Sharpe ratio of 1.02, compared with 11.80%, 16.20%, and 0.73 for the ESG-only portfolio and 10.20%, 18.50%, and 0.55 for the traditional strategy. On these point estimates, the AI-driven portfolio combines the highest return and lowest volatility. However, the risk-free rate and measurement frequency underlying the Sharpe ratios are not provided; the reported values are therefore retained without independent recalculation.

D. Original visual evidence

Fig. 1 illustrates portfolio performance over time, showing how investment outcomes evolve throughout the observation period. The temporal presentation supports examination of performance trends, fluctuations, and periods of growth or decline. It provides a basis for assessing the consistency and stability of portfolio performance across the study's specified evaluation horizon.



Fig. 1. Portfolio performance over time

Fig. 2 plots expected return against volatility for simulated portfolios, with colors representing Sharpe ratios. The red marker identifies the designated optimal portfolio at approximately 0.32 volatility and 0.215 expected return. Portfolios toward the upper left generally exhibit higher Sharpe ratios, indicating more favorable returns relative to their measured volatility.

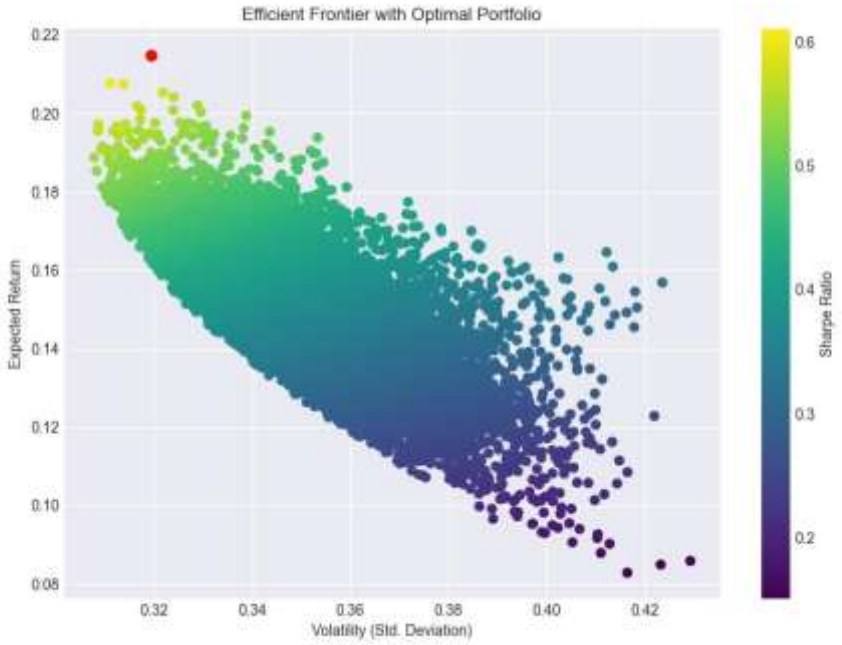


Fig. 2. Risk-return analysis and efficient frontier

Fig. 3 compares AUROC and training time across four classifiers using fivefold cross-validation on one million synthetic observations with 20 features. XGBoost achieved the highest AUROC (0.9662) in 24 seconds, closely matching gradient boosting while training substantially faster. Logistic regression trained fastest, whereas random forest showed intermediate discrimination and runtime.

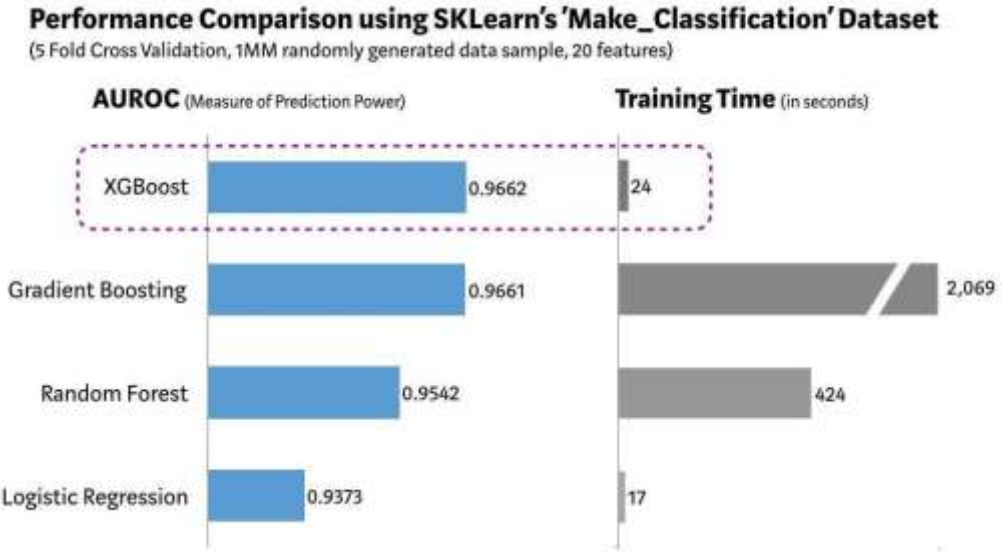


Fig. 3. Model accuracy comparison

Fig. 4 illustrates a two-tailed independent-samples t-test with critical values of −2.101 and 2.101. The observed t-statistic (−4.380) falls within the left rejection region, supporting

rejection of the null hypothesis of equal population means. The shaded tails identify rejection regions, while the dashed blue line marks the observed test statistic.

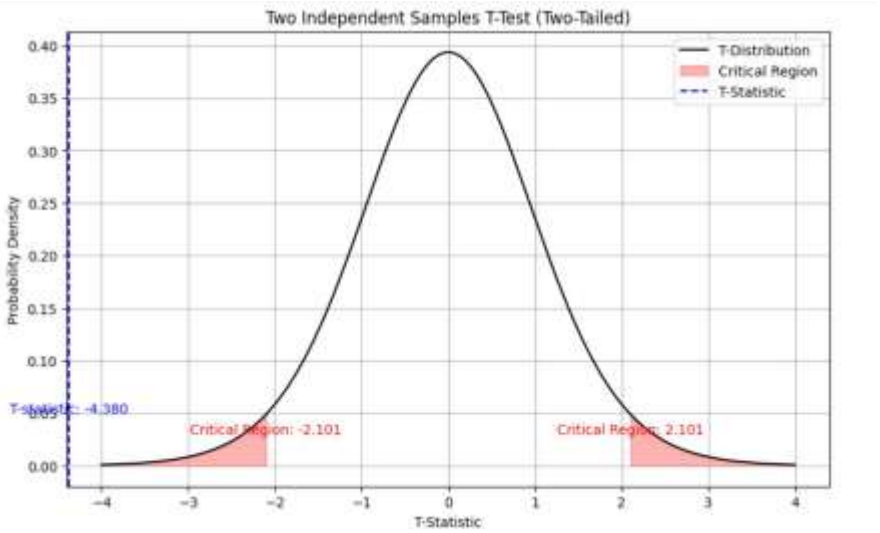


Fig. 4. T-test comparison of portfolio returns

The portfolio comparisons also require interpretation against investment strategies rather than solely rating levels. Nagy et al. [23] study ESG tilt and momentum strategies, showing why a replicable allocation rule is important when comparing ESG portfolios. Their approach also highlights the need to distinguish return forecasting from ESG-driven reweighting. Kotsantonis et al. [24] discuss misconceptions and practical data challenges in ESG integration. Investor demand itself can affect the interpretation of responsible investment outcomes: Bollen [25] considers how fund characteristics and investor behavior interact, underscoring that realized performance is not the only reason investors select sustainability-oriented products.

Discussion

The reported results place XGBoost ahead of Random Forest and LSTM on four predictive indicators. This ranking is consistent with the capacity of boosted-tree methods to fit nonlinear interactions in tabular datasets [9], [11], whereas Random Forest offers an alternative ensemble strategy for reducing prediction variance [8]. Nevertheless, the available figures do not isolate whether superior performance arises from ESG features, conventional financial variables, tuning choices, or a particular data partition. An ablation experiment comparing financial-only, ESG-only, and combined feature sets would be necessary to identify ESG's incremental predictive contribution.

At the portfolio level, the tabulated AI-driven strategy appears to have both greater average return and lower volatility than the reported conventional and ESG-only alternatives. The ESG-efficient frontier framework provides an appropriate theoretical reference for evaluating this balance [3]. However, the results should not be interpreted as evidence that sustainable assets invariably outperform: asset-pricing theory suggests that high demand for

green assets can alter expected returns [4], and firms' carbon exposures can carry distinct financial risk premia [5]. Results may also depend on the study period, sector weights, and benchmark definition.

The apparent benefits must be assessed against data heterogeneity. ESG rating disagreement [6] can lead to materially different portfolio rankings, and professional investors use ESG data for diverse purposes [7]. The supplied methods list multiple providers but do not explain whether their scores were merged, selected, or standardized. As a consequence, the reproducibility and stability of the portfolio construction remain uncertain. Sensitivity analyses using each provider separately and examining the E, S, and G pillars would address this issue.

There are additional methodological limitations. Financial data are inherently temporal, and random splitting may contaminate evaluations when observations from the same company and adjacent years appear across training and test partitions. A walk-forward or expanding-window protocol would align predictions with the information actually available at each investment date. Transaction costs, turnover, short-sale restrictions, and the risk-free rate should be incorporated before drawing conclusions about implementable Sharpe ratios. Likewise, uncertainty should be estimated from matched portfolio return series, preferably with methods accounting for serial dependence.

The visuals are helpful for illustrating the study's intended comparisons but cannot all be treated as direct evidence from the specified ESG dataset. In particular, Fig. 3 explicitly uses a synthetic classification exercise, and Fig. 4 lacks the raw inferential output needed to support a formal test of portfolio-return differences. Preserving these figures while identifying their limited evidentiary status is preferable to presenting them as independent confirmation. Publication readiness ultimately depends on obtaining the underlying calculations or replacing illustrative graphics with faithfully regenerated empirical plots.

The study's practical relevance lies in its proposed integration of sustainability-related signals with predictive asset selection. Under transparent backtesting and external validation, such a workflow could help portfolio managers compare investment performance and sustainability objectives. Current results should be viewed as reported exploratory comparisons, not as established causal proof that using machine learning or ESG information alone increases returns. Further research should examine robustness across market regimes, industries, data vendors, and alternative asset universes.

Conclusion

The source manuscript reports that XGBoost performs best among the evaluated learning models and that an AI-driven ESG portfolio achieves higher return, lower volatility, and a higher Sharpe ratio than the two comparator portfolios. Reorganized in a conventional

journal structure, these results illustrate the potential of combining machine learning with sustainability information for investment selection. The strength of the conclusion is nonetheless limited by unavailable raw data, unspecified model targets and parameter settings, inconsistent partition ratios, incomplete backtesting details, and illustrative figures that do not fully correspond to the reported ESG analysis. Future work should document the investable universe, use time-appropriate validation, test incremental ESG information, disclose realistic portfolio construction assumptions, and publish uncertainty estimates. These steps are essential before claims of reproducible outperformance can be established.

Conflict of Interest

The authors declare no conflict of interest.

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Authors



Dr. T. Venkatesan is an Associate Professor and Head of the Department of Management Studies at Knowledge Institute of Technology (Autonomous), Salem, Tamil Nadu, India. He has over 18 years of experience in teaching, research, and academic administration, specializing in Finance and Accounting. He holds a Ph.D. in Management Studies (Finance) from Bharathiar University. His research interests include Corporate Finance, Financial Management, Working Capital Management, Banking, and Investment Analysis. He has also served as Vice-Principal, guided research scholars, and contributed significantly to management education and academic research. (email: proftvv@gmail.com).



Dr. A. Stephen serves as the Director of the MBA program in the Department of MBA at Knowledge Institute of Technology (KIOT), Salem, Tamil Nadu, India. In his leadership role, he contributes to the administration and academic development of the MBA program. His responsibilities include supporting management education, facilitating academic activities, and promoting a learning environment that prepares students for professional careers. He is associated with institutional efforts to strengthen management education. (email: directorkbs@kiot.ac.in).



P. Deepan Kumar is an MBA student specializing in Finance and Business Analytics. His interests include banking, financial management, investment analysis, and business analytics. He is developing practical skills in financial operations, data analysis, Excel, Power BI, and financial markets. A quick learner, he is self-motivated and career-focused. He seeks practical industry experience to strengthen his professional capabilities and pursue a career in finance and banking through continuous learning and development. (email: pdeepankumar2005@gmail.com).



Talha is a dedicated PhD Scholar at Abasyn University, Peshawar, Pakistan, and serves as an Assistant Professor at the same institution. His academic interests lie in organizational behavior, management sciences, and strategic leadership. As a faculty member, he teaches and supervises research and scholarly publications that advance management theory and practice. His doctoral research explores innovative solutions in educational and business management systems. Mr. Talha is also involved in curriculum development and institutional research activities that support the growth of quality assurance in academic settings. (email: talha1857@gmail.com).