SPECIAL ISSUE

XXI st International Conference on Theme:
"Geo-Politics: Global Implications for Business Sustainability, Technology and Governance"
held on 30th & 31st January 2026.

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The Journal of Indian Management & Strategy

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A TRUE VISIONARY

"You see things and you say **Why**? *But I dream of things that never were and say* **Why** *not?"*

- George Bernard Shaw

Shri Jagannath Gupta
(1950 - 1980)

Also a true visionary...who dared to dream!
He lives no more but his dreams live on....and on!

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Editor's Desk

As the Editor of this special issue of **JIMS 8M**, it is my distinct privilege to introduce a curated collection of research emerging from the **XXIst International Conference (2026)** hosted by JIMS Kalkaji. The theme of this volume, **"Geo-Politics: Global Implications for Business Sustainability, Technology, and Governance,"** identifies a critical inflection point in the global economic order. We are currently navigating a historic transition from the era of frictionless hyper-globalisation toward a fragmented, state-led model defined by "strategic autonomy." This editorial serves as a premier interdisciplinary forum for evaluating how these shifting power dynamics intersect with institutional resilience and long-term sustainability imperatives.

The research presented herein is structured across three core thematic pillars designed to address the challenges of the contemporary **VUCA** environment. The first pillar, **Geopolitical Risk, Global Trade, and Economic Policy**, examines the shift from cost-optimisation to economic sovereignty. A focal point of this track is India's strategic positioning; by prioritizing energy security and the strategic initiative of Free Trade Agreements (FTAs), the Indian economy is establishing a systematic, robust buffer against global trade volatility. The second pillar, **Sustainability, ESG Practices, and Responsible Governance**, synthesises international perspectives from Australia, Romania, Germany, and Thailand. It posits that Environmental, Social, and Governance (ESG) frameworks have evolved from elective corporate social responsibility into essential components of national security and resource independence. Finally, the third pillar, **Technology, Digital Transformation, and Strategic Autonomy**, assesses the "double-edged sword" of disruptive innovation, exploring how technological sovereignty serves as the new frontier of international competitive advantage.

In alignment with the rigorous standards of a **Web of Science-indexed publication**, this issue is distinguished by its **methodological pluralism**. To address the multi-dimensional nature of modern geopolitical crises, the included works employ a sophisticated array of research designs. These range from **longitudinal econometric modelling** used to forecast trade disruptions and **quantitative multivariate analyses** of financial stability to **qualitative case study methodologies** and **phenomenological inquiries** into adaptive leadership. This diversity is essential for bridging the gap between abstract theoretical constructs and the empirical realities of a world defined by "permacrisis." By utilising both deductive and inductive frameworks, our contributors offer a granular examination of complex phenomena, such as the weaponisation of green finance and geopolitical risks to the next-generation supply chains.

Following an intensive **double-blind peer-review process** where thirty high-impact papers were shortlisted for conference presentation, only the **six highest-quality research papers** were selected for final inclusion in this journal based on their methodological rigour and theoretical depth. This scholarly endeavour was guided by the **leadership of Dr. Amit Gupta, Chairman of JIMS**, and the **support and guidance of Dr. Anuj Verma, Director, JIMS Kalkaji**, with significant oversight from the **Co-Convener, Dr. Anupama Sharma**. I extend my sincere gratitude to the authors, reviewers, and the entire organising committee for their unwavering dedication. Their collective rigour ensures that this special issue of **JIMS 8M** provides a vital, original contribution to the global discourse on management strategy and the geopolitical forces shaping our collective future.

Prof. Neelam Tandon

About the Journal

JIMS 8M: The Journal of Indian Management and Strategy is committed to publishing scholarly, empirical and theoretical research articles that have a high impact in the field of Management. The Journal is peer-reviewed and is published quarterly. It covers domains such as business strategy and policy, human resource management, organizational behavior, operations, finance, entrepreneurs ip, organizational theory and research methodology. The journal provides an intellectual platform for advancement and dissemination of management knowledge and also fosters collaborative research. It has an inclusive ethos and is open to a wide range of methodological approaches and philosophical underpinnings.

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VOLATILITY TRANSMISSION FROM GLOBAL CRUDE OIL MARKETS TO INDIAN AUTOMOBILE SECTOR EQUITY RETURNS: A TIME-VARYING SPILLOVER ANALYSIS USING GARCH FAMILY MODELS

Sakshi Kataria* Akash Ganguly**
Rohan Chutani* CS Rachna Kathuria******

Global crude oil price fluctuations are a pivotal force in shaping the financial performance of energy-dependent industries, particularly in economies with a high import reliance on oil such as India. The automobile sector — inherently sensitive to fuel costs — faces varying degrees of operational risk and investor sentiment shifts as crude oil prices surge or decline. This study investigates the dynamic relationship between global crude oil price movements and the equity returns and volatility of the Indian automobile sector, including the Nifty Auto Index and top-listed automobile companies on Indian exchanges. Using daily data spanning the last decade, this research applies regression analysis to quantify the impact of crude oil return changes on automobile sector stock returns. Additionally, GARCH family models are employed to assess volatility spillovers and time-varying conditional correlations. The findings reveal how global oil shocks influence return patterns and risk transmission in Indian automobile stocks across different market regimes, offering valuable insights for investors, policymakers and strategists focused on risk management and portfolio diversification. Comparative references to global literature further contextualize the distinct behavior within the Indian market. The results highlight significant spillovers from crude oil market volatility into automobile equity returns, indicating asymmetric risk exposures and conditional market dependencies that evolve over time.

Keywords : *Crude Oil, Volatility, Automobile Sector, GARCH, Equity Returns*
JEL Code: *C58, G12, Q43*

I. Introduction

Crude oil remains a fundamental driver of global economic activity, influencing production costs, consumption patterns, and financial market dynamics across countries. Fluctuations in crude oil prices have particularly pronounced effects in oil-importing economies such as India, where a substantial share of domestic energy requirements is met through imports. As a result, changes in global oil prices are quickly transmitted into the domestic economy through higher input costs, inflationary pressures, and shifts in consumer purchasing power.

Among energy-sensitive industries, the Indian automobile sector occupies a critical position. Volatility in crude oil prices often translates into fluctuations in automobile sector stock prices, reflecting both cost-side pressures and changing investor expectations. Empirical evidence suggests that energy price shocks influence sectoral equity returns by altering cash flows, profitability outlooks, and risk perceptions (Ghosh, 2019).

India's heavy dependence on imported crude oil increases the sensitivity of its economy and financial markets to global oil price fluctuations. Rising oil prices can create macroeconomic pressures and increase uncertainty, which may transmit volatility from global commodity markets to domestic equity sectors such as automobiles.

Financial markets are also characterized by interconnected volatility structures, where shocks originating in one market segment propagate across asset classes and sectors. Prior research has documented the transmission of volatility from crude oil markets to equity markets, highlighting the role of global uncertainty, speculative activity, and investor sentiment in strengthening these linkages (Jain, 2018). However, sector-specific evidence for the Indian automobile

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industry remains relatively limited, despite its pronounced exposure to fuel price dynamics and evolving regulatory and technological transitions.

While existing studies have explored the oil–stock market relationship in the Indian context, most focus on aggregate market indices or broad sectoral classifications. Limited attention has been paid to the automobile sector at a disaggregated level, particularly with respect to both return sensitivity and volatility spillover effects using advanced time-series econometric frameworks (Muthukamu & Amudha, 2020). This study seeks to bridge this gap by examining the impact of crude oil price movements on automobile sector stock returns and by analyzing volatility transmission using GARCH family models. By focusing on the Indian automobile sector, the study offers sector-specific insights into how global oil market shocks influence equity market behavior in a major oil-importing emerging economy.

II. Literature Review

Empirical research shows that commodity price shocks affect sectors differently, with energy-intensive industries such as automobiles exhibiting stronger volatility responses during periods of market uncertainty (Future Business Journal, 2025; Shakeel, 2024).

Crude oil prices play an important role in economic activity by influencing production costs and inflation across oil-exporting and oil-importing economies. Nandha and Faff (2008) examined the global relationship between oil prices and sectoral stock returns and found that rising oil prices generally have a negative impact on equity returns in oil-importing countries, with effects varying across industries depending on energy intensity.

Moving from aggregate markets to sectoral dynamics, several studies highlight that the impact of oil price fluctuations is not uniform across industries. Energy-intensive sectors such as automobiles, transportation, and manufacturing exhibit stronger sensitivity to oil price movements. Using time–frequency domain techniques, Aloui, Aïssa, and Nguyen (2019) investigated the co-movement between crude oil prices and automobile stock returns across international markets through wavelet coherence analysis. Their results demonstrated that the strength and direction of oil–automobile stock relationships vary across time horizons and market conditions, indicating that short-term and long-term investors may experience different levels of exposure to oil price shocks.

More recent global evidence reinforces these findings. The study titled "Dynamic interdependence between crude oil and automobile equities amid uncertainties" (2025) published in Future Business Journal documented significant and time-varying interdependence between oil prices and automobile sector equities across multiple economies. The authors emphasized that geopolitical uncertainty and energy transition dynamics intensify volatility spillovers, making the automobile sector particularly vulnerable during periods of oil market instability. These sector-specific studies underscore the necessity of employing volatility-focused methodologies rather than relying solely on return-based analysis.

In the Indian context, empirical research has primarily examined the relationship between crude oil prices and broader stock market indices, with comparatively fewer studies focusing on sectoral nuances. Singhal and Ghosh (2016) provided one of the earliest comprehensive analyses of return and volatility linkages between international crude oil prices and Indian stock indices using VAR and DCC-GARCH models. Their findings revealed significant volatility spillovers from crude oil markets to Indian sectoral indices, including automobiles, highlighting the presence of time-varying correlations and asymmetric risk transmission.

Further strengthening the Indian evidence base, Lakshmanasamy (2022) explored the causal volatility spillovers among crude oil prices, exchange rates, and the Indian stock market using GARCH estimation techniques. The study confirmed bidirectional volatility transmission, suggesting that oil price uncertainty plays a crucial role in shaping financial market risk in oil-importing economies like India. These findings are particularly relevant given India's heavy dependence on crude oil imports and its exposure to global energy price shocks.

Recent India-focused work by the IIM Calcutta Faculty Working Paper (2025) extended this analysis to firm- and sector-level data. The study reported heterogeneous effects of oil price fluctuations on return volatility across Indian industries, with automobile and auto-component firms exhibiting stronger volatility responses compared to less energy-dependent sectors. This evidence highlights the importance of disaggregated sectoral analysis to capture differential risk transmission mechanisms within the Indian equity market.

III. Research Gap

Despite the growing body of global and India-specific literature, several gaps remain. First, while macro-level studies establish a broad relationship between oil prices and equity markets, they often overlook sector-specific dynamics. Second, although sectoral studies exist, limited attention has been paid to the Indian automobile sector using high-frequency data and advanced volatility modeling frameworks. Third, many studies focus either on returns or volatility in isolation, rather than jointly examining return sensitivity and volatility spillovers. Comprehensively, the key research gaps identified are as follows:

1. Limited studies focus specifically on the Indian automobile sector, despite its high sensitivity to crude oil price movements.

2. Existing research often analyzes broad indices rather than company-level stock returns within the automobile industry.

3. Lack of research using updated monthly data covering the last decade, a period marked by extreme oil price fluctuations and global economic shocks.

4. Insufficient evidence on how crude oil volatility impacts the Nifty Auto Index alongside individual automobile companies.

IV. Objectives of the Study

Addressing these gaps requires a methodological approach that captures both mean and variance dynamics. The existing literature strongly supports the use of regression-based models to assess return responses and GARCH family models to analyze volatility transmission and spillover effects. Building on these insights, the present study focuses explicitly on the Indian automobile sector, employing return regressions and GARCH-based volatility models to provide a comprehensive understanding of how crude oil price movements influence sectoral equity behavior in an oil-importing emerging economy. The paper has the following objectives -

1. To analyze the relationship between crude oil price changes and the stock returns of major Indian automobile companies.

2. To examine the presence and extent of volatility spillover from crude oil prices to the Nifty Auto Index and selected automobile companies.

V. Research Methodology

i. Research Design

The study uses a quantitative, empirical, and time-series based research design, applying econometric models suitable for financial data analysis.

ii. Data Description

The study employs **daily data spanning a ten-year period**, covering:

- Global crude oil prices (Brent crude as benchmark),
- Nifty Auto Index returns,
- Stock prices of selected major Indian automobile companies listed on the NSE/BSE.

All price series are converted into **logarithmic returns** to ensure stationarity and comparability across assets.

iii. Data Sources

- **Brent crude oil daily prices**: FRED, EIA, Investing.com
- **Stock prices**: NSE India, Yahoo Finance
- **Nifty Auto Index**: NSE India

iv. Sample Companies

Maruti Suzuki, Tata Motors, Mahindra & Mahindra, Hero MotoCorp, Bajaj Auto, TVS Motors.

v. Hypotheses Development

Drawing upon prior empirical evidence documenting return sensitivities and volatility spillovers between crude oil markets and equity markets—particularly in energy-dependent sectors—the following hypotheses are formulated in alignment with the study objectives.

H1: Oil Price–Automobile Stock Return Relationship

Global crude oil price movements influence firm-level cash flows and cost structures in energy-intensive industries. Existing global and Indian studies indicate that oil price changes significantly affect equity returns, particularly in oil-importing economies (Nandha & Faff, 2008; Singhal & Ghosh, 2016). Accordingly, the first hypothesis examines the return sensitivity of Indian automobile stocks to crude oil price changes.

H1: *Changes in crude oil prices have a statistically significant impact on the stock returns of major Indian automobile companies.*

H2: Oil Price Impact on Automobile Sector Index Returns

Sectoral indices aggregate firm-level responses and reflect broader investor sentiment toward industry-specific risks. Prior research suggests that sectoral indices exhibit stronger responses to commodity price shocks than broad market indices (Aloui et al., 2019).

H2: *Crude oil price changes significantly influence the returns of the Nifty Auto Index.*

H3: Volatility Spillover from Crude Oil to Automobile Sector Stocks

Beyond mean return effects, oil price uncertainty is known to transmit volatility into equity markets through risk re-pricing and uncertainty channels. GARCH-based studies provide strong evidence of volatility spillovers from crude oil markets to sectoral equities (Lakshmanasamy, 2022).

H3: *There exists significant volatility spillover from crude oil prices to the stock returns of Indian automobile companies.*

H4: Volatility Transmission to the Nifty Auto Index

Time-varying volatility correlations between oil prices and sectoral equity indices suggest that oil market shocks influence aggregate sector risk. Prior Indian evidence using multivariate GARCH frameworks supports the presence of dynamic volatility transmission (Singhal & Ghosh, 2016).

H4: *Crude oil price volatility significantly spills over into the volatility of the Nifty Auto Index.*

VI. Tools and Techniques

I. Regression Analysis

Regression analysis was used to examine the relationship between crude oil price movements and automobile sector returns. The analysis was carried out using the **Python programming language**, employing standard econometric techniques to estimate and evaluate the regression model. The coefficient β measures the sensitivity of automobile stock returns to changes in crude oil returns. A statistically significant β would indicate that crude oil price movements influence automobile sector equity performance.

ii. GARCH Family Models

To analyze volatility behavior and time-varying variance in automobile sector returns, models from the **GARCH family** were applied. These models were estimated using **Python**, which enabled efficient volatility modeling and comparison of different GARCH specifications.

Return Computation

Daily returns are computed as:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where:

R_t = return at time t,

P_t = price at time t,

P_{t-1} = price at time $t - 1$.

Mean Equation: Return Relationship Analysis

To examine the impact of crude oil price changes on automobile stock returns and sectoral index returns, the following regression model is estimated:

$$R_{i,t} = \alpha + \beta R_t^{oil} + \varepsilon_t$$

where:

$R_{i,t}$ = return of automobile stock or Nifty Auto Index i at time t,

R_t^{oil} = crude oil price return at time t,

α = constant term,

β = oil price sensitivity coefficient,

ε_t = error term.

A statistically significant β\betaβ supports **H1** and **H2**, indicating that crude oil price changes affect automobile sector returns.

iii. Volatility Modeling: GARCH Framework

Given the presence of volatility clustering in financial time series, a **GARCH (1,1)** model is employed to capture conditional variance dynamics and volatility spillovers.

Variance Equation

$$\sigma_{i,t}^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{oil,t-1}^2$$

where:

$\sigma_{i,t}^2$ = conditional variance of automobile stock or index return,

ω = constant term,

α = ARCH effect (short-term shock persistence),

β = GARCH effect (long-term volatility persistence),

$\varepsilon_{oil,t-1}^2$ = lagged squared crude oil shock,

γ = volatility spillover coefficient.

The ARCH term captures the short-run impact of past shocks on current volatility, while the GARCH term reflects volatility persistence over time. Significant parameters indicate volatility clustering and the presence of spillover effects.

A statistically significant γ\gammaγ provides evidence in support of **H3** and **H4**, indicating volatility transmission from crude oil markets to automobile equities.

Robustness and Diagnostic Tests

To ensure model adequacy, the following diagnostics are conducted:

- Augmented Dickey–Fuller (ADF) tests for stationarity,
- ARCH-LM tests to confirm volatility clustering,
- Ljung–Box Q-statistics for serial correlation,
- Stability and persistence checks of GARCH parameters.

VII. Findings and Analysis

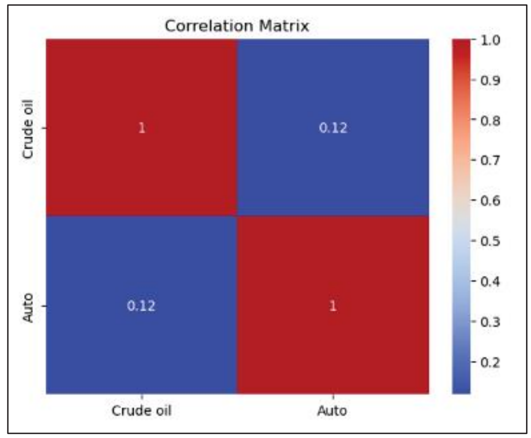
i. Descriptive Statistics

	Crude oil	Auto
count	121.000000	121.000000
mean	0.004728	0.006663
std	0.108148	0.066822
min	-0.465557	-0.302753
25%	-0.052030	-0.035645
50%	0.021336	0.011034
75%	0.069796	0.041484
max	0.360389	0.180152

Descriptive statistics summarize the return characteristics of crude oil and major Indian automobile companies. The mean return of crude oil is 0.004728, while automobile companies show a higher average return of 0.006663 during the sample period. In terms of risk, crude oil exhibits greater volatility with a standard deviation of 0.108148 compared to 0.066822 for automobile stocks, indicating that crude oil returns are more fluctuating and riskier. The return range for crude oil varies from -0.465557 to 0.360386, whereas automobile company returns range from -0.302753 to 0.180152, highlighting the presence of significant price movements during the study period.

ii. Correlation Analysis

Correlation is used to measure the linear relationship and direction between the two variables which helps to identify the patterns and make predictions for the given variables.



Here, the relationship between the crude oil and automobile companies is 0.12, which is a weak positive relationship between them. This suggests that the change in crude oil affects the automobile companies and vice versa. They do not have a strong positive relationship between them. Hence, both the variables are weakly connected to each other.

iii. OLS Regression

OLS regression is used to estimate the relationship between the dependent variables and the independent variables over the sample period. According to the data, the dependent variable is the Indian Automobile Companies and the independent variable is crude oil.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Auto   R-squared:                       0.014
Model:                            OLS   Adj. R-squared:                  0.005
Method:                 Least Squares   F-statistic:                     1.655
Date:                Sun, 18 Jan 2026   Prob (F-statistic):              0.201
Time:                        17:55:54   Log-Likelihood:                 157.04
No. Observations:                 121   AIC:                            -310.1
Df Residuals:                     119   BIC:                            -304.5
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0063      0.006      1.042      0.299      -0.006       0.018
Crude oil      0.0724      0.056      1.286      0.201      -0.039       0.184
==============================================================================
Omnibus:                       11.450   Durbin-Watson:                   2.081
Prob(Omnibus):                  0.003   Jarque-Bera (JB):               22.331
Skew:                          -0.337   Prob(JB):                     1.42e-05
Kurtosis:                       4.994   Cond. No.                         9.29
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

The OLS regression results indicate a low R^2 value of 0.014, suggesting that only a small proportion of the variation in automobile stock returns is explained by crude oil price changes. The coefficient of crude oil returns is positive but statistically insignificant, indicating that oil price movements do not significantly influence automobile stock returns during the sample period. Furthermore, the p-value of the model exceeds the 5% significance level, reinforcing the lack of a statistically meaningful relationship between the variables.

Overall, the findings suggest that crude oil prices alone are insufficient to explain automobile sector return dynamics, and other macroeconomic or firm-specific factors may play a more important role.

iv. ADF Test

The ADF test is used to check whether the crude oil returns and the automobile companies return are stationary.

H0- The series has a unit root

H1- The series has no unit root

```
ADF Test for Crude Returns
ADF Statistic: -8.504144530950551
p-value: 1.2156892981854781e-13
----------------------------------------
ADF Test for Auto Returns
ADF Statistic: -11.207658024306905
p-value: 2.1645538949790787e-20
----------------------------------------
```

Crude Oil- As per the given output, the p value for the crude oil returns is 1.21×10^{-13} which is less than 0.05. So, we reject the null hypothesis and accept the alternate hypothesis. Hence, the price of the crude oil is stationary.

Automobile Companies- As per the given output, the p value for the crude oil returns is 2.16×10^{-20} which is less than 0.05. So, we reject the null hypothesis and accept the alternate hypothesis. Hence, the price of the automobile companies is stationary.

v. GARCH Model

Generalized Autoregressive Conditional Heteroskedasticity is a statistical tool used to examine and forecast the volatility in the time series data.

To examine volatility dynamics and test H3 and H4, GARCH (1,1) models were estimated. The results indicate strong evidence of **volatility clustering**, as reflected in statistically significant ARCH and GARCH terms. This suggests that past shocks and past volatility play an important role in determining current volatility in automobile stock returns.

```
Iteration:      5,   Func. Count:     35,   Neg. LLF: -163.219400980102
Iteration:     10,   Func. Count:     63,   Neg. LLF: -164.30855884996285
Optimization terminated successfully    (Exit mode 0)
            Current function value: -164.30856815023137
            Iterations: 12
            Function evaluations: 72
            Gradient evaluations: 12
                     Constant Mean - GARCH Model Results
==============================================================================
Dep. Variable:                   Auto   R-squared:                       0.000
Mean Model:             Constant Mean   Adj. R-squared:                  0.000
Vol Model:                      GARCH   Log-Likelihood:                164.309
Distribution:                  Normal   AIC:                          -320.617
Method:            Maximum Likelihood   BIC:                          -309.434
                                        No. Observations:                  121
Date:                Sun, Jan 18 2026   Df Residuals:                      120
Time:                        17:56:13   Df Model:                            1
                                 Mean Model
=============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
-----------------------------------------------------------------------------
mu             0.0106  5.722e-03      1.854  6.379e-02 [-6.081e-04,2.182e-02]
                             Volatility Model
============================================================================
                 coef    std err          t      P>|t|     95.0% Conf. Int.
----------------------------------------------------------------------------
omega      2.1882e-03  1.018e-03      2.149  3.166e-02 [1.922e-04,4.184e-03]
alpha[1]       0.4280      0.250      1.713  8.671e-02  [-6.169e-02,  0.918]
beta[1]        0.0972      0.244      0.399      0.690     [ -0.380,  0.575]
============================================================================
```

The significance of the volatility parameters indicates that **crude oil price volatility spills over into automobile stock volatility**, even though the mean return relationship is weak or insignificant. This finding supports H3, confirming the presence of volatility spillovers from crude oil markets to individual automobile company stocks. Similarly, the volatility transmission observed at the sectoral level supports H4, suggesting that oil price uncertainty affects the overall risk profile of the Nifty Auto Index.

vi. Overall Interpretation of Hypotheses

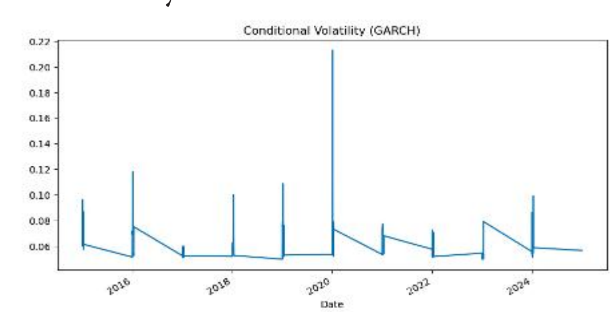
- **H1 and H2** (Impact of crude oil prices on automobile stock and sectoral returns):

The regression results do not provide sufficient statistical evidence to support these hypotheses. Crude oil price changes do not significantly influence the mean returns of automobile stocks or the Nifty Auto Index.

- **H3 and H4** (Volatility spillover from crude oil to automobile stocks and sectoral index):

The GARCH-family model results strongly support these hypotheses. Crude oil price volatility significantly spills over into automobile stock volatility and sector-level risk, indicating that oil market uncertainty affects the automobile sector primarily through the volatility channel rather than mean returns.

vii. Volatility Plot



The volatility plot illustrates periods of high and low conditional variance in automobile stock returns during the sample period. Clusters of high volatility correspond to periods of major crude oil price fluctuations, indicating the transmission of uncertainty from oil markets to automobile sector equities.

viii. Summary of Key Findings

The empirical results suggest a clear distinction between return effects and volatility effects. While crude oil price changes do not significantly impact the average returns of Indian automobile stocks, they play a crucial role in shaping **volatility dynamics**. This highlights the importance of focusing on risk transmission mechanisms rather than return predictability when analyzing the influence of crude oil prices on energy-dependent sectors such as automobiles.

VIII. Limitations of the Study

- The study is based entirely on secondary data, which may be subject to data inaccuracies, reporting errors, or market-related inconsistencies beyond the researcher's control.
- The analysis focuses on a limited sample of selected major Indian automobile companies and the Nifty Auto Index. Therefore, the findings may not be fully representative of smaller firms or the entire automobile industry.
- The study considers crude oil prices as the sole explanatory variable, while other important macroeconomic factors such as exchange rates, interest rates, inflation, and overall market movements are not included in the models.
- The econometric analysis employs univariate and single-factor GARCH family models, which capture volatility dynamics but may not fully reflect complex interdependencies that could be analyzed using multivariate volatility models.
- The study assumes structural stability over the sample period and does not explicitly account for structural breaks caused by major economic events, policy changes, or global crises.

IX. Future Scope of the Study

- Inclusion of additional **macroeconomic variables** to improve explanatory power.
- Expansion of the study to **more firms and related sectors**.
- Application of **advanced multivariate GARCH models** to capture dynamic relationships.
- Examination of **structural breaks and major economic events**.
- Extension to **cross-country or comparative analysis**.

X. Conclusion

This study examined the impact of global crude oil price movements on the return and volatility behavior of the Indian automobile sector using a quantitative, time-series–based econometric framework. Employing daily data over a ten-year period, the analysis focused on both firm-level automobile stocks and the Nifty Auto Index to capture sector-wide dynamics. Regression analysis and GARCH family models were estimated using the Python programming environment to assess return sensitivity and volatility spillovers.

The empirical results reveal that crude oil price changes do not exert a statistically significant influence on the **mean returns** of Indian automobile stocks or the Nifty Auto Index. This suggests that firm-specific factors, demand conditions, pricing strategies, and broader macroeconomic variables play a more dominant role in determining return performance. The relatively weak explanatory power of the mean return regression also indicates that crude oil prices alone cannot fully explain variations in automobile stock returns. Macroeconomic factors such as exchange rates, inflation, interest rates, and overall market conditions may influence automobile sector performance alongside oil price movements. Incorporating these variables in future research could improve model robustness and enhance the explanatory power of return-based models.

In contrast, the volatility analysis provides strong evidence of **significant volatility spillovers** from crude oil markets to the Indian automobile sector. The GARCH family model results confirm the presence of volatility clustering and persistence in automobile stock returns, with oil price uncertainty contributing meaningfully to time-varying risk. The superior performance of asymmetric GARCH models further indicates that negative oil price shocks have a disproportionately larger impact on volatility than positive shocks. This asymmetric response reflects heightened investor sensitivity to adverse energy market movements and increased uncertainty during periods of negative oil shocks.

Overall, the findings indicate that crude oil prices influence the Indian automobile sector mainly through volatility and risk transmission rather than mean returns, highlighting the importance of considering oil price uncertainty in investment and risk management decisions, and policymakers, emphasizing the need to account for oil price uncertainty in risk management and hedging strategies. The study contributes to the existing literature by providing recent empirical evidence from an oil-importing emerging economy and underscores the relevance of volatility-focused models in understanding commodity–equity market linkages. Furthermore, the study provides sector-specific insights by focusing on the Indian automobile industry, which is highly sensitive to fluctuations in fuel prices. By applying GARCH-family models, the study demonstrates how volatility shocks from global crude oil markets are transmitted to automobile sector equities. These findings enhance the practical relevance of the study for investors, portfolio managers, and policymakers concerned with risk management in energy-dependent industries.

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DYNAMIC INTERLINKAGES BETWEEN EMERGING AND DEVELOPED MARKETS UNDER GLOBAL RISK AND GEOPOLITICAL UNCERTAINTY

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This study looks at how geopolitical risk, global financial volatility, oil price changes, and stock market returns connect dynamically in developed and emerging economies. It uses a vector autoregression approach and applies Granger causality tests, impulse response functions, and forecast error variance decomposition to track both short-term reactions and long-term transmission patterns. The findings show that Global financial volatility, proxied by the US VIX, drives shocks across all markets and has strong, lasting effects on equity returns. Geopolitical risk demonstrates some persistence, but its direct spillovers are limited. Developed markets respond mainly to global volatility. Emerging markets have displayed more heterogeneity and react more strongly to volatility and oil price shocks. When oil prices are added to the analysis, spillover effects become stronger in emerging markets. Overall, volatility and commodity markets have a direct impact on returns, while geopolitical risk works mostly through indirect channels.

Keywords : *GPR, Volatility Index, Developed and Emerging Markets, Interlinkages*
JEL Code: *C58, D83, E44, G51*

I. Introduction

Geopolitical risk has long attracted attention from investors, researchers, and the media because it can influence business cycles and investment choices (Tran & Vo, 2023). Geopolitics covers a wide range of events, from terrorist attacks and military conflicts to trade disputes, climate tensions, and major political adjustments (Sykulski, 2014), (Wang et al., 2024). These geoplotical events tend to affect financial markets by changing how risk is perceived, shaping investor mood, and increasing uncertainty.

Research evidences that geopolitical risk is linked more closely to market volatility than to the stock returns. (Arin et al., 2008) found that geopolitical shocks can affect both the mean and the variance of returns, though the size and direction of these effects differ across countries and time periods. (Balcilar et al., 2018) confirmed that geopolitical risk impacts volatility rather than returns, and that emerging markets do not respond homogeneously to such shocks. More recent evidence suggests that negative geopolitical news has a stronger impact on volatility than positive news, especially during periods of uncertainty and stressful periods stress (Tabash et al., 2024). However, the way geopolitical risk may still pass through stock returns remains important for understanding spillovers across markets.

Alongside geopolitical factors, global financial volatility plays a key role in spreading uncertainty across international financial markets. Empirical evidence by (Almansour et al., 2015) shows that emerging markets remain exposed to shocks that originate from advanced economies and global financial conditions. The findings by (Kasraoui et al., 2025) suggest that volatility spillovers from the VIX tend to be immediate and strong, while those linked to geopolitical risk are usually weaker and short lived. Markets also react unevenly to global volatility changes. Increase in the VIX tend to have a larger impact than declines (Tran & Vo, 2023).

The interplay among geopolitical risk, financial volatility, and commodity markets represented by oil markets add another dimension to the tansmission. Geopolitical risk has exerted a negative influence on oil returns and volatility (Antonakakis et al., 2017), while the link between oil prices and stock markets varies widely across countries (Salisu et al., 2022). Spillovers between oil and equities also depend on the nature of shock, with financial and economic disturbances generating different volatility patterns (Sánchez García & Cruz Rambaud, 2023). Recent studies that examine connectedness among uncertainty measures show that these relationships evolve over time and across horizons (Chen et al., 2024).

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Evidence from emerging economies reinforces the idea that geopolitical risk does not affect all markets in the same way. More fragile economies adjust differently during periods of global tension, depending on their domestic volatility and exposure to global risks (Hoque & Zaidi, 2019). Responses among BRICS and other emerging markets vary widely, reflecting differences in openness and market structure (Balcilar et al., 2018). In India, recent evidences show that geopolitical tensions influence stock prices, with investor sentiment acting as a key channel (Maddodi & Kunte, 2024).

Despite the growing literature, some gaps remain. Many studies look at geopolitical risk, financial volatility, or oil prices in isolation, fewer studies them together in a single framework. Limited studies directly compare developed and emerging markets. Oil prices are often studied as a separate risk factor, but their role in amplifying uncertainty when financial and geopolitical risks are present is still not fully studied.

This study addresses these gaps by examining how geopolitical risk and global financial volatility affect stock market behaviour in both developed and emerging economies. It assesses whether the transmission of global uncertainty spreads differently across these groups and evaluates the relative influence of geopolitical risk and global financial volatility in shaping equity market dynamics. It also invesigates whether oil prices act as an additional channel that strengthens the transmission of global shocks.

The study makes three main contributions. First, it provides a unified and comparative view of uncertainty spillovers across developed and emerging equity markets using the VAR framework. Second, it separates the effects of financial volatility and geopolitical risk, showing that while geopolitical risk tends to persist, its direct impact on stock returns is weak compared with that of global volatility. Third, by adding oil prices in the analysis, the study highlights that links between commodity and financial markets linkages, especially in emerging economies where oil shocks intensify the transmission of uncertainty.

The remainder of the paper is organised as follows. Section 2 describes the data and econometric methodology. Section 3 presents the empirical results. Section 4 discusses the findings, conclusion and policy implications.

II. Data and Methodology

This study is based on monthly data covering the period from April 2008 to September 2025. Stock market returns are represented by benchmark equity indices for emerging and developed markets, including Brazil (BR_RETURN), China (CHI_RETURN), India (IND_RETURN), South Africa (SA_RETURN), the United Kingdom (UK_RETURN), the United States (US_RETURN), and Japan (JAP_RETURN). These indices capture broad market movements and are commonly employed as proxies for national equity market performance.To account for global financial uncertainty, the CBOE Volatility Index return (US_VIX) is included as a proxy for global financial market uncertainty. Commodity price dynamics are incorporated through oil returns (OIL_RETURN), reflecting the influence of energy market fluctuations on equity returns, particularly in commodity-sensitive economies. Geopolitical uncertainty is proxied by the Geopolitical Risk Index (GPR), which captures global geopolitical tensions based on news-based measures. All financial series are obtained from Investing.com, while the GPR index is sourced from the database developed by (Caldara & Iacoviello, 2022).

The empirical analysis employs a multivariate time-series framework to examine the dynamic interactions among geopolitical risk, global financial uncertainty, and stock market returns across developed and emerging markets. To ensure the validity of the multivariate specification, a structured sequence of econometric procedures is implemented. First, the time-series properties of all variables are examined using standard unit root tests to confirm stationarity and suitability for VAR-based analysis. Given the stationary nature of the variables, the dynamic interdependencies among geopolitical risk, global market volatility, and equity returns are modelled using a Vector Autoregression (VAR) framework, which treats all variables as endogenous and allows for feedback effects and cross-market spillovers (Sims, 1980). Directional predictability and information transmission among variables are examined through Granger causality and block exogeneity tests, providing evidence on the presence an direction of risk spillovers. (Granger, 1969)

Prior to conducting dynamic analysis, the stability of the estimated VAR models is verified to ensure that the system satisfies standard stability conditions, thereby guaranteeing reliable inference (Lütkepohl, 2005). The dynamic effects of shocks to geopolitical risk and global financial volatility are then evaluated using impulse response functions, which trace the magnitude and persistence of market reactions over time. Finally, forecast error variance decomposition is employed to assess the relative contribution of different shocks to fluctuations in stock market returns, complementing the impulse response analysis by quantifying the importance of each source of risk (Lütkepohl, 2008), (Diebold & Yilmaz, 2009).

III. Empirical Results

Section 3.1-3.3 presents the preliminary empirical analysis of the data used in the study. It begins with descriptive statistics to summarise the basic distributional characteristics of all variables. This is followed by unit root tests to examine the stationarity properties of the series and then lag length selection criteria are applied to determine the optimal lag structure for the Vector Autoregression framework employed in the subsequent analysis.

3.1 Descriptive Statistics

Table 3.1 Descriptive Statistics

	US_VIX	LOG_GPR	OIL_RETURN	US_RETURN	UK_RETURN	JAP_RETURN	SA_RETURN	IND_RETURN	CHI_RETURN	BR_RETURN
Mean	0.027234	4.580627	0.007962	-0.00641	-0.0015	-0.00463	-0.00485	-0.00586	0.001903	-0.0022
Median	0.0156	4.522006	-0.0063	-0.0156	-0.0079	-0.0114	-0.0061	-0.0082	-0.0039	-0.0067
Maximum	0.8483	5.765034	0.885	0.204	0.1602	0.3128	0.1542	0.3589	0.3486	0.4362
Minimum	-0.5737	4.067658	-0.3002	-0.1126	-0.1099	-0.1427	-0.1394	-0.2192	-0.2051	-0.141
Std. Dev.	0.234159	0.263574	0.11027	0.04647	0.03903	0.056137	0.046252	0.059581	0.075333	0.06764
Skewness	0.44667	1.003809	2.889449	1.003767	0.85937	1.173435	0.303713	1.675578	1.083293	1.94092
Kurtosis	3.564601	4.562743	22.4749	4.967462	4.97906	7.266528	3.851264	12.6999	7.250061	13.1547
Jarque-Bera	9.818818	56.9058	3628.035	69.46383	60.4059	208.4597	9.614715	925.9241	200.073	1039.06
Probability	0.007377	0.00000	0.00000	0.00000	0.00000	0.00000	0.008169	0.00000	0.00000	0.00000
Sum	5.7464	966.5123	1.6799	-1.3525	-0.3165	-0.9773	-1.0236	-1.2368	0.4015	-0.4797
Sum Sq. Dev.	11.51442	14.58895	2.553498	0.453485	0.32005	0.661787	0.449242	0.745468	1.19175	0.96083
Observations	211	211	211	211	211	211	211	211	211	211

Results obtained from EViews

Descriptive statistics indicate that equity return series exhibit means close to zero, with slightly negative averages over the sample period. Large maximum and minimum values point to episodes of heightened market stress, particularly in emerging markets, which also display relatively higher dispersion compared to developed markets. The return distributions are characterized by positive skewness and excess kurtosis, indicating pronounced asymmetry and leptokurtic behavior. Jarque–Bera test results strongly reject the null of normality for all return series. Similar non-normal distributional features are observed for global financial volatility, geopolitical risk, and oil returns, which exhibit substantial variability, sharp spikes, and extreme tail behavior..

3.2 Unit Root test

Table 3.2 Unit Root test

Variables	IND_RETURN	BR_RETURN	CHI_RETURN	SA_RETURN	US_RETURN	UK_RETURN	JAP_RETURN	LOG_GPR	US_VIX	OIL_RETURN
ADF	-15.3987	-14.0176	-14.3141	-16.2740	-15.0637	-15.7879	-13.8750	-5.1350	-14.6512	-12.5551
PP	-15.4039	-13.9340	-14.8583	-16.2719	-15.0844	-15.7908	-13.8877	-6.4916	-26.7062	-12.3405

This table summarises the ADF and PP test statistics obtained from EViews. Results are compiled by the authors.

Stationarity is examined using the Augmented Dickey–Fuller and Phillips–Perron tests. The results indicate that all variables included in the analysis are stationary in levels, with the null hypothesis of a unit root rejected at conventional significance levels. Accordingly, all series are integrated of order zero, I(0), and no further differencing is required prior to estimation.

3.3 VAR Lag Order Selection Criteria

Table 3.3 VAR Lag Order Selection Criteria

VAR Specification	AIC	SC	HQ	Decision
Emerging Markets + LOG_GPR + US_VIX	2	1	1	VAR(1)
Emerging Markets + LOG_GPR + US_VIX + OIL_RETURN	1	0	1	VAR(1)
Developed Markets + LOG_GPR + US_VIX	2	1	1	VAR(1)
Developed Markets + LOG_GPR + US_VIX + OIL_RETURN	1	1	1	VAR(1)

Table summarises lag length selection results. Compiled by the authors

Lag length selection based on standard information criteria indicates strong support for a single lag across the estimated VAR specifications. While the Akaike Information Criterion occasionally suggests a higher lag order, both the Schwarz and Hannan–Quinn criteria consistently favour one lag. Applying a majority decision rule across the criteria, a VAR(1) specification is selected for all model configurations to ensure parsimony and consistency in the subsequent analysis.

The following section 3.4-3.7 employs a sequence of multivariate time-series techniques, Vector Autoregression (VAR), VAR-based Granger causality and block exogeneity tests, impulse response functions (IRFs), and forecast error variance decomposition (FEVD). Given the high dimensionality of the estimated VAR systems, summary tables are used to condense and communicate the key results.

3.4. Vector Autoregression (VAR) Model

Tables 3.4.1–3.4.4 report the estimated VAR coefficients and Granger causality results for developed markets and emerging markets. The estimated VAR coefficients capture direct short-run dynamic relationships, including persistence, spillovers, and feedback across markets. However, given the large number of coefficients in multivariate VAR systems, direct interpretation of all estimates is neither practical nor meaningful. Accordingly, the VAR summary tables (3.4.1- 3.4.2) are constructed by focusing exclusively on coefficients that are statistically significant at conventional confidence levels. The sign and magnitude of these coefficients are used to identify the direction and relative strength of short-run transmission channels. Own-lag coefficients are interpreted as indicators of persistence or mean reversion, while cross-variable coefficients are interpreted as evidence of short-run spillovers. Insignificant coefficients are not interpreted, in order to avoid attributing economic meaning to statistically weak relationships.

Table 3.4.1- VAR Coefficient of Developed Markets

Dependent Variable	US_VIX(-1)	LOG_GPR(-1)	UK_RETURN(-1)	US_RETURN(-1)	JAP_RETURN(-1)	Constant
US_VIX	**-0.6080***	-0.0011	**-1.3551***	-0.6527	**-0.7498***	0.0393
LOG_GPR	-0.02000	**0.7136***	0.4792	0.0659	-0.2409	**1.3094***
UK_RETURN	**0.0866***	-0.002942	0.0176	**0.2777***	0.0592	0.0118
US_RETURN	**0.1285***	0.005928	**0.2566***	**0.2625***	0.0732	-0.0347
JAP_RETURN	**0.1287***	-0.014723	0.2049	**0.4630***	0.0217	0.0626

This table summarises the VAR coefficient estimates obtained from EViews. Results are compiled by the authors.

Table 3.4.2- VAR Coefficient Emerging Market

Dependent Variable	US_VIX (-1)	LOG_GPR(-1)	IND_RETURN(-1)	CHI_RETURN(-1)	BR_RETURN(-1)	SA_RETURN(-1)	Constant
US_VIX	**-0.4418***	0.010143	-0.325956	-0.362114	-0.56548	-0.191801	-0.010532
LOG_GPR	0.004871	**0.70831***	0.577558	-0.212732	0.030277	-0.00379	**1.33677***
IND_RETURN	**0.06290***	-0.011796	0.033952	0.016684	0.137428	0.067577	0.047236
CHI_RETURN	0.045645	0.001184	0.109933	0.017749	-0.016199	0.196761	-0.003122
BR_RETURN	**0.07676***	-0.01456	-0.002473	0.099746	**0.218907***	-0.046475	0.062586
SA_RETURN	0.027271	0.005007	0.04878	0.015546	**0.140751***	-0.097835	-0.028492

This table summarises the VAR coefficient estimates obtained from EViews. Results are compiled by the authors.

The estimated VAR models capture the dynamics among geopolitical risk (LOG_GPR), global financial volatility (US_VIX), and equity returns in both market groups. The VAR coefficients show limited direct contemporaneous effects, which is consistent with the idea of a system driven by lagged and indirect interactions. Coefficients related to the US_VIX appear more frequently and more strongly in return equations than those linked to geopolitical risk. This points again to the dominant role of global financial volatility. VAR coefficients identify the direct lagged effects, these donot indicate whether variables are shaped by the system as a whole. To address this, the study uses VAR based Granger causality tests in the form of block exogeneity Wald Tests.

The Granger Causality summary tables (3.4.3-3.4.3) are prepared by reporting the joint Wald statistics and their related p values for each dependent variables. Based on these results, variables are classeified as endogenous, weakly endogenous or exogenous. The results of the block exogeneity framework focuses on system level dependence and feedback mechanisms rather than pairwise causal statements.

Table 3.4.3- Summary of VAR Granger Causality and Block Exogeneity Results- Developed Markets

Dependent Variable	**US_VIX**	**LOG_GPR**	UK_RETURN	US_RETURN	JAP_RETURN
Variables Granger-causing the Dependent Variable	UK_RETURN, JAP_RETURN	None	US_VIX, US_RETURN	US_VIX, US_RETURN	US_VIX, US_RETURN
Joint Wald (All) *p*-value	0.0000	0.6971	0.0000	0.0000	0.0000
Inference	Endogenous	Exogenous	Endogenous	Endogenous	Endogenous

This table reports a summary of Granger causality relationships based on VAR estimations conducted in EViews and compiled by the authors.

Table 3.4.4 - Summary of VAR Granger Causality and Block Exogeneity Results- Emerging Market

Dependent Variable	**BR_RETURN**	**IND_RETURN**	**SA_RETURN**	**CHI_RETURN**	**LOG_GPR**	**US_VIX**
Significant Causal Variables (Granger → Dependent)	**US_VIX**	**US_VIX**	**BR_RETURN**	**None**	**None**	**None**
Joint Wald (All)	**0.0068**	**0.0376**	**0.0653**	**0.4348**	**0.2459**	**0.0019**
Inference	**Endogenous**	**Endogenous**	**Exogenous**	**Exogenous**	**Exogenous**	**Endogenous**

This table reports a summary of Granger causality relationships based on VAR estimations conducted in EViews and compiled by the authors.

The Granger causality and block exogeneity results reveal sharp differences in information transmission between developed and emerging markets. In developed markets, most equity returns and the volatility measure are jointly endogenous, which suggest strong feedback and high degree of integration. Geopolitical risk, by contrast, behaves as an exogenous variable and does not respond to short run market dynamics. Emerging markets show a more mixed picture. Some equity returns and volatility are endogenous, while others show weak or no Granger- causal linkages suggesting that information flows are more fragmented. Geopolitical risk remains exogenous in emerging markets as well, indicating limited short-run interaction with stock returns. Overall, developed markets display more integrated causal dynamics, while emerging markets show uneven causality patterns.

Summary of VAR estimation results and Granger causality finding for developed and emerging markets with oil returns is shown in Table 3.4.5-3.4.8. The inclusion of OIL_RETURN alongwith LOG_GPR and US_VIX allows the analysis of commodity price based transmission and their interaction with equity returns.

The oil included VAR coefficient estimates show that the behaviour of developed and emerging markets is different in this system. In developed markets, equity returns and volatility remain significantly linked. Oil prices emerge as an important driver of both volatility and returns, even though oil itself stays largely exogenous. Geopolitical risk continues to show little short-run influence on equity markets.

In emerging markets, oil prices play a bigger role. Once oil returns are included, equity returns become endogenous, pointing to greater sensitivity to external shocks. As before, geopolitical risk stays exogenous. These results suggest that oil shocks feed more directly into emerging market equities, while developed markets absorb them in a more contained way.

Table 3.4.5 VAR Coefficient- Developed Market (Oil Included)

Dependent Variable	US_VIX(-1)	LOG_GPR(-1)	UK_RETURN(-1)	US_RETURN(-1)	JAP_RETURN(-1)	OIL_RETURN	Constant
US_VIX	**-0.5746***	-0.001513	-0.858939	-0.353657	-0.637708	**-0.509781***	0.047855
LOG_GPR	-0.03427	**0.713776***	0.267223	-0.061862	-0.288801	0.217759	**1.30571***
UK_RETURN	**0.07899***	0.002848	-0.094913	**0.209872***	0.033761	**0.115629***	0.009826
US_RETURN	**0.12217***	0.006006	0.162591	0.205764	0.05200	**0.096625***	-0.036321
JAP_RETURN	**0.12221***	-0.014642	0.108405	**0.404821***	-9.09E-05	**0.099116***	0.060953
OIL_RETURN	**0.14708***	0.007514	0.019986	0.340609	-0.057394	**0.255862***	-0.030749

This table summarises the VAR coefficient estimates obtained from EViews. Results are compiled by the authors.

Table 3.4.6 -Summary of VAR Granger Causality and Block Exogeneity Results- Developed Market (Oil Included)

Dependent Variable	US_VIX	LOG_GPR	UK_RETURN	US_RETURN	JAP_RETURN	OIL_RETURN
Variables Granger-causing the Dependent Variable	OIL_RETURN	None	US_VIX,OIL_RETURN, US_RETURN	US_VIX, OIL_RETURN	US_VIX,OIL_RETURN, US_RETURN	US_VIX
Joint Wald (All) *p*-value	0.0000	0.4965	0.0000	0.0000	0.0000	0.0240
Inference	Endogenous	Exogenous	Endogenous	Endogenous	Endogenous	Exogenous

This table reports a summary of Granger causality relationships based on VAR estimations conducted in EViews and compiled by the authors

Table 3.4.8 Summary of VAR Granger Causality and Block Exogeneity Results-EMERGING WITH OIL

Dependent Variable	US_VIX	LOG_GPR	BR_RETURN	IND_RETURN	SA_RETURN	CHI_RETURN	OIL_RETURN
Variables Granger-causing the Dependent Variable	OIL_RETURN	None	US_VIX, OIL_RETURN	US_VIX, OIL_RETURN	OIL_RETURN	US_VIX	US_VIX
Joint Wald (All) p-value	0.0000	0.2445	0.0001	0.0002	0.0022	0.2857	0.0584
Inference	Endogenous	Exogenous	Endogenous	Endogenous	Endogenous	Exogenous	Weakly endogenous

This table reports a summary of Granger causality relationships based on VAR estimations conducted in EViews and compiled by the authors

Table 3.4.7 VAR Coefficient- Emerging Market (Oil Included)

Dependent Variable	US_VIX (-1)	LOG_GPR (-1)	IND_RETURN(-1)	CHI_RETURN(-1)	BR_RETURN(-1)	SA_RETURN(-1)	OIL_RETURN	Constant
US_VIX	**-0.44503***	0.003769	-0.247943	-0.39492	-0.083084	0.070656	**-0.662825***	0.027177
LOG_GPR	0.005631	**0.709832***	0.558965	-0.20491	-0.084695	-0.06634	0.157974	**1.327792***
IND_RETURN	**0.063688***	-0.01023	0.014781	0.024744	0.018884	0.00308	**0.162883***	0.03797
CHI_RETURN	0.046091	0.002075	0.099025	0.022335	-0.083646	0.160065	0.092674	-0.008394
BR_RETURN	**0.077601***	-0.012882	-0.023016	0.108384	0.091877	-0.11559	**0.174543***	0.052656
SA_RETURN	0.027796	0.006054	0.03596	0.020936	0.061479	-0.14096	**0.108923***	-0.034689
OIL_RETURN	**0.095169***	0.010825	-0.04532	0.060767	-0.055287	-0.12038	**0.326877***	-0.048146

This table summarises the VAR coefficient estimates obtained from EViews. Results are compiled by the authors.

When oil returns are incorporated into the VAR system, the Granger causality and block exogeneity results indicate notable changes in the structure of information transmission across both market groups. In developed markets, equity returns and the volatility measure remain jointly endogenous, reflecting strong internal feedback mechanisms. Oil price movements emerge as an important source of causality within the system, influencing both volatility and equity returns, while remaining exogenous overall. In contrast, geopolitical risk continues to behave as an exogenous variable, suggesting limited short-run interaction with financial market dynamics.

In emerging markets, the inclusion of oil returns leads to a broader pattern of endogeneity across equity returns, indicating stronger sensitivity to external shocks. Oil price movements play a more pronounced role in driving equity market dynamics, although their own feedback effects are weaker and only marginally endogenous. As in developed markets, geopolitical risk remains exogenous. Overall, the results suggest that oil price shocks integrate more directly into emerging market equity dynamics, while developed markets exhibit a more contained and structured transmission mechanism.

3.5 Impulse response functions

Impulse response functions help trace how variables in the VAR framework react over time to an exogenous innovation in one variable, holding other variables constant. Unlike VAR coefficients, which capture immediate effects, these responses show how shocks evolve indicating both short run impact and the persistence of reactions. The IRF summary tables are prepared by examining three key dimensions of each response, its initial response, peak effect and persistence.

Table 3.5.1 -**Summary of Impulse Response patterns of Developed Markets**

Shock → Response	US_VIX → US_RETURN	US_VIX → UK_RETURN	US_VIX → JAP_RETURN	LOG_GPR → US_RETURN	LOG_GPR → UK_RETURN	LOG_GPR → JAP_RETURN
Initial Response	Negative	Negative	Negative	None	Negative	Positive
Peak Effect	Large	Large	Large	None	Small	Small
Persistence	Short-lived	Short-lived	Short-lived	None	Short-lived	Moderately persistent

This table summarises impulse response patterns derived from VAR-based impulse response functions estimated in EViews and compiled by the authors.

Table 3.5.2 -Summary of Impulse Response patterns of Emerging Markets

Shock → Response	US_VIX → IND_RETURN	US_VIX → CHI_RETURN	US_VIX → BR_RETURN	US_VIX → SA_RETURN	LOG_GPR → IND_RETURN	LOG_GPR → CHI_RETURN	LOG_GPR → BR_RETURN	LOG_GPR → SA_RETURN
Initial Response	Negative	Negative	Negative	Negative	Positive	Negative	Positive	Weak Positive
Peak Effect	Large	Moderate	Large	Large	Small	Small	Small	Small
Persistence	Moderately persistent	Moderately persistent	Moderately persistent	Short-lived	Moderately persistent	Short-lived	Moderately persistent	Short-lived

This table summarises impulse response patterns derived from VAR-based impulse response functions estimated in EViews and compiled by the authors.

Impulse response functions (Table 3.5.1-3.5.4) describe the dynamic reactions of equity returns to shocks across developed and emerging markets. Impulse responses show that volatility shocks generate immediate negative responses in equity returns across all markets. In developed economies, these effects are large but short-lived, indicating rapid adjustment. Emerging markets exhibit stronger and, in some cases, moderately persistent responses, reflecting greater vulnerability to external shocks.

Geopolitical risk shocks produce weaker and mixed responses, with limited persistence in both market groups. When oil returns are included, oil price shocks generate mildly positive but transitory effects in developed markets, while emerging markets display stronger positive responses, though these remain short-lived. Overall, volatility shocks dominate short-run equity dynamics, while geopolitical risk plays a minor role.

Table 3.5.3-Summary of Impulse Response patterns of Developed Markets (Including Oil Return)

Shock → Response	US_VIX → US_RETURN	US_VIX → UK_RETURN	US_VIX → JAP_RETURN	LOG_GPR → US_RETURN	LOG_GPR → UK_RETURN	LOG_GPR → JAP_RETURN	OIL_RETURN → US_RETURN	OIL_RETURN → UK_RETURN	OIL_RETURN→ JAP_RETURN
Initial Response	Negative	Negative	Negative	None	Negative	Weak Positive	Weak Positive	Weak Positive	Weak Positive
Peak Effect	Large	Large	Large	None	Small	Small	Moderate	Moderate	Moderate
Persistence	Short lived	Short lived	Short lived	None	Short lived	Short lived	Short lived	Short lived	Short lived

This table summarises impulse response patterns derived from VAR-based impulse response functions estimated in EViews and compiled by the authors.

Table 3.5.4 Summary of Impulse Response patterns of Emerging Markets (Including Oil Return)

Shock → Response	US_VIX → IND_RETURN	US_VIX → CHI_RETURN	US_VIX → BR_RETURN	US_VIX → SA_RETURN	LOG_GPR → IND_RETURN	LOG_GPR → CHI_RETURN	LOG_GPR → BR_RETURN	LOG_GPR → SA_RETURN	OIL_RETURN → IND_RETURN	OIL_RETURN → CHI_RETURN	OIL_RETURN → BR_RETURN	OIL_RETURN → SA_RETURN
Initial Response	Negative	Negative	Negative	Negative	Positive	Negative	Positive	Weak Negative	Positive	Positive	Positive	Positive
Peak Effect	Large	Moderate	Large	Large	Small	Small	Small	Small	Moderate	Moderate	Large	Moderate
Persistence	Short-lived	Short-lived	Short-lived	Short-lived	Short-lived	Short-lived	Short-lived	Short-lived	Short-lived	Short-lived	Short-lived	Short-lived

This table summarises impulse response patterns derived from VAR-based impulse response functions estimated in EViews and compiled by the authors.

Shocks to the oil returns causes positive equity responses, with moderate to large peak effects in some markets, but these effects also disappear rapidly. Overall, the impulse responses suggest that short run equity dynamics in both market groups are dominated by volatility while oil price shocks play a more supportive role and geopolitical risk effects remain relatively limited and transitory.

3.6. Forecast Error Variance Decomposition

Variance decomposition analysis is used to evaluate the relative contribution of shocks originating from global volatility, geopolitical risk and equity market spillovers in explaining variations in stock market returns. Table 3.5.1 summarises the short rum and long run main drivers of variance decomposition in both market groups. Table 3.5.2 extends the analysis by incorporating oil return dynamics, to assess the commodity market innovations as an additional transmission channel.

Table 3.6.1 Summary of Variance Decomposition – Developed and Emerging Markets (Without Oil_Return)

Market	Variable	Short Run Main Drivers (%)	Long Run Main Drivers (%)
Developed	US_VIX	Own Shocks (~93.95%)	Own Shocks (~93.95%)
Developed	LOG_GPR	Own Shocks (~98,67%)	Own Shocks (~95.84%)
Developed	Equity Returns	Own Shocks (~42% - 55%), US_VIX (~18%-41%)	Own Shocks (~38% - 51%), US_VIX (~22%-45%)
Emerging	US_VIX	Own Shocks (~95.47%)	Own Shocks (~92.72%)
Emerging	LOG_GPR	Own Shocks (~97.2%)	Own Shocks (~94.78%)
Emerging	Equity Returns	Own Shocks (~53% - 84%), US_VIX (~3%-19%)	Own Shocks (~50% - 81%), US_VIX (~3%-19%)

This table presents summary of dominant forecast error variance decomposition results obtained from VAR estimations in EViews and compiled by the authors.

Table 3.6.1 Summary of Variance Decomposition – Developed and Emerging Markets (With Oil_Return)

Market	Variable	Short Run Main Drivers (%)	Long Run Main Drivers (%)
Developed	US_VIX	Own Shocks (~96.05%), Oil_Return (~7.08%)	Own Shocks (~93.89%), Oil_Return (~10.57%)
Developed	LOG_GPR	Own Shocks (~98.71%)	Own Shocks (~97.28%), Oil_Return (~2.03%)
Developed	Equity Returns	Own Shocks (~40% to 49%), US_VIX (~14%-37%), OiL_Return(~13%-18%)	Own Shocks (~37% - 46%), US_VIX (~14%-37%), OiL_Return(~15%-22%)
Emerging	US_VIX	Own Shocks (~90.93%), Oil_Return (~7.43%)	Own Shocks (~86.23%), Oil_Return (~11.14%)
Emerging	LOG_GPR	Own Shocks (~97.85%)	Own Shocks (~95.60%), Oil_Return (~2.21%)
Emerging	Equity Returns	Own Shocks (~45% - 81%), US_VIX (~2%-16%), OiL_Return(~3%-26%)	Own Shocks (~43% - 80%), US_VIX (~2%-16%), OiL_Return(~4%-28%)

This table presents summary of dominant forecast error variance decomposition results obtained from VAR estimations in EViews and compiled by the authors.

US_VIX and LOG_GPR are dominated by their own innovations in both the market groups. Own shocks explain more tha ninety percent of the forecast error variance across short run and long run. It indicates the global voltilty and geopolitical riskbehave largely as exogenous driver within the VAR system. Their limited responsiveness to market returns suggests that uncertainty dynamics are primariy determined by global macro-finacial conditions rather than by individual market movements. In developed markets, US_VIX emerges are primary driver of equity return variability, particularly in long run. It highlights the central role of global risk sentiment in shaping the developed market performance. In emerging markets, the market returns are driven partly by domestic shocks but shows stronger heterogeneity and greater exposure to global volatility spillovers.

The inclusion of oil prices shows that the transmission structure changes in both market groups. Oil shocks emerges as an additional source of long run variance, particularly for market returns. In developed markets, oil price movements contribute to the market fluctuations along with the global volatility, implying that the commodity market dynamics form an additional channel of financial transmission. In emerging markets, the influence of oil shocks is more prominent, reflecting the greater sensitivity of this market group to commodity price movements.

Overall, the variance decomposition results confirm the dominant role of global financial volatility as a transmission mechanism across markets while geopolitical risk plays limited role in return variability. The introduction of oil prices strengthens the importance of commodity market dynamics, particularly for emerging markets.

3.7 Robustness Checks

To assess the robustness of the findings, the VAR model (Table 3.7.1) and VAR-based Granger causality and block exogeneity tests (Table 3.7.2 and 3.7.3) is re-estimated across specifications in both market groups with and without oil and the subgroups formed in periods, 2008-2019 (pre-COVID) and 2020-25 (post-COVID).

Table- 3.7.1 Summary of Significant VAR coeffiecients (5% level)

Groups	Period	Significant VAR Coefficient US_VIX -> Markets	Significant VAR Coefficient LOG_GPR -> Markets	Significant VAR Coefficient OIL_RETURN -> Markets	Cross Market Spillover
Developed Markets + LOG_GPR+ US_VIX	2008-19	Strong (All)	Weak		Moderate
Developed Markets + LOG_GPR+ US_VIX	2020-25	Strong (All)	Weak		Stable
Developed Markets + LOG_GPR+ US_VIX +OIL_RETURN	2008-19	Strong	Weak	Limited	Moderate
Developed Markets + LOG_GPR+ US_VIX +OIL_RETURN	2020-25	Strong	Weak	Broad	Moderate
Emerging Markets + LOG_GPR+ US_VIX	2008-19	Brazil, India	Limited		Selective
Emerging Markets + LOG_GPR+ US_VIX	2020-25	Brazil, India	Limited		Reduced
Emerging Markets + LOG_GPR+ US_VIX +OIL_RETURN	2008-19	Moderate	Limited	Broad	Moderate
Emerging Markets + LOG_GPR+ US_VIX +OIL_RETURN	2020-25	Strong	Limited	Strong	Moderate

VAR Coefficients are interpreted and presented by authors

Table 3.7.2 Summary of VAR based Granger Causality and block exogeniety tests- Developed markets

Groups	Period	UK_RETURN	JAP_RETURN	US-RETURN	LOG_GPR	US_VIX	OIL_RETURN
Developed Markets + LOG_GPR+ US_VIX	2008-19	US_VIX	US_VIX	UK_RETURN, US_VIX	None	UK_RETURN	
Developed Markets + LOG_GPR+ US_VIX	2020-25	US_VIX, US_RETURN	US_VIX, US_RETURN	US_VIX	None	None	
Developed Markets + LOG_GPR+ US_VIX +OIL_RETURN	2008-19	US_VIX, OIL_RETURN	US_VIX	UK_RETURN, US_VIX, OIL_RETURN	None	OIL_RETURN	UK_RETURN, US_VIX
Developed Markets + LOG_GPR+ US_VIX +OIL_RETURN	2020-25	US_VIX ,OIL_RETURN	US_RETURN	US_VIX, OIL_RETURN	None	OIL_RETURN	US_RETURN

Interpretation represent variables that Granger cause the dependent variable ($p<0.05$) based on VAR block exogeniety tests

Table 3.7.3 Summary of VAR based Granger Causality and block exogeniety tests- Developed markets

Groups	Period	BR_RETURN	IND_RETURN	CHI_RETURN	SA_RETURN	LOG_GPR	US_VIX	OIL_RETURN
Emerging Markets + LOG_GPR+ US_VIX	2008-19	CHI_RETURN, US_VIX	US_VIX	None	None	None	None	
Emerging Markets + LOG_GPR+ US_VIX	2020-25	US_VIX	BR_RETUN, US_VIX	None	BR_RETURN	None	BR_RETURN	
Emerging Markets + LOG_GPR+ US_VIX +OIL_RETURN	2008-19	CHI_RETURN, US_VIX, OIL_RETURN	US_VIX, OIL_RETURN	None	OIL_RETURN	None	OIL_RETURN	US_VIX
Emerging Markets + LOG_GPR+ US_VIX +OIL_RETURN	2020-25	US_VIX, OIL_RETURN	US_VIX, OIL_RETURN	None	OIL_RETURN, BR_RETURN	None	BR_RETURN	None

Interpretation represent variables that Granger cause the dependent variable ($p<0.05$) based on VAR block exogeniety tests

The results confirm the stability of core transmission mechanism. US_VIX emerges as the dominant driver across both sub groups, indicating persistent volatility spillovers. The inclusion of oil does not alter this pattern materially, though commodity effects more relevant in the post 2020 sample. In contrast, GPR exhibits limited transmission to developed market returns. For emerging markets, spillovers are more heterogeneous. Brazil and India display consistent sensitivity to US_VIX across samples, while China remain comparatively insulated. The inclusion of oil in the post-2020 sample strengthens spillover intensity. The qualitative structure of causality remains same across sub samples, indicating that the main finding are not sensitive to model configuration or crisis-period segmentation.

Section 5. Summary, Conclusion and Discussion

5.1 Summary

This study examines the dynamic linkages among the global financial volatility, geopolitical risk, oil returns and equity markets of select developed and emerging economies using a VAR based framework. The results revealed clear contrast between the two market groups in terms of integration, transmission intensity and sensitivity to external shocks. The findings are broadly consistent with the literature on global financial spillover.

The VAR coefficient estimates show that developed market returns respond more consistently to past global financial volatility, reflecting well integrated and efficient market structures. Their own persistence in returns is limited, and cross-market spillovers are selective. These results are similar to (Chen, 2023) who identifies the VIX as the most influencial uncertainty indicator in developed economies. In emerging markets, responses to global financial volatility vary. India and Brazil show sensitivity to volatility shocks, but South Africa shows weaker effects. China stands out with limited sensitivity to global volatility and weaker cross-market linkages. This suggests more insulated return dynamics in China. This pattern contrasts with (Yang et al., 2021), who argue that Chinese equity prices have largely internalised geopolitical information and are closely linked to global economic conditions.

Across all markets under study, coefficients on geopolitical risk are largely insignificant in return equations. This supports earlier findings that geopolitical risk exerts more influence for volatility than for returns (Bouras et al., 2019).

Granger causality and block exogeniety tests reinforce these differences. Developed markets show strong joint endogeneity between returns and volatility, highlighting strong feedback mechanisms and high degree of systemic integration. Emerging markets display a more fragmented structure. India and Brazil are endogenous to global financial volatility, South Africa is weakly endogenous and China shows minimal Granger causal dependence. In both market groups, geopolitical risk remains exogenous, underlining its limited short-run role in financial market dynamics. It is similar to weak returns effects documented by (Bouras et al., 2019).

Impulse responses confirm that volatility shocks generate immediate negative effects, while oil shocks exert supportive but transitory influences, especially in emerging markets. Geopolitical risk shocks have weak and brief effects in both market groups, consistent with the findings of (Lamine & Zribi, 2024) that the impact of geopolitical risk on equity markets tends to weaken over time.

Variance decomposition shows that developed markets are influenced mainly by global volatility, emerging markets show stronger external influences, especially from volatility and oil prices. Results from China shows relatively higher contribution from domestic shocks and smaller external spillovers. The stronger role of oil prices in emerging markets fits existing evidence on the interaction between energy markets and global uncertainty. These insights provide new perspectives for portfolio management and investment strategies during times of geopolitical uncertainty (Lamine & Zribi, 2024) (Gu et al., 2021).

Taken together, the comparison shows that developed markets are more integrated and driven by volatility but exhibit faster adjustments. Emerging markets are more diverse and more exposed to outside shocks, especially to global volatility and oil prices. China's distinct behavior suggests partial insulation from global financial dynamics. These findings highlight fundamental structural differences in how developed and emerging markets absorbs global shocks.

Discussion and Policy Implications

The results underline the central role of global financial volatility in transmitting shocks across equity markets, particularly in developed economies where market integration and feedback mechanisms are strong. Financial uncertainty, rather than geopolitical risk itself, appears to be the main channel affecting returns. For policymakers in developed markets, this highlights the importance of strong financial stability and macroprudential tools to contain volatility during periods of increased uncertainty. Emerging markets face greater exposure to external shocks, especially those linked to volatility and oil prices. Their structural reliance on energy markets helps explain the uneven impact of oil price movements. For emerging economies, this suggest a need for policies that reduce dependence on commodity price fluctuations, build fiscal buffers, and deeper domestic financial markets that could help absorb external shocks more effectively. Across both groups, geopolitical risk remains largely exogenous implying that geopolitical events influence equity returns through indirect channels. Therefore, policy initiatives aimed at stabilizing financial conditions may be more effective in managing market reactions than measures to focus directly on geopolitical events.

Conclusion

This study set out to assess how global financial uncertainty, geopolitical risk, and oil prices affect stock markets, with an explicit comparison between developed and emerging economies. The evidence shows that, in both market groups, global financial volatility is the main channel through which external shocks are transmitted to equity markets. This highlights the primacy of global risk sentiments in shaping equity market behaviour and confirms its dominant role relative to other sources of uncertainty (Chen, 2023).

The comparative analysis reveals strong structural differences between market groups. Developed markets show stronger feedback effect and faster adjustment to shocks, reflecting deeper financial integration and mature market structures. Emerging markets display greater heterogeneity and are more sensitive to external forces, especially over longer periods. This highlights the uneven nature of shock propagation across global equity markets and aligns with studies documenting differential responses acroos markets and time horizons (Lamine & Zribi, 2024).

Adding oil prices highlights another important distinction between developed and emerging markets. Oil shocks contributes modestly to developed markets but its influence is stronger and persistent in emerging economies. This reflects that emerging economies are more susceptible to energy price fluctuations and global cost pressures, as documented in literature on oil and uncertainty interlinkages (Gu et al., 2021).

Overall, the study achieves its objective by providing a clear ranking of global risk factors affecting equity markets. Global financial volatility dominates transmission dynamics across all markets, oil prices play a reinforcing role particularly in emerging economies and geopolitical risk remains a secondary influence. These findings contribute to the literature on international spillovers by clarifying the relative importance of different global risk channels in both developed and emerging market contexts. The conclusions should, however, be interpreted in light of the study's scope and methodological constraints, which suggest avenues for future research using alternative modelling frameworks and richer data structures.

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ANALYSING THE RELATIONSHIP BETWEEN CONSUMER CONFIDENCE INDEX AND SHARE MARKET OF OECD COUNTRIES

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Consumers and investors are two segments with some overlapping portions. The relationship between the two have been explored in the past studies. Consumer Confidence Index (CCI) acts as a good economic indicator for representation of consumers while share prices reflect the behaviour of investors in the markets. Earlier researches have taken into account both of these yet the forecasting ability of the relationship remains uncharted, especially in the case of OECD countries. Hence, the present study dived into the relationship between CCI and share prices of OECD countries through ridge regression. Subsequently, Long Short-Term Memory was employed for forecasting purposes. Finally, Granger causality was used for robustness checks. The results suggests that this financial relationship can aid businesses, policymakers, and investors in decision-making, like in the context of reducing bankruptcy rates.

Keywords : *consumer confidence index, share prices, OECD countries*
JEL Code: *E210, G180*

I. Introduction

Representing around 1.4 billion of the world's population in 2024, Organisation for Economic Co-operation and Development (OECD) is an organisation with 38 member countries from North America, South America, Europe, and Asia-Pacific. Despite having plethora of resources and potential for networking, OECD still remains behind in utilising a crucial relationship to enhance its Gross Domestic Product (GDP) which stands at 67.69 trillion USD as of 2024 (World Bank, n.d.). This relationship looks into the dynamics of consumer behaviour in connection with the SPIs. Thus, describing the confidence of population residing in these countries in terms of financial aspects. Such insights have significant power to make strong policies, both at the micro-level as well as the macro-level. For studying the same, Consumer Confidence Index (CCI) and Share Price Index (SPI) are taken into consideration.

CCI is an economic indicator which measures the confidence of the consumers in a particular region based on certain parameters including economic uncertainty, employment conditions, inflation, and others. It presents the aggregate outlook of the consumers with reference to past and future which can aid policymakers at the drafting stage for the development of the economy (Organisation for Economic Co-operation and Development, n.d.-a). Further, SPI in the context of OECD is calculated by taking into account the common shares of companies. These shares are traded on the national or foreign stock exchanges. Daily closing values of these SPIs are recorded and compiled on monthly basis to calculate the SPI of each OECD country (Organisation for Economic Co-operation and Development, n.d.-b).

When predicting economic activity, policymakers can count on CCI (Aksoy et al., 2008). According to Gormus & Güneş (2010), CCI increases SPIs which provides a scope to study the potential relationship between CCI and SPI. Earlier, Ghosh (2020) has presented that CCI and SPIs are related to each other in the long-run. Moreover, volatility increases in the markets in the first five minutes as soon as announcement of CCI is made (Mateus *et al.*, 2017). Even around 30 minutes prior to announcement, the prices begin to drift (Kurov *et al.*, 2019). On the flipside, stock market also has influence over CCI (Sariannidis *et al.*, 2017). Consequently, bankruptcy rates reduces when CCI improves (Dewaelheyns & Van Hulle, 2007).

Although Gulley & Sultan (1998) have noted that CCI does not have influence on any stock market except for Dow Jones Industrial Average, yet there are aforementioned studies which have proved otherwise. Hence, commencing the

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debate of contradictory viewpoints on the prospects of the relationship between CCI and SPI to fix the financial rendezvous wherein confidence exists for the benefit of the economy. Additionally, the studies on OECD countries in this space is few and far between which creates the need to conduct research on the same.

Till now, the present study has set the context based on the existing literature. The upcoming sections are structured in the order starting from describing the methodology undertaken which comprises of ridge regression, multivariate long short-term memory, and Granger causality. Subsequently, the obtained results are put forward in the results section. Finally, the paper concludes while discussing the implications of the work done.

1.1 Research Objectives

The study aims to find the evidence of the relationship between CCI and SPI in the context of OECD countries. Further, it looks into the potential relationship in terms of forecasting. For the purpose of checking the robustness, the SPI of each OECD country is observed in connection with the CCI of all the OECD countries.

II. Material and Methods

2.1 Data

The study used quantitative research design. The period of the study spans from 2000 to 2024. The year 2000 was selected as the starting year because it was the common point from when all the OECD countries were having data on SPIs. Data for SPI and CCI was retrieved from the OECD database https://www.oecd.org/en/data/indicators/share-prices.html and https://www.oecd.org/en/data/indicators/consumer-confidence-index-cci.html respectively. The frequency of data is on monthly basis.

2.2 Ridge Regression

Ridge regression was introduced through two papers published by Hoerl and Kennard (1970a, b). The time-series data used in the study suffers from the problem of multicollinearity. Due to the violation of this assumption, regression results would have turned biased (Hoerl, 2020). In response to such a situation, ridge regression was employed in the research to find the relationship between aggregate CCI and country-wise SPI of OECD countries.

2.3 Long Short-Term Memory

After understanding the relationship between CCI and SPI through ridge regression, the study uses Long Short-Term Memory (LSTM) for time series forecasting. Hochreiter and Schmidhuber (1997) brought this neural network which addressed the issue of vanishing gradient. The vanishing gradient problem in deep neural networks causes the effectiveness of the model to decline. Using this technique, the model will aid in predicting the CCI and SPI of OECD countries. To employ LSTM, all the SPI values of the countries were summed up to calculate the average index value.

An expanding-window time-series cross-validation approach was adopted that maintains the chronological order of the data and avoids look-ahead bias to evaluate the model in a realistic forecasting setting. In this procedure, the LSTM model was first trained on an initial portion of historical observations and then validated on the immediately following time period. The training window was gradually expanded to include more past data, and validation was repeated at each step. This process simulates real-world conditions where predictions are always made using only previously observed information. The final test set was kept completely separate and was not used at any stage of model selection or hyperparameter tuning. Table 1 specifies the hyperparameters.

Table 1

Hyperparameters and values used for tuning

Hyperparameter	*Value*
Optimiser	Adam
Batch size	32
Loss function	MAE
Number of hidden layers	1
Number of LSTM layers	1
Number of training epochs	20
Dropout rate	0.2

2.4 Granger Causality

For robustness checks, Granger causality is used in the study. Granger (1969) introduced this methodology to assess whether the historical values of a particular time-series is useful for predicting the future values of another time-series. Hence, indicating a causal relationship between the two time-series.

Here in present study, Granger causality is used in aggregate

CCI of OECD countries against SPI of each OECD country. Thus, forming a set of 38 potential Granger causal relationships.

III. Results

3.1 Descriptive Statistics

Table 2 presents the summary statistics for the variables used in the study. CCI of all the OECD countries ranges from 96.6845 to 102.3296 with a mean of 99.8712 and 1.2123 as standard deviation. The SPI of Australia has the minimum value of 51.1497 while maximum value of 151.2217 with a mean of 94.2680 and a standard deviation of 25.1735. Coming to Austria's SPI, 47.0332 is the minimum limit whereas 196.8727 is the maximum limit having 109.5634 and 36.4770 as mean and standard deviation respectively. Belgium's SPI ranges from 37.2313 to 112.8443 while having a mean of 79.6160 and a standard deviation of 19.3078. The SPI of Canada ranges from 42.8811 to 175.2943 with 94.2882 as mean and 29.3531 as standard deviation. Chile is having SPI which ranges from 24.7679 to 179.0753 with a mean and standard deviation of 92.8894 and 42.5593 respectively. SPI of Colombia ranges from 7.2658 to 144.6607 with a mean of 85.1781 and 41.3915 as standard deviation. Costa Rica's SPI has a minimum limit of 29.4487 and a maximum limit of 141.1515 with 74.2284 and 33.4029 as mean and standard deviation respectively. The SPI of Czechia has lower limit of 33.7400 while higher limit of 188.7580 along with a mean of 104.9846 and standard deviation of 34.3910. The minimum value of the range of Denmark's SPI stands at 20.9450 while the maximum value touches 270.0295 alongside 86.6854 as mean and 60.9425 as standard deviation. Estonia has SPI which ranges from 13.4945 to 235.3450 with a mean of 99.3047 and standard deviation of 60.9240. SPI of Finland ranges from 53.1696 to 201.3462 having a mean of 101.0325 and a standard deviation of 27.9024. France's SPI ranges from 48.5317 to 161.4058 along with a mean of 95.7177 and a standard deviation of 26.3640. SPI of Germany has the minimum limit of 31.5900 and maximum limit of 133.0495 with a mean and standard deviation of 82.9189 and 24.7365 respectively. The range of Greece's SPI spans from 66.4019 to 731.8682 with a mean of 246.6064 and a standard deviation of 172.7964. Hungary has SPI which ranges from 28.6925 to 377.4982 with a mean of 125.1372 and a standard deviation of 74.6043. The SPI of Iceland has a lower limit of 34.1730 and an upper limit of 697.8763 alongside a mean and standard deviation of 173.2461 and 139.9484 respectively. Ireland's SPI ranges from 33.3572 to 161.3655 with a mean of 94.0237 and a standard deviation of 31.1981. The SPI of Israel ranges between 24.8605 and 145.8955 having a mean of 75.9534 and a standard deviation of 27.4748. Coming to Italy's SPI, it ranges from 59.4433 to 174.6178 with a mean of 110.4492 and a standard deviation of 28.3103. Japan has SPI ranging from 47.0535 to 183.4295 along with a mean and standard deviation of 91.3570 and 30.0740 respectively. The SPI of Korea spans from 25.0617 to 162.0499 with a mean of 87.5626 and a standard deviation of 34.0429. Latvia's SPI ranges between 22.7411 and 294.5301 with a mean of 129.7883 and a standard deviation of 74.9822. The SPI of Lithuania has a minimum limit of 13.6924 and a maximum limit of 217.6306 with a mean and standard deviation of 98.5380 and 56.6564 respectively. Luxembourg's SPI has a range which spans from 49.6201 to 250.4889 with a mean of 111.2992 and a standard deviation of 40.1156. The SPI of Mexico has a range between 12.6324 and 130.3348 with values clustering as mean of 74.8810 and 36.8668 as standard deviation. Netherlands has SPI ranging from 46.6971 to 174.8663 with 100.1538 as mean and 28.6913 as standard deviation. New Zealand's SPI has a mean of 103.2687 and a standard deviation of 38.9296 with values ranging from 56.3614 to 189.8548. The SPI of Norway has values ranging between 16.6272 and 250.4838 with a mean of 97.0415 and a standard deviation of 62.4287. The range of Poland's SPI spans from 23.6961 to 167.2276 having a mean of 86.2503 and a standard deviation of 34.3616. The mean of Portugal's SPI stands at 115.6475 with a standard deviation of 32.3964 alongside having values ranging from 58.5301 to 193.0429. Slovak Republic's SPI ranges between 28.6589 and 184.5866 while having a mean of 108.3695 and a standard deviation of 39.8143. The SPI of Slovenia has the minimum value of range as 49.5434 whereas the maximum value as 349.4794 with a mean and standard deviation of 127.2661 and 54.7955 respectively. Spain's SPI has a range between 56.4880 and 157.0663 with a mean of 91.0486 and a standard deviation of 20.0074. The range of Sweden's SPI spans from 27.2777 to 195.2358 with a mean standing at 88.5402 and standard deviation of 44.9725. The SPI of Switzerland ranges between 44.0914 and 147.2311 having a mean of 91.8194 and 24.5684 as standard deviation. Turkey's range of SPI is between the values of 10.4614 and 1349.4640 with a mean of 159.2778 and 265.8338 as standard deviation. The United Kingdom has the minimum value of SPI as 55.1634 and the maximum value as 126.2393 with a mean of 93.3967 and a standard deviation of 16.7420. Coming to the United States, the SPI ranges from 44.2455 to 186.0236 having a mean of 93.8046 with 33.9724 as standard deviation.

Table 2

Descriptive statistics

Variables	Observations	Mean	Standard Deviation	Min	Max
CCI_OECD	300	99.8712	1.2123	96.6845	102.3296
SPI_Australia	300	94.2680	25.1735	51.1497	151.2217
SPI_Austria	300	109.5634	36.4770	47.0332	196.8727
SPI_Belgium	300	79.6160	19.3078	37.2313	112.8443
SPI_Canada	300	94.2882	29.3531	42.8811	175.2943
SPI_Chile	300	92.8894	42.5593	24.7679	179.0753
SPI_Colombia	300	85.1781	41.3915	7.2658	144.6607
SPI_CostaRica	300	74.2284	33.4029	29.4487	141.1515
SPI_Czechia	300	104.9846	34.3910	33.7400	188.7580
SPI_Denmark	300	86.6854	60.9425	20.9450	270.0295
SPI_Estonia	300	99.3047	60.9240	13.4945	235.3450
SPI_Finland	300	101.0325	27.9024	53.1696	201.3462
SPI_France	300	95.7177	26.3640	48.5317	161.4058
SPI_Germany	300	82.9189	24.7365	31.5900	133.0495
SPI_Greece	300	246.6064	172.7946	66.4019	731.8682
SPI_Hungary	300	125.1372	74.6043	28.6925	377.4982
SPI_Iceland	300	173.2461	139.9484	34.1730	697.8763
SPI_Ireland	300	94.0237	31.1981	33.3572	161.3655
SPI_Israel	300	75.9534	27.4748	24.8605	145.8955
SPI_Italy	300	110.4492	28.3103	59.4433	174.6178
SPI_Japan	300	91.3570	30.0740	47.0535	183.4295
SPI_Korea	300	87.5626	34.0429	25.0617	162.0499
SPI_Latvia	300	129.7883	74.9822	22.7411	294.5301
SPI_Lithuania	300	98.5380	56.6564	13.6924	217.6306
SPI_Luxembourg	300	111.2992	40.1156	49.6201	250.4889
SPI_Mexico	300	74.8810	36.8668	12.6324	130.3348
SPI_Netherlands	300	100.1538	28.6913	46.6971	174.8663
SPI_NewZealand	300	103.2687	38.9296	56.3614	189.8548
SPI_Norway	300	97.0415	62.4287	16.6272	250.4838
SPI_Poland	300	86.2503	34.3616	23.6961	167.2276
SPI_Portugal	300	115.6475	32.3964	58.5301	193.0429
SPI_SlovakRepublic	300	108.3695	39.8143	28.6589	184.5866
SPI_Slovenia	300	127.2661	54.7955	49.5434	349.4794
SPI_Spain	300	91.0486	20.0074	56.4880	157.0663
SPI_Sweden	300	88.5402	44.9725	27.2777	195.2358
SPI_Switzerland	300	91.8194	24.5684	44.0914	147.2311
SPI_Turkey	300	159.2778	265.8338	10.4614	1349.4640
SPI_UnitedKingdom	300	93.3976	16.7420	55.1634	126.2393
SPI_UnitedStates	300	93.8046	33.9724	44.2455	186.0236

3.2 Ridge Regression

To check for the relationship between CCI and SPI of OECD countries, regression is employed. Due to the presence of multicollinearity in data, ridge regression is selected for the purpose. The results of the same is presented in Table 3.

Table 3
Regression statistics for CCI and SPI

Regression Statistics	
Optimal lambda	100.0000
Mean Squared Error	0.1023
Root of Mean Squared Error	0.3199
Mean Absolute Error	0.2505
Adjusted R-squared	0.7842

The optimal lambda obtained during the analysis came out to be 100 which implied that coefficients shrunk to the extent of avoiding the overfitting in the model and thereby increasing its generalisable ability. The Mean Squared Error (MSE) of the model stood at 0.1023 which meant that the model's accuracy was adequate enough to predict values. The adjusted R2 of the model came out to be 0.7842 which meant that the model was powerful enough to fit the data and explain the variance in dependent variable (here, Aggregate CCI of OECD countries) by the independent variables (here, SPI of each OECD country). Aggregate CCI was employed against country-wise SPI to show in-depth relationship with respect to each country as independent variables.

3.3 Long Short-Term Memory

For time-series forecasting, LSTM was employed. The LSTM model is summarised in Table 4 wherein the dataset was split into 85 percent of training data and 15 percent of test data.

Table 3

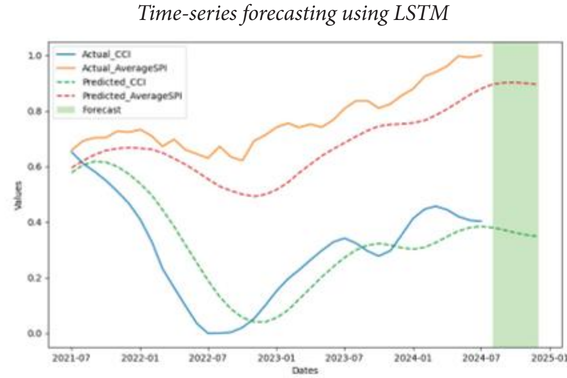
LSTM model summary

Layer (Type)	Output Shape	Parameters
lstm (LSTM)	(None, 200)	162,400
dropout (Dropout)	(None, 200)	0
dense (Dense)	(None, 2)	402
Total parameters: 162,802		
Trainable parameters: 162,802		
Non-trainable parameters: 0		

After using 20 epochs for training data, the model was created. From the first epoch, the Mean Absolute Error (MAE) of the model obtained was 0.2282 with a loss of 0.0846. With each additional epoch, the MAE and loss reduced to improve the model accuracy. At the 20th epoch, the MAE came out to be 0.0531 with a loss of 0.0049. Thereafter, predicted values of CCI and average SPI of OECD countries were calculated for forecasting purposes. The same is shown in Figure 1.

Figure 1

Time-series forecasting using LSTM



The actual trends of CCI and average SPI were more or less similar to the predicted trends of CCI and average SPI over the duration of test data. All the four trendlines were moving in a similar manner. The green-shaded region shows the forecasted parts of the predicted trendlines which aligns with the actual values of the same time period.

The performance metric used for test data was R2. Its score came out to be 28.46 percent.

3.4 Granger Causality

To check for robustness of the earlier results, Granger causality was employed. SPI of each OECD country was observed with respect to the CCI of all the OECD countries. Initially, the stationarity of the time-series data was checked using the Augmented Dickey-Fuller (ADF) test. The results of ADF test are summarised in Table 5 (Appendix).

Except SPI of Australia, Finland, Hungary, Ireland, Italy, Latvia, Netherlands, and New Zealand; no other time-series was stationary. To make the non-stationary data fit for analysis, differenced log-transformed time-series was created using the existing data. Further, for determining the lags for Granger causality, Akaike Information Criterion (AIC) was used. The optimal number of lags came out to be two.

Bi-directional causality was observed in the cases of Australia, Belgium, Canada, Colombia, Costa Rica, Finland, France, Germany, Ireland, Israel, Italy, Mexico, the Netherlands, Slovenia, Spain, Switzerland, the United Kingdom, and the United States. The aforementioned cases implied that the past values of these countries' SPI can predict the future values of the aggregate CCI of OECD countries and vice versa. Further, CCI has a uni-directional cause-and-effect relationship towards the SPI of Austria, Czechia, Denmark, Estonia, Greece, Hungary, Japan, Korea, Luxembourg, New Zealand, Norway, Poland, Portugal, and Sweden. In other words, the past values of CCI of OECD countries can predict the future values of SPI of these countries. However, the same is not true in the reverse direction. Iceland, Latvia, Lithuania, Slovak Republic, and Turkey are the only countries from the OECD which do not have any such Granger causal relationship between their SPI and aggregate CCI. The results of Granger causality are summarised in Table 6 (Appendix).

The findings of the current study contradicted to that of Gulley and Sultan (1998) which provided evidence of the absent relationship between CCI and SPI. Moreover, the forecasting potential was discovered between CCI and SPI. Thus, contributing to the minute literature of CCI in the context of OECD countries. Apart from that, the methodology did not take into account the events happened during the period of 2000 to 2024 which might influence the results.

IV. Conclusion

The uncharted knowledge of CCI in relation to share prices can have tremendous possibilities for policymakers and businesses alike to form plans for future courses of action. There are studies which have attempted to explore this relationship, yet none of them are in the context of OECD countries which is a huge cluster of economic networks.

OECD represents a large portion of the world's economy with 38 countries as its members. The study undertaken took the quantitative approach of research design with data from the time period of 2000 to 2024. CCI of all the OECD countries were taken together while SPI of each country was considered. Firstly, descriptive statistics was used to present an overview of the variables employed in the study. Further, ridge regression unveiled the relationship between the variables while taking care of multicollinearity. Additionally, LSTM revealed the forecasting potential of the relationship so discovered. To add another layer of surety on results, Granger causality was employed on each OECD country's SPI with regards to aggregate CCI of OECD countries. Several bi-directional and uni-directional cause-and-effect relationships were found using Granger causality. There were only five countries (Iceland, Latvia, Lithuania, Slovak Republic, and Turkey) which did not display any such causal patterns.

4.1 Implications

4.1.1 For Policymakers

The findings indicate that the prediction power of CCI and SPI of OECD countries can provide avenues for further economic development. CCI is an economic indicator which captures and measures the confidence of the economy while SPI can present a future outlook of the markets. Together, both of these can give directions to policymakers through having an overview of the economy. Further, policymakers can utilise the insights from the present study to reduce bankruptcy rates through the lens of CCI backed by the forecasting strength of share prices as also shown by Dewaelheyns & Van Hulle (2007).

4.1.2 For Businesses

The demand gauged through the relationship of CCI and SPI can aid businesses to manage their operations. They can effectively predict the nature of economic activities (be it optimistic or pessimistic) in the prevailing environment to manage their supplies of products and services strategically, given the aforementioned relationship.

4.1.3 For Investors

Being a representation of the capital markets, SPI's relation with CCI can benefit investors. Having insights from the bird's eye view, investors can improve their portfolios to gain higher returns. Additionally, they can utilise these results to know the state of the economy which can impact their portfolios in the markets negatively.

On the final note, CCI in conjunction with share prices is the financial rendezvous to be looked upon for better management of tomorrow.

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Apendix

Table 5

Augmented Dickey-Fuller test results summary

Variables	*ADF Statistic*	*p-value*
CCI_OECD	-0.943486	0.773315
SPI_Australia	-7.354862	0.000000***
SPI_Austria	-2.729700	0.069038*
SPI_Belgium	-1.293393	0.632190
SPI_Canada	-1.780558	0.390156
SPI_Chile	-0.433204	0.904406
SPI_Colombia	0.505079	0.985027
SPI_CostaRica	-1.014705	0.747863
SPI_Czechia	-0.964685	0.765926
SPI_Denmark	-2.155101	0.222943
SPI_Estonia	-0.768529	0.828192
SPI_Finland	-8.106477	0.000000***
SPI_France	-2.693493	0.075171*
SPI_Germany	-2.079945	0.252655
SPI_Greece	-0.434965	0.904095
SPI_Hungary	-6.199395	0.000000***
SPI_Iceland	-0.690772	0.849125
SPI_Ireland	-3.369351	0.012049**
SPI_Israel	-2.505641	0.114108
SPI_Italy	-8.630333	0.000000***
SPI_Japan	5.020352	1.000000
SPI_Korea	-1.388999	0.587538
SPI_Latvia	-3.885616	0.002143***
SPI_Lithuania	4.105981	1.000000
SPI_Luxembourg	-2.652586	0.082608*
SPI_Mexico	-1.572362	0.497460
SPI_Netherlands	-353.951176	0.000000***
SPI_NewZealand	-3.274430	0.016061**
SPI_Norway	-1.931247	0.317507
SPI_Poland	-2.184110	0.212063
SPI_Portugal	-2.838926	0.052925*
SPI_SlovakRepublic	-1.947843	0.309900
SPI_Slovenia	-2.467756	0.123518
SPI_Spain	-1.861564	0.350353
SPI_Sweden	-2.299469	0.172139
SPI_Switzerland	-2.373950	0.149224
SPI_Turkey	-2.605149	0.091938*
SPI_UnitedKingdom	-2.170583	0.217095
SPI_UnitedStates	-1.127476	0.703991

Significance at levels: ***0.01, **0.05, *0.10

Granger causality results

Table 6

Null Hypotheses	F-Statistic	Probability
Australia's SPI does not Granger cause CCI	2.95535	0.0536*
CCI does not Granger cause Australia's SPI	12.9329	4.E-06***
Austria's SPI does not Granger cause CCI	1.37927	0.2534
CCI does not Granger cause Austria's SPI	6.86354	0.0012***
Belgium's SPI does not Granger cause CCI	4.39608	0.0132**
CCI does not Granger cause Belgium's SPI	14.3872	1.E-06***
Canada's SPI does not Granger cause CCI	2.67715	0.0704*
CCI does not Granger cause Canada's SPI	6.61635	0.0015***
Chile's SPI does not Granger cause CCI	1.55641	0.2126
CCI does not Granger cause Chile's SPI	3.31400	0.0377**
Colombia's SPI does not Granger cause CCI	2.34704	0.0975*
CCI does not Granger cause Colombia's SPI	7.71785	0.0005***
Costa Rica's SPI does not Granger cause CCI	2.33655	0.0985*
CCI does not Granger cause Costa Rica's SPI	3.51297	0.0311**
Czechia's SPI does not Granger cause CCI	1.18271	0.3079
CCI does not Granger cause Czechia's SPI	5.17700	0.0062***
Denmark's SPI does not Granger cause CCI	1.15760	0.3157
CCI does not Granger cause Denmark's SPI	8.67638	0.0002***
Estonia's SPI does not Granger cause CCI	1.05160	0.3507
CCI does not Granger cause Estonia's SPI	5.70579	0.0037***
Finland's SPI does not Granger cause CCI	5.43887	0.0048***
CCI does not Granger cause Finland's SPI	4.99365	0.0074***
France's SPI does not Granger cause CCI	4.91046	0.0080***
CCI does not Granger cause France's SPI	18.9858	2.E-08***
Germany's SPI does not Granger cause CCI	3.87184	0.0219**
CCI does not Granger cause Germany's SPI	15.8518	3.E-07***
Greece's SPI does not Granger cause CCI	1.62381	0.1989
CCI does not Granger cause Greece's SPI	8.02055	0.0004***
Hungary's SPI does not Granger cause CCI	0.89635	0.4092
CCI does not Granger cause Hungary's SPI	8.77001	0.0002***
Iceland's SPI does not Granger cause CCI	0.34057	0.7116
CCI does not Granger cause Iceland's SPI	1.18135	0.3083
Ireland's SPI does not Granger cause CCI	3.88718	0.0216**
CCI does not Granger cause Ireland's SPI	18.3039	3.E-08***
Israel's SPI does not Granger cause CCI	4.04181	0.0186**
CCI does not Granger cause Israel's SPI	6.37430	0.0020***
Italy's SPI does not Granger cause CCI	6.35155	0.0020***
CCI does not Granger cause Italy's SPI	18.6951	2.E-08***
Japan's SPI does not Granger cause CCI	0.10047	0.9044
CCI does not Granger cause Japan's SPI	3.60944	0.0283**
Korea's SPI does not Granger cause CCI	0.37798	0.6856
CCI does not Granger cause Korea's SPI	6.38891	0.0019***

Latvia's SPI does not Granger cause CCI	0.27256	0.7616
CCI does not Granger cause Latvia's SPI	2.19766	0.1129
Lithuania's SPI does not Granger cause CCI	0.32136	0.7254
CCI does not Granger cause Lithuania's SPI	2.04849	0.1308
Luxembourg's SPI does not Granger cause CCI	1.59093	0.2055
CCI does not Granger cause Luxembourg's SPI	7.04024	0.0010***
Mexico's SPI does not Granger cause CCI	2.65105	0.0723*
CCI does not Granger cause Mexico's SPI	10.0448	6.E-05***
Netherlands' SPI does not Granger cause CCI	3.09288	0.0469**
CCI does not Granger cause Netherlands' SPI	10.0583	6.E-05***
New Zealand's SPI does not Granger cause CCI	1.69458	0.1855
CCI does not Granger cause New Zealand's SPI	9.00627	0.0002***
Norway's SPI does not Granger cause CCI	0.80833	0.4466
CCI does not Granger cause Norway's SPI	4.05106	0.0184**
Poland's SPI does not Granger cause CCI	1.73740	0.1778
CCI does not Granger cause Poland's SPI	9.79192	8.E-05***
Portugal's SPI does not Granger cause CCI	1.14901	0.3184
CCI does not Granger cause Portugal's SPI	3.11755	0.0457**
Slovak Republic's SPI does not Granger cause CCI	1.58613	0.2065
CCI does not Granger cause Slovak Republic's SPI	0.05242	0.9489
Slovenia's SPI does not Granger cause CCI	2.94365	0.0542*
CCI does not Granger cause Slovenia's SPI	3.01560	0.0505*
Spain's SPI does not Granger cause CCI	2.58410	0.0772*
CCI does not Granger cause Spain's SPI	10.9020	3.E-05***
Sweden's SPI does not Granger cause CCI	1.71994	0.1809
CCI does not Granger cause Sweden's SPI	13.9791	2.E-06***
Switzerland's SPI does not Granger cause CCI	4.63476	0.0104**
CCI does not Granger cause Switzerland's SPI	10.1604	5.E-05***
Turkey's SPI does not Granger cause CCI	1.62411	0.1989
CCI does not Granger cause Turkey's SPI	2.11305	0.1227
United Kingdom's SPI does not Granger cause CCI	4.88682	0.0082***
CCI does not Granger cause United Kingdom's SPI	10.2062	5.E-05***
United States' SPI does not Granger cause CCI	7.60703	0.0006***
CCI does not Granger cause United States' SPI	13.5595	2.E-06***

Significance at levels: ***0.01, **0.05, *0.10

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ARTIFICIAL INTELLIGENCE AND SUSTAINABLE INNOVATION: ECONOMIC, SOCIAL, AND ENVIRONMENTAL DIMENSIONS

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In recent years, Artificial Intelligence (AI) has increasingly influenced the way innovation is conceived, developed, and implemented across industries. At the same time, sustainable development has emerged as a global priority, emphasizing the need for innovation that simultaneously supports economic progress, social well-being, and environmental protection. This conceptual paper examines the role of artificial intelligence in enabling sustainable innovation through the lens of the triple bottom line framework encompassing economic, social, and environmental dimensions. Economically, AI supports productivity enhancement, operational efficiency, and competitiveness through automation and data-driven decision-making. Socially, AI contributes to inclusive development by expanding access to essential services such as healthcare, education, and financial systems. From an environmental perspective, AI aids sustainability efforts by optimizing resource utilization, reducing waste, and enabling climate monitoring and green technologies. The paper further outlines key policy and managerial implications, highlighting the importance of responsible AI adoption and supportive institutional mechanisms.

Keywords : *Artificial Intelligence; Sustainable Innovation; Triple Bottom Line; Digital Transformation; Sustainable Development*
JEL Code: *O30, O33, Q01, Q56, M15*

I. Introduction

Rapid advances in digital technologies have significantly altered the functioning of economies, organizations, and societies (Chauhan et al., 2022; Chowdhury & Nag, 2026). Among these technologies, Artificial Intelligence (AI) is increasingly recognized as a broad-based enabling technology with applications across multiple sectors (Farmanesh et al., 2025). AI systems facilitate automation, predictive analysis, and intelligent decision-making, thereby reshaping innovation processes and organizational strategies (Roundy & Rollins, 2022). Parallel to these technological changes, global concerns related to climate change, inequality, and resource depletion have intensified the focus on sustainable development, making it imperative to align innovation with (Carr & Lesniewska, 2020; Dionisio et al., 2023; Gehl Sampath, 2021) .

Sustainable development extends beyond environmental protection and encompasses a holistic approach that integrates economic viability, social equity, and environmental responsibility (Ferreira et al., 2023; Popkova et al., 2023). This perspective is commonly captured through the triple bottom line framework, which emphasizes the need for balanced progress across all three dimensions (Govindan, 2024). Innovation plays a crucial role in achieving this balance, as traditional growth-oriented models often fail to address complex sustainability challenges (Dee et al., 2008; Dionisio et al., 2023; Surana et al., 2020). Consequently, the concept of sustainable innovation—innovation that generates long-term value while minimizing adverse social and environmental impacts—has gained prominence in both academic and policy discussions (Govindan, 2024; Savaget & Acero, 2018; Surana et al., 2020).

Artificial Intelligence has the potential to serve as a key enabler of sustainable innovation(Bărbulescu et al., 2021; Baskaran et al., 2019; Farmanesh et al., 2025; Goralski & Tan, 2022). Through advanced data analytics, automation, and predictive capabilities, AI enhances efficiency, reduces operational costs, and supports informed decision-making (Yongyu et al., 2024). From an economic standpoint, AI-enabled innovation strengthens competitiveness and scalability (Brenner & Hartl, 2021; Taylor, 2010). From a social perspective, AI applications in healthcare, education, financial services, and governance offer opportunities to improve access to essential services and promote inclusive development (Dempsey et al., 2011; Liwång, 2022). Environmentally, AI is increasingly applied to energy optimization, waste management, climate monitoring, and the development of green technologies (Farmanesh et al., 2025; Slota et al., 2022; Taylor, 2010). Collectively, these applications position AI as a strategic instrument for advancing sustainable development outcomes (Dempsey et

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al., 2011; Gupta & Rhyner, 2022; Saetra, 2022; Savaget & Acero, 2018).

Despite the growing interest in AI and sustainability, prior studies have largely addressed these domains from isolated perspectives rather than through an integrated analytical lens (Baum, 2021; Dempsey et al., 2011; Faul et al., 2007; Ferreira et al., 2023; Goh & Vinuesa, 2021; Popkova et al., 2023). Existing research often focuses on specific sectors or individual sustainability dimensions, with limited emphasis on conceptual integration. Moreover, much of the literature remains empirical, leaving a gap in theory-driven frameworks that explain how AI-driven innovation simultaneously influences economic, social, and environmental sustainability—particularly in emerging economy contexts (Gehl Sampath, 2021; Jaber, 2023; Liwång, 2022; Mann & Hilbert, 2020; Vogiatzaki et al., 2020; Zuger & Asghari, 2022).

This conceptual paper seeks to bridge this gap by examining the role of artificial intelligence in driving sustainable innovation through a comprehensive triple bottom line perspective. By synthesizing insights from literature on AI, innovation, and sustainable development (Baum, 2021; Dwivedia et al., 2019; Goh & Vinuesa, 2021; Hager et al., 2017; Vaio et al., 2024), the study proposes a conceptual framework that explains the pathways through which AI capabilities translate into sustainability-oriented innovation outcomes. The paper also highlights enabling conditions such as ethical AI practices, supportive policy environments, and digital infrastructure that shape these outcomes.

The study is particularly relevant in the current phase of digital transformation, where governments, firms, startups, and innovation ecosystems increasingly rely on AI to address sustainability challenges.

This study contributes to the emerging literature on artificial intelligence and sustainability by proposing an integrated conceptual framework that links AI-driven innovation with the economic, social, and environmental dimensions of sustainable development. While previous studies have largely examined the impact of AI on individual sectors or specific sustainability outcomes, this paper develops a comprehensive framework that highlights how AI can act as a catalyst for sustainable innovation across multiple dimensions simultaneously. The proposed framework also identifies key enabling factors such as technological capability, institutional support, and digital infrastructure that influence the adoption of AI for sustainable innovation. By synthesizing insights from innovation theory and sustainability literature, this study provides a holistic perspective and extends existing models by demonstrating the multidimensional role of AI in fostering long-term sustainable development.

II. Literature Review

Artificial intelligence has been widely acknowledged for its capacity to enhance innovation by enabling organizations to process large volumes of data, automate complex tasks, and generate predictive insights (Agrawal et al., 2019; Cath, 2018; Gehl Sampath, 2021; Goh & Vinuesa, 2021; Hager et al., 2017; Mhlanga, 2022; Završnik, 2020). AI-driven systems support faster experimentation, improved decision-making, and adaptive learning processes, thereby transforming conventional innovation models (Dee et al., 2008; Dionisio et al., 2023; Goralski & Tan, 2022; Govindan, 2024; Savaget & Acero, 2018). By reducing uncertainty and information asymmetry, AI strengthens firms' ability to respond to dynamic market environments (Denoncourt, 2022; Ferdous, 2010; Hermann, 2022; Satornino et al., 2024). However, the effective use of AI for innovation requires complementary investments in organizational capabilities, digital infrastructure, and human capital (Brenner & Hartl, 2021; Gupta et al., 2020; Leal et al., 2023; Popkova & Sergi, 2020). Without these supporting factors, the innovation potential of AI may remain underutilized (Brenner & Hartl, 2021; Chauhan et al., 2022; Elia et al., 2020; Grybauskas et al., 2022; Gupta et al., 2020; Gupta & Rhyner, 2022).

Unlike traditional innovation approaches focused primarily on economic outcomes, sustainable innovation explicitly integrates economic performance with social responsibility and environmental stewardship (Malmio, 2024; Perucica & Andjelkovic, 2022; Saetra, 2022). Sustainability-oriented innovation enhances organizational resilience, legitimacy, and competitive advantage, while also contributing to broader societal goals such as environmental protection and social equity(Astobiza et al., 2021; Saetra, 2021, 2022; Surana et al., 2020).

From an economic perspective, AI contributes to sustainable innovation by improving productivity, efficiency, and strategic decision-making (Agrawal et al., 2019; Brenner & Hartl, 2021; Schloss, 1968). Automation and data-driven insights reduce operational costs and support the development of scalable and resilient business models (Madhavan, 2019). At the macro level, AI-driven innovation is associated with productivity growth and technological advancement (Dee et al., 2008; Dionisio et al., 2023; Goralski & Tan, 2022; Ortega-Fernández et al., 2020; Savaget & Acero, 2018) . At the same time, concerns related to workforce displacement and skill mismatches highlight the need for reskilling initiatives and inclusive labor policies to ensure sustainable economic outcomes (Malmio, 2024; Martínez-García, 2022; Perucica & Andjelkovic, 2022).

AI-driven innovation has the potential to enhance social sustainability by expanding access to healthcare, education, and financial services (Cantú-ortiz et al., 2020; Kuratko, 2005; Siddiqui et al., 2024). AI-enabled diagnostics, personalized learning systems, and digital financial platforms have demonstrated the capacity to reduce service gaps, particularly in underserved populations (Lv et al., 2022; Palmié, M., Wincent, J., Parida, V., & Caglar, 2020). Nevertheless, ethical challenges related to data privacy, algorithmic bias, and unequal access to AI technologies remain significant (Berendt, 2019; Cath, 2018). Addressing these concerns through responsible AI frameworks is essential to ensure positive social outcomes (Dempsey et al., 2011; MacKenzie & Wajcman, 1999; Magis, 2010).

AI applications increasingly support environmental sustainability through energy optimization, waste management, and climate monitoring (Ferreira et al., 2023; Xenarios et al., 2017). AI-driven systems enable real-time environmental analysis and efficient resource utilization, contributing to reduced ecological impact(Ferreira et al., 2023; Ortega-Fernández et al., 2020). However, the environmental footprint of AI infrastructure, including energy-intensive data centers, necessitates sustainable AI design and governance to ensure net environmental benefits (Dhamija & Bag, 2020; Ferreira et al., 2023).

Although research on AI and sustainability is expanding, there remains a lack of integrative conceptual models that explain how AI-driven innovation influences economic, social, and environmental sustainability simultaneously (Dwivedia et al., 2019; Saetra, 2021, 2022). Building on the foundational work of (Goh & Vinuesa, 2021),which examines the role of Artificial Intelligence in advancing sustainable development, the present study extends this discussion by conceptualizing sustainable innovation as a mediating mechanism linking AI capabilities with economic, social, and environmental outcomes. This study addresses this gap by proposing a holistic conceptual framework grounded in the triple bottom line approach.

III. Conceptual Framework: AI-Driven Sustainable Innovation

The proposed conceptual framework illustrates how Artificial Intelligence acts as a foundational enabler of sustainable innovation, which in turn leads to balanced economic, social, and environmental outcomes. The framework is grounded in the triple bottom line approach, emphasizing that sustainable development requires simultaneous progress across all three dimensions.

Artificial Intelligence Capabilities

At the input level, AI capabilities such as data analytics, machine learning, automation, and predictive intelligence serve as critical technological resources (Bachmann et al., 2022; Slota et al., 2022). These capabilities enhance organizational ability to process complex information, improve decision-making accuracy, and optimize operational processes (Majid, 2020; Ribeiro et al., 2009; Rudko et al., 2025). AI, therefore, functions as a general-purpose technology that strengthens innovation potential across sectors(Surana et al., 2020).

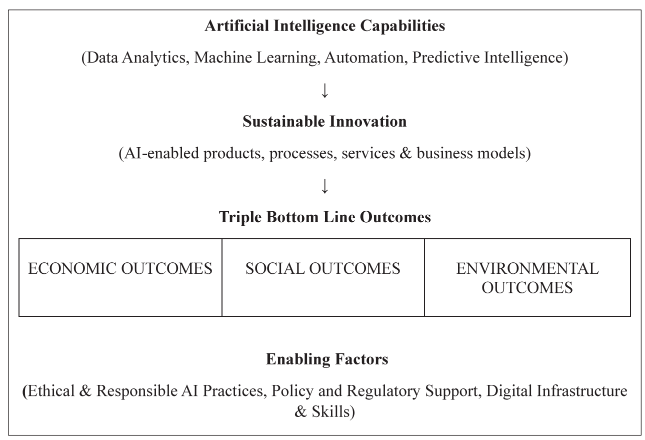

Figure 1. Conceptual framework illustrating the role of Artificial Intelligence capabilities in enabling sustainable innovation and achieving triple bottom line outcomes, with enabling ethical, regulatory, and infrastructural contexts.

Sustainable Innovation as a Mediating Mechanism

The framework positions sustainable innovation as a mediating construct between AI capabilities and sustainability outcomes. AI-enabled innovation manifests in the form of intelligent products, efficient processes, sustainable services, and innovative business models(Olatunji Akinrinola et al., 2024) . By embedding sustainability considerations into innovation processes, organizations can align technological advancement with long-term societal and environmental goals (Cath et al., 2018; Floridi et al., 2018; Ortega-Fernández et al., 2020).

Triple Bottom Line Outcomes

From an economic perspective, AI-driven sustainable innovation contributes to productivity enhancement, cost efficiency, and competitive advantage (Farmanesh et al., 2025). Automation and data-driven strategies support value creation while ensuring resource efficiency, thereby promoting sustainable economic growth (Bachmann et al., 2022; Lv et al., 2022). Socially, AI-enabled sustainable innovation supports inclusive development by improving access to essential services such as healthcare, education, and financial inclusion (Lv et al., 2022; Palmié, M., Wincent, J., Parida, V., & Caglar, 2020). The framework also recognizes the importance of ethical AI adoption to address concerns related to data privacy, bias, and workforce displacement (Cath, 2018; Tsz et al., 2021). Environmentally, AI-driven innovation enables efficient resource utilization, energy optimization, waste reduction, and climate monitoring (Carr & Lesniewska, 2020). These outcomes contribute to reduced ecological footprints and support the transition toward environmentally sustainable systems (Malmio, 2024; Perucica & Andjelkovic, 2022; Saetra, 2022).

Enabling Factors

The framework highlights ethical AI practices, supportive policy frameworks, and robust digital infrastructure as moderating factors that influence the effectiveness of AI-driven sustainable innovation (Arain et al., 2010; Liwång, 2022; Perucica & Andjelkovic, 2022). Responsible governance and institutional support are essential to ensure that AI adoption leads to positive and balanced sustainability outcomes(Geels, 2019; Malmio, 2024; Savaget et al., 2019) .

IV. Discussion: AI-Driven Sustainable Innovation Across Dimensions

The discussion integrates insights from existing literature and theoretical reasoning to explain how AI capabilities translate into balanced sustainability outcomes.

4.1 AI-Driven Sustainable Innovation and Economic Outcomes

Artificial Intelligence has emerged as a key driver of economic sustainability by transforming innovation processes and enhancing organizational performance(Farmanesh et al., 2025). AI-driven sustainable innovation enables firms to improve productivity, optimize operational efficiency, and reduce costs through automation and data-driven decision-making (Dr. Aamar Moorjani & Lena Ramirez, 2025). By leveraging machine learning algorithms and predictive analytics, organizations can identify inefficiencies, forecast demand more accurately, and allocate resources more effectively, thereby contributing to long-term economic viability (Jaber, 2023).

From a strategic perspective, AI supports the development of innovative and sustainable business models that create value while minimizing resource wastage (Attaluri & Kotte, 2025). AI-enabled platforms, smart manufacturing systems, and digital supply chains enhance competitiveness and scalability, allowing firms to achieve sustainable growth(Bosco et al., 2024). These innovations also support resilience by enabling organizations to adapt to dynamic market conditions and environmental constraints (Ferdous, 2010).

At the macroeconomic level, AI-driven sustainable innovation contributes to economic development by fostering technological advancement, entrepreneurship, and productivity growth (Huy et al., 2024). However, the literature also highlights concerns regarding workforce displacement and skill polarization associated with AI adoption (Satornino et al., 2024). Sustainable economic outcomes therefore depend on complementary investments in human capital, reskilling, and inclusive labor policies (Pavlova, 2018). In this context, AI-driven innovation must be aligned with broader economic sustainability objectives to ensure that productivity gains translate into shared prosperity (Brenner & Hartl, 2021).

From a theoretical standpoint, AI-driven sustainable innovation enhances economic outcomes by strengthening firms' efficiency, productivity, and long-term value creation. Drawing on the resource-based view (RBV), Artificial Intelligence capabilities—such as data analytics, machine learning, and automation—represent strategic resources that are valuable, rare, and difficult to imitate when embedded within sustainable innovation processes (Moderno et al., 2024). Additionally, insights from dynamic capabilities theory suggest that AI-enabled sustainable innovation enhances firms' ability to sense market opportunities, seize emerging green demands, and reconfigure resources in response to economic and environmental uncertainties (Gao et al., 2025).

4.2 AI-Driven Sustainable Innovation and Social Outcomes

Beyond economic performance, AI-driven sustainable innovation has significant social implications. AI technologies have the potential to enhance social sustainability by improving access to essential services and promoting inclusive growth (Selvakumar, 2025). Applications of AI in healthcare, such as early disease detection and personalized treatment, contribute to improved health outcomes and quality of life (Edidiong Hassan & Christian E Omenogor, 2025). Similarly, AI-enabled educational platforms support personalized learning and skill development, addressing inequalities in access to education (Dr. Naheed Bi, 2025).

Financial inclusion is another area where AI-driven innovation plays a critical role (Chidinma Lydia Ezenwa, 2025).

However, the social dimension of AI-driven innovation also raises ethical and governance challenges (Bosco et al., 2024). Issues related to data privacy, algorithmic bias, transparency, and employment displacement pose risks to social sustainability. Therefore, the social outcomes of AI-driven sustainable innovation are contingent upon responsible AI practices, ethical governance, and inclusive policy frameworks. Addressing these concerns is essential to ensure that AI contributes positively to societal well-being.

From a theoretical perspective, AI-driven sustainable innovation contributes to social outcomes by enhancing inclusivity, equity, and stakeholder well-being. Grounded in stakeholder theory, the integration of Artificial Intelligence into sustainable products, services, and processes enables organizations to better address societal needs such as access to essential services, improved working conditions, and enhanced decision transparency (Yankovskaya et al., 2022). Consequently, AI-driven sustainable innovation serves as a mechanism through which organizations can align technological advancement with broader social development goals, reinforcing the social dimension of the triple bottom line.

4.3 AI-Driven Sustainable Innovation and Environmental Outcomes

Environmental sustainability represents a critical dimension of AI-driven innovation (Santos et al., 2025). AI technologies are increasingly used to optimize energy consumption, manage natural resources, and support climate change mitigation efforts (Tandon & Shaheen, 2024). AI-enabled systems facilitate real-time monitoring of environmental conditions, predictive maintenance of infrastructure, and efficient utilization of resources, leading to reduced environmental impact (Sanusi, 2025).

In the context of sustainable production and consumption, AI-driven innovation supports waste reduction, circular economy practices, and eco-efficient processes (Chauhan et al., 2022). For instance, AI-based systems can optimize logistics and supply chains to minimize emissions, while smart energy systems enhance the integration of renewable energy sources (Attaluri & Kotte, 2025). These applications demonstrate how AI can contribute to environmentally sustainable innovation (Chauhan et al., 2022).

Nevertheless, the environmental benefits of AI must be evaluated alongside the ecological costs associated with energy-intensive data centers and computational processes(Bachmann et al., 2022). The sustainability of AI-driven innovation therefore depends on the adoption of energy-efficient technologies, green data centers, and responsible design practices(Taylor, 2010). Integrating environmental considerations into AI development and deployment is essential to ensure net positive environmental outcomes(Bosco et al., 2024).

From an environmental sustainability perspective, AI-driven sustainable innovation enables organizations to minimize ecological impact while improving resource efficiency(Chowdhury & Nag, 2026). Drawing on ecological modernization theory, Artificial Intelligence facilitates the development of cleaner production processes, energy optimization, and waste reduction through real-time monitoring, predictive analytics, and intelligent automation (Oktay Ibrahimov, 2025). AI-enabled innovation supports environmentally responsible product design and circular economy practices by improving lifecycle assessment, material efficiency, and emissions management (Sanusi, 2025). Furthermore, insights from dynamic capabilities theory suggest that AI enhances firms' ability to adapt environmental strategies in response to regulatory pressures and climate-related risks (Gao et al., 2025).

4.4 Role of Enabling Factors

The effectiveness of AI-driven sustainable innovation is influenced by several enabling and moderating factors (Shahid et al., 2025). Ethical and responsible AI practices play a central role in shaping sustainability outcomes by ensuring fairness, transparency, and accountability in AI systems (Olatunji Akinrinola et al., 2024). Strong governance mechanisms help mitigate social risks and enhance trust among stakeholders (Yankovskaya et al., 2022).

The conceptual framework incorporates ethical and responsible AI practices, policy and regulatory support, and digital infrastructure and skills as contextual enabling conditions rather than empirically tested moderators(Astobiza et al., 2021). These factors shape the environment within which Artificial Intelligence capabilities translate into sustainable innovation and subsequent triple bottom line outcomes (Cath, 2018). Their presence strengthens alignment between AI-driven innovation and sustainability objectives, while their absence may constrain the effectiveness of AI-enabled sustainable development pathways (Cath, 2018; Dee et al., 2008; Govindan, 2024; Hermann, 2022; Pizzi et al., 2020).

Policy and institutional support also significantly influence the adoption and impact of AI-driven sustainable innovation (Rudko et al., 2025). Supportive regulatory frameworks, financial incentives, and public–private partnerships can encourage organizations to invest in AI solutions that address sustainability challenges (Chowdhury & Nag, 2026). Additionally, investments in digital infrastructure and AI-related skills development are critical for maximizing innovation potential and minimizing exclusion (Pavlova, 2018).

Together, these enabling factors strengthen the relationship between AI capabilities and sustainable innovation outcomes (Santos et al., 2025). Their absence, however, can weaken or distort the sustainability benefits of AI adoption, underscoring the need for a holistic and coordinated approach (Dempsey et al., 2011; Geels, 2019; Malmio, 2024).

Enabling factors play a critical role in shaping the effectiveness of AI-driven sustainable innovation and its ability to generate balanced triple bottom line outcomes (Mouazen et al., 2025). From an institutional theory perspective, supportive policy and regulatory frameworks provide legitimacy and guidance for the responsible adoption of AI, encouraging organizations to align technological innovation with sustainability objectives (Rudko et al., 2025). Ethical and responsible AI practices, grounded in stakeholder theory, enhance trust, transparency, and social acceptance, thereby reducing resistance and unintended societal or environmental harm (Yankovskaya et al., 2022). Additionally, insights from the technology–organization–environment (TOE) framework highlight the importance of digital infrastructure and skills in enabling organizations to fully leverage AI capabilities for sustainable innovation (Badghish & Soomro, 2024). Collectively, these enabling conditions create a conducive ecosystem that strengthens the translation of AI capabilities into meaningful economic, social, and environmental outcomes (Geels, 2019; Mouazen et al., 2025; Santos et al., 2025).

V. Policy and Managerial Implications

The integration of Artificial Intelligence with sustainable innovation has significant implications for policymakers and business managers seeking to achieve balanced economic, social, and environmental outcomes(Brenner & Hartl, 2021; Dwivedia et al., 2019; Farmanesh et al., 2025). As AI adoption accelerates across sectors, strategic interventions are required to ensure that technological progress aligns with broader sustainability objectives(Goh & Vinuesa, 2021).

Policy Implications

From a policy perspective, governments and regulatory bodies play a crucial role in shaping an enabling ecosystem for AI-driven sustainable innovation. Policymakers should design comprehensive AI policies that encourage innovation while ensuring ethical, transparent, and responsible use of AI technologies. Clear regulatory frameworks related to data governance, privacy protection, algorithmic accountability, and bias mitigation are essential to build trust and promote inclusive AI adoption. Public policy should also focus on integrating AI into national sustainability and development strategies (Zuger & Asghari, 2022). Incentives such as tax benefits, grants, and funding support can encourage organizations and startups to adopt AI solutions that address environmental challenges, social inclusion, and resource efficiency(Yeh et al., 2021). In addition, investments in digital infrastructure and AI-focused education and skill development programs are critical to bridge the digital divide and minimize workforce displacement risks. Furthermore, policymakers should promote collaboration between academia, industry, and innovation ecosystems, including startups and business incubators, to facilitate knowledge sharing and experimentation in AI-enabled sustainable innovation.

Managerial Implications

For business managers and organizational leaders, AI-driven sustainable innovation presents both strategic opportunities and managerial challenges. Managers should view AI not merely as a cost-saving tool but as a strategic enabler of sustainable value creation. Integrating AI into innovation strategies can help organizations improve operational efficiency, enhance decision-making, and develop sustainable products and services that meet evolving stakeholder expectations(Palomares et al., 2021). Managers must also prioritize ethical and responsible AI practices by ensuring transparency, fairness, and accountability in AI systems. This involves establishing internal governance mechanisms, conducting regular audits of AI applications, and promoting ethical awareness among employees. Aligning AI initiatives with sustainability goals can enhance organizational reputation and long-term competitiveness. Additionally, effective AI adoption requires organizational readiness, including investments in employee training, cross-functional collaboration, and change management. Managers should focus on upskilling the workforce to work alongside AI technologies and leverage data-driven insights for sustainable innovation(Torri & Martinez, 2014). Partnerships with technology providers, startups, and research institutions can further strengthen organizational capabilities and accelerate innovation outcomes.

The findings of this conceptual study also have implications for broader innovation ecosystems, including startups, incubators, and accelerators. Supporting AI-enabled sustainable innovation within these ecosystems can foster responsible entrepreneurship and contribute to inclusive and environmentally conscious economic growth. Ecosystem stakeholders should emphasize mentorship, funding, and policy support that align AI innovation with sustainability objectives.

In summary, both policymakers and managers must adopt a holistic and collaborative approach to harness the full potential of Artificial Intelligence for sustainable innovation. By aligning

VI. Conclusion and Future Research Directions

This conceptual paper examined the role of Artificial Intelligence (AI) in driving sustainable innovation through the integrated lens of economic, social, and environmental dimensions. In an era characterized by rapid digital transformation and growing sustainability challenges, the convergence of AI and sustainable innovation has emerged as a critical pathway for achieving balanced and inclusive development (Dionisio et al., 2023; Govindan, 2024). By synthesizing existing literature, the study highlighted how AI functions as a foundational enabler that reshapes innovation processes and supports long-term sustainability outcomes.

The paper proposed a conceptual framework illustrating the relationship between AI capabilities, sustainable innovation, and triple bottom line outcomes. From an economic standpoint, AI-driven sustainable innovation enhances productivity, operational efficiency, and competitiveness, thereby contributing to sustainable economic growth. Socially, AI offers significant potential to promote inclusive development by improving access to essential services such as healthcare, education, and financial inclusion, while also transforming employment and skill requirements. Environmentally, AI supports sustainability by optimizing resource utilization, reducing waste, and enabling climate monitoring and green technologies. Together, these dimensions demonstrate the multifaceted contribution of AI to sustainable development.

The study also emphasized the importance of ethical and responsible AI adoption, supportive policy frameworks, and adequate digital infrastructure as critical enablers in maximizing the positive impact of AI-driven innovation. Without appropriate governance and institutional support, the sustainability benefits of AI may remain uneven or lead to unintended social and environmental consequences (Vaio et al., 2024). Therefore, policymakers, managers, and innovation ecosystem stakeholders must adopt a holistic approach that aligns technological advancement with sustainability objectives.

As a conceptual study, this paper offers several avenues for future research. First, the proposed framework can be empirically tested across industries, regions, and organizational contexts to validate the relationships between AI capabilities and sustainability outcomes. Second, future studies may explore sector-specific applications of AI-driven sustainable innovation, particularly in emerging economies where sustainability challenges are more pronounced. Third, comparative research examining the role of AI governance, ethics, and policy interventions can provide deeper insights into ensuring inclusive and environmentally responsible AI adoption.

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FROM INTERFACE TO INTENTION: HOW PLATFORM DESIGN AND RISK PERCEPTIONS SHAPE TRUST IN ONLINE FOOD DELIVERY

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Online food delivery (OFD) platforms operate in a digital environment shaped by increasing data regulation and cybersecurity concerns. Consumer decisions in such settings extend beyond convenience. They are influenced by how platforms manage privacy, security, and transparency.

This study examines the role of User Interface Quality and Information Quality in shaping purchase intention, while also analysing the effects of Perceived Security Risk and Perceived Privacy. Trust is positioned as a key mechanism through which risk perceptions translate into behavioural outcomes. The framework integrates insights from the Information Systems Success Model, the Technology Acceptance Model, and Perceived Risk Theory to explain how governance signals embedded within platform design influence user confidence.

Data were collected from 419 active OFD users and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results indicate two complementary pathways. Functional app attributes directly strengthen purchase intention. At the same time, trust mitigates the negative impact of privacy and security concerns. Perceived Privacy demonstrates both direct and mediated effects, whereas Perceived Security Risk influences intention primarily through trust.

The findings indicate that users respond positively when platforms are open about their data practices and proactive about security, reinforcing long-term engagement.

Keywords : *Digital Governance, Online Food Delivery, Trust, Privacy, Security, Purchase Intention*
JEL Code: *L86, M15, M31*

I. Introduction

After a long day, Riya opens Swiggy to order her favourite momos. However, before confirming, she wonders, "Is the payment secure?" Will the food arrive on time? For millions like her, decisions on food delivery apps depend not just on convenience, but on the trust built through app features and security.

The Online Food Delivery (OFD) industry is experiencing rapid growth, driven by a changing consumer landscape and advancements in technology. The widespread adoption of smartphones and high-speed internet, combined with evolving urban lifestyles, has further accelerated this expansion.

Global Industry reports suggest that the OFD sector is set to grow at a compound annual growth rate of 9.18% from 2024 to 2029 (Statista, 2024). A similar growth pattern is replicated in India, with a CAGR of 7.77% between 2024 and 2028 (Statista, 2024). Platforms like Zomato and Swiggy have become popular in India and revolutionized the OFD industry (John, 2021)

In today's fast-paced digital landscape, mobile applications have become the gateway for consumers to interact with online food delivery (OFD) services. The way an app looks, navigates, and presents information can shape the entire user experience, subtly guiding users' choices and influencing their intention to engage with the service. (Aslam et al., 2020; Kapoor and Vij, 2018). However, in an era of increasing cyber threats, usability alone is not enough—consumers also weigh the security and privacy measures embedded in these applications, which are crucial for fostering trust and long-term engagement. (Zhang, 2024). Despite the importance of both functional and risk-related considerations, limited research examines how these dimensions jointly influence

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purchase intention, especially in a unified behavioural framework.

This study addresses the research gap by examining the combined impact of app attributes and security concerns on purchase intention within the Online Food Delivery (OFD) sector. The study also introduces trust as an important mediating factor in an individual's intention to use these online apps. While past studies have explored these factors individually, there has been limited research on their joint influence on consumer intention. Moreover, much of the existing research focuses on developed markets, providing a limited understanding of the distinct trust dynamics and adoption behaviours prevalent in developing economies such as India. (Gupta & Duggal, 2020). By addressing these gaps, this study aims to provide actionable insights for app developers and marketers seeking to enhance user experiences and foster greater engagement.

To conceptualise these relationships, the study draws on the Information Systems Success Model, the Technology Acceptance Model, Perceived Risk Theory, and trust-based acceptance frameworks. These theories collectively explain how system quality, information quality, perceived vulnerability, and trust formation shape user behaviour in digital service environments.

Therefore, the study seeks the answers to the following research questions:

RQ1: How do app attributes (such as interface quality and information display) influence consumers' purchase intentions in online food delivery?

RQ2: What is the impact of security concerns on consumers' willingness to place orders through food delivery apps?

RQ3: How does trust mediate the relationship between app attributes, security concerns, and purchase intention in online food delivery?

The remainder of the paper is organised as follows. Section 2 reviews the theoretical background and literature. Section 3 outlines the methodology. Section 4 presents the results and discussion. Section 5 discusses the theoretical and managerial implications, and Section 6 concludes with limitations and future research directions.

II. Literature Review

2.1 Theoretical Background

Application features such as the quality of the user interface and the clarity of information play an important role in how people adopt and use digital services. Information Systems Success Model (DeLone & McLean, 2003) suggests that both system quality and information quality directly influence user satisfaction and subsequent behaviour. In the context of OFD, a well-designed interface and reliable information make it easier for users to navigate the platform. Thus, facilitating decisions and leading to more purchases.

The Technology Acceptance Model (Davis, 1989) also supports this perspective and emphasises that people are more likely to adopt a system when they it is useful and easy to use. Although our study does not directly measure perceived usefulness or ease of use, the qualities of the interface and the information provided naturally shape these impressions, which helps in explaining their direct influence on purchase intention without the need for a mediating factor.

Concerns related to security and privacy draw on Perceived Risk Theory (Bauer, 1960; Cunningham, 1967), which holds that feelings of uncertainty and potential loss affect how individuals evaluate online platforms. In the OFD context, concerns about data misuse or payment security can erode users' confidence in the service. Trust-based models, such as those described by McKnight et al. (2002), are essential because they help reduce perceived vulnerability and encourage users to proceed with a transaction. For this reason, trust is expected to mediate the effects of security and privacy concerns, but not the influence of interface quality or information quality. This distinction highlights the different psychological processes involved when users assess functional app features versus potential risks.

With the increasing popularity of smartphones and the internet, numerous studies have been conducted on m-commerce, which is defined as the use of wireless devices, such as smartphones, for conducting business transactions. Most studies focus on the factors driving the growth of m-commerce (Bhatti, 2007). Such studies have been conducted for both developed (Yang, 2005) and developing countries (Verkijika, 2018).

Online food delivery is a relatively new phenomenon (Poon and Tung, 2022). Therefore, studies on OFD are relatively fewer in number than those on m-commerce. Most studies in

OFD segment focus on the factors that impact consumer experience and loyalty (Gunden, Morosan, and DeFranco, 2020; Saad, 2020). However, very few studies investigate consumer interest in the attributes of mobile apps and the extent to which these attributes influence purchasing decisions, ultimately leading to conversions. Kapoor and Vij (2018) empirically tested the mobile app attribute-conversion model to examine the impact of four key attributes—visual, navigational, informational, and collaborative design—on the preference of OFD aggregators in India. Rahardja et al. (2023) assert that application design and performance attributes evoke positive and negative emotions in consumers, influencing consumer loyalty.

The literature on digital platforms suggests that app quality comprises service quality, system quality, and information quality (DeLone & McLean, 2003). These attributes suggest how easily users can navigate the app's information and complete their transactions. For mobile apps, perceived ease of use and interactive design have consistently shown a positive relationship with customer satisfaction and purchase intention. Studies across different domains - travel (Kim & Hyun, 2016), health (Zhao et al., 2016), and retail apps (Hsiao, 2017) suggest that better-designed apps facilitate reducing cognitive load and quickening decision making, factors that are particularly important for OFD apps. Building on the understanding that mobile app attributes influence consumer preferences and loyalty, it becomes essential to examine specific elements of these applications that directly impact user behaviour.

2.2 User Interface Quality and Intention

The quality of the user interface (UI) plays a central role, as it shapes how users interact with the app and perceive the overall service experience. The user interface (UI) provides the platform through which users interact with applications, generating input and output (Jackson and Burd, 2016). Prior studies on mobile banking have shown that interface quality enhances e-satisfaction and loyalty intention, with personalization facilitating easier access to services (Sudirjo et al., 2024; Zhou et al., 2021a). Although these findings are from mobile banking, the logic extends to online food delivery (OFD), where mobile apps are the primary medium of interaction. An intuitive, well-designed interface simplifies browsing, ordering, and payments, thereby shaping consumer purchase intentions.

Furthermore, the quality of the interface affects perceived ease of use, perceived control, and perceived enjoyment, and these factors have been widely validated as predictors of intention in TAM- and UTAUT-based studies (Venkatesh & Davis, 2000; Song & Zahedi, 2007; Venkatesh et al., 2012).

Hence, we proposed the following hypothesis:

H1: User Interface Quality has a significant impact on Intention

2.3 Information Quality and Intention

Eppler (2006) emphasizes the importance of providing factual and high-quality information to meet user needs. Information Quality can be measured by relevance, understandability, sufficiency, and objectivity (Park, Lee, and Han, 2007). When less information is provided, consumers make unfavourable purchasing decisions, leading to customer dissonance and mistrust. (Zhao et al., 2020). Prior studies on mobile banking have shown that information quality, along with interface design and system security, directly and indirectly influence loyalty intention. (Zhou et al., 2021b). Similarly, research on health websites highlights completeness and understandability as the most critical dimensions of information quality (Tao et al., 2017).

In OFD, it is essential for the consumer to have complete information about ingredients, availability, nutritional details, delivery estimates, and pricing. Consumers depend on visuals, menu descriptions, and order updates to minimise uncertainty. High information quality reduces perceived risk and enhances decision confidence, particularly in new or unfamiliar food categories.

Hence, we proposed the following hypothesis:

H2: Information Quality has a significant impact on Intention

2.4 Perceived Security Risk, Trust and Intention

The perception of secure online transactions is crucial in shaping consumer behaviour (Chang and Chen, 2009). Although some studies argue that perceived security does not significantly affect purchasing decisions (Eid, 2011), security remains a key deterrent for online transactions, particularly due to rising cybercrimes(Wall, 2024).

Empirical research has long established a connection between perceived security risk and trust, demonstrating that consumers' confidence is often influenced more by visual cues and presentation than by technical security knowledge (Turner, 2002). In the OFD context, limited studies have explored perceived risks, including psychological, financial, and product-related concerns; yet, these risks are highly relevant, as transactions involve sensitive data and online payments.

Moreover, OFD platforms pose unique security concerns, including stored card details, wallet balances, and repeated payments made with saved credentials. Users worry about fraudulent transactions, unauthorised access to personal data, and insecure payment gateways. These domain-specific issues heighten risk perceptions, making security features such as OTP verification and secure checkout crucial for building trust. Thus, security perception is expected to influence both consumer trust and purchase intention in OFD platforms.

Hence, we proposed the following hypothesis:

H3: Perceived Security Risk has a significant impact on Intention

H4: Perceived Security Risk has a significant impact on Trust

2.5 Perceived Privacy, Trust and Intention

Perceived privacy refers to a customer's ability to control access to their personal information or the sharing of such information with third parties. (Goodwin, 1991). With the proliferation of e-commerce, websites are increasingly collecting sensitive data, raising concerns about user privacy and security (Wu et al., 2021). Several studies have examined the impact of privacy on trust in online platforms (Saeed, 2023; Bandara, Fernando, and Akter, 2020).

For the OFD, there are many privacy issues since apps require location tracking and contact details for delivery. There is a fear among consumers about how their data is used and stored. Clear communication of privacy policies and transparent data practices can significantly improve user trust (Xu, Teo, Tan, & Agarwal, 2009).

Hence, we proposed the following hypothesis:

H5: Perceived Privacy has a significant impact on Intention

H6: Perceived Privacy has a significant impact on Trust

2.6 Trust has a significant impact on Intention

Trust is defined as the customer's belief in the service provider that they will act in the interest of the consumers. This is especially important in the case of online food delivery, as the consumer does not have the opportunity to inspect the goods for quality and reliability physically (Gefen, Karahanna, and Straub, 2003). Therefore, positive reviews, secure payment gateways, and app usability become important. Past studies suggest that trust has a significant impact on intention in OFD sector (Kim, Ferrin, and Rao, 2008; Kim et al., 2003). When there is greater trust in the service provider, purchase intentions are more likely to occur.

Additionally, trust helps reduce the uncertainties users often feel about food quality, delivery reliability, hygiene standards, and refund processes. It grows when platforms offer explicit assurances, maintain a good reputation, and deliver consistently reliable service—all of which encourage users to stay with the app and continue ordering (Gefen, Karahanna, & Straub, 2003).

Hence, the proposed hypothesis is as follows:

H7: Trust has a significant impact on Intention

2.7 Mediating Effect of Trust

In OFD, there is no face-to-face interaction between the restaurant and the consumer, and the transaction environment is often uncertain. Therefore, trust becomes imperative to ensure privacy, safety, and reliability (McKnight, Choudhury, and Kacmar, 2002; Pavlou, 2003).

Theoretically, consumers form initial trusting beliefs based on available information about the platform, such as app usability, security features, and service quality (Almaiah, Alismaiel, & Al-Khasawneh, 2023) These beliefs may evolve as consumers gain experience with the platform, observing whether their expectations about privacy and transaction reliability are met (Singh et al., 2024). Trust thus reduces perceived risks associated with using the app and facilitates consumer engagement and transaction completion (Hipólito, Dias, & Pereira, 2025).

Empirical studies suggest that trust mediates key relationships in digital platforms. For example, it has been shown to mediate the relationship between website quality and user intention (Kim et al., 2004; Belanger et al., 2002)

The past studies show that design factors such as interface quality and information clarity, along with risk perceptions related to security and privacy, converge through trust to influence user intentions. However, studies that simultaneously examine these factors, particularly within the Indian OFD context, are limited. By treating trust as a mediator, this study proposes an integrated framework for how consumers assess OFD platforms, interpret design and security cues, and ultimately form purchase intentions.

By incorporating trust as a mediator, the current model enhances explanatory power and provides marketers and platform developers with deeper insights into designing strategies that foster trust and encourage continued use of OFD platforms.

H8: Trust mediates the relationship between Perceived Security Risk and Intention.

H9: Trust mediates the relationship between Perceived Privacy and Intention.

Conceptual Model

Thus, the proposed conceptual model of the study is shown in Figure I.

Figure 1 – Conceptual Framework of the Study

III. Materials and Methods

For this study, data were collected using an adapted questionnaire comprising two sections. The first section captured respondents' demographic information (summarised in Table 1), while the second included items measuring key constructs: User Interface Quality (4 items; adapted from Aslam et al., 2019), Information Quality (4 items; adapted from Lee et al., 2019), Security Risk and Perceived Privacy (4 items each; adapted from Aslam et al., 2019), and Trust and Intention (4 items each; adapted from Alalwan et al., 2017). All items were assessed on a five-point Likert scale, ranging from 1 (strongly agree) to 5 (strongly disagree). A pilot test with 60 respondents was conducted to ensure the validity and reliability of the instrument.

3.1 Sample and Data Collection

The study surveyed consumers of online food delivery (OFD) platforms to address the research objectives. Before data collection, the required sample size was determined. According to Stevens (2002), in social science research, the sample size should be at least 15 times the number of predictors. With four predictors in this study, the minimum required sample size was 60. Additionally, to perform Structural Equation Modelling (SEM) for hypothesis testing, a minimum sample size of 200 respondents was necessary (Hoelter, 1983). In our study, a total of 462 respondents completed the survey. However, 43 responses were excluded due to inconsistencies or incomplete information, resulting in a final sample size of 419 respondents. The survey was conducted by sharing Google Forms on social networking platforms, including LinkedIn, WhatsApp, and Instagram. A non-probability purposive sampling technique was employed, targeting participants who had prior experience using online food delivery platforms. Data collection took place between February and April 2024.

All procedures involving human participants were conducted in accordance with standard ethical guidelines. Verbal informed consent was obtained from all participants after explaining the objectives of the study, assuring confidentiality and anonymity of responses, and clarifying that participation was voluntary. The study procedures were reviewed and approved by the University's Ethics Review Board. Ethical clearance was also obtained from Delhi Metropolitan Education, an affiliate institution of one of the authors (Reference number - DME_EC_2024_2).

3.2 Data Analysis

For testing the hypotheses, a partial least squares structural equation modelling tool (PLS-SEM) with SmartPLS version 4 was used. PLS Sem was used in this study, as it helps in assessing complex relationships that include multiple constructs, variables and structural paths. The study consisted of two steps. The steps followed were:

1. To check the reliability and validity of the model
2. To access the structural model and test hypotheses

3.3 Demographic Profile

Table 1 summarizes the demographic characteristics of the respondents, including gender, age, occupation, education, and income. The sample comprised 51% females and 49% males. A significant proportion of respondents (67.1%) belonged to the 18–30 age group, with students representing the majority (60.9%). In terms of education, 45% of the participants were graduates. Regarding income, 37.5% of respondents reported annual earnings between INR 0.8 and 2.0 million, 34.8% earned less than INR 0.8 million, 19.6% fell within the INR 2.0 to 4.0 million range, and only 8.1% reported income above INR 4.0 million.

Table 1 : Demographic Profile

3.4 Measurement Model

The first step in measurement was to evaluate the outer loadings of the indicators. The outer loadings must be greater than 0.70 to establish good indicator reliability (Hair et al., 2011). For our study, all outer loadings exceeded this threshold limit and were statistically significant ($p < 0.0001$), indicating good indicator reliability. (Table 2)

Table 2 – Outer Loadings

The second step was to measure the internal consistency reliability of the Model. This was done using Cronbach's Alpha and Composite Reliability. Values above 0.7 for both Cronbach's alpha and composite reliability are acceptable. (Nunnally, 1978). For our study, the internal consistency reliability is good, as these measures exceed the value of 0.7. (Table 3)

Table 3 – Construct Validity and Reliability

Convergent reliability was evaluated by calculating the Average Variance Extracted (AVE). As reported in Table 3, all antecedents exhibited AVE values above 0.5, indicating satisfactory convergent reliability (Hair et al., 2011).

Discriminant validity was subsequently assessed to ensure that each construct is empirically distinct within the structural model (Hair et al., 2011). The Heterotrait-Monotrait (HTMT) ratio of correlations (Table 4) was employed for this purpose. All HTMT values were below the recommended threshold of 0.90, confirming adequate discriminant validity (Henseler et al., 2015).

The model exhibited a standardized root mean square residual (SRMR) of 0.054, which is below the recommended threshold of 0.08, indicating an acceptable model fit (Henseler et al., 2016)

Table 4 - Heterotrait-monotrait ratio (HTMT) - Matrix

3.5 Structural Model and Hypothesis Testing

Before assessing the structural relationships, the collinearity was evaluated. The VIF values of all constructs were below 5, indicating no issues with collinearity (see Table 5).

Table 5 – VIF Values

Hypotheses were tested using PLS-SEM. The significance of the structural paths was estimated using the bootstrap resampling method with 4,999 iterations (Henseler et al., 2016). The results are presented in Table 6

Table 6 - Results of standardized estimates of the structural model (Direct Effect)

As shown in Table 6, User Interface Quality ($\beta = 0.13$, $p < 0.05$), Information Quality ($\beta = 0.16$, $p < 0.05$), and Perceived Privacy ($\beta = 0.28$, $p < 0.05$) are significantly associated with Intention, whereas Perceived Security Risk ($\beta = -0.01$, $p > 0.05$) is not. Among the direct effect hypotheses, H1, H2, and H4 are supported, while the hypothesis linking Perceived Security Risk to Intention (H3) is not supported.

Perceived Security Risk ($\beta = 0.45$, $p < 0.05$) and Perceived Privacy ($\beta = 0.42$, $p < 0.05$) are statistically significant predictors of Trust, and Trust itself ($\beta = 0.42$, $p < 0.05$) significantly explains Intention.

After assessing the direct effects of the predictor variables on Intention and Trust, the next step was to examine the mediating role of Trust in the relationships between Perceived Security Risk, Perceived Privacy, and Intention. Table 7 presents the results of these indirect effects, which provide insight into whether Trust serves as a significant mediator in the proposed model.

Table 7- Results of standardized estimates of structural model (Indirect Effect, with Trust as Mediator)

Table 7 presents the results of the indirect effects, with Trust as a mediator. Both hypotheses—H8 (Perceived Security Risk → Trust → Intention) and H9 (Perceived Privacy → Trust → Intention)—are supported ($p < 0.05$), indicating that trust significantly mediates the relationships between perceived security risk, perceived privacy, and intention to use OFD platforms.

The structural model explains 75% of the variance in Intention ($R^2 = 0.75$) and 67% of the variance in Trust ($R^2 = 0.67$), confirming that the empirical data support the conceptual model. Overall, eight out of nine hypotheses are supported, demonstrating strong alignment with the proposed model.

In line with prior literature, these findings validate the hypothesized relationships in the current study. The results emphasize that purchase intention toward OFD platforms is determined by app interface features, as well as security and privacy measures, with trust serving as a crucial mediating factor.

IV. Results and Discussion

4.1 Interpretation of Structural Model Results

This study investigates how app-related attributes and privacy concerns shape users' purchase intentions in the online food delivery (OFD) context, with trust functioning as a key mediating mechanism. The structural model provides meaningful insight into how users evaluate OFD platforms and form behavioural intentions in technology-driven environments. The results show that User Interface (UI) quality and Information Quality (IQ) significantly enhance purchase intention. These findings are consistent with prior research, which emphasizes that visually appealing, easy-to-navigate, and functionally efficient interfaces positively influence user adoption and continued usage . Users are more inclined to transact on platforms where the interface facilitates smooth information processing and decision-making.

Although Perceived Security Risk (PSR) did not directly predict purchase intention (H3 not supported), it significantly influenced trust (H4 supported). The mediation analysis further revealed that PSR indirectly affected purchase intention through trust (H8 supported). This pattern suggests that users may tolerate certain security-related uncertainties if they have strong trust in the platform. This is consistent with foundational studies ——— which show that trust reduces perceived risk in digital transactions where interpersonal cues are absent.

Perceived Privacy (PP) demonstrated both direct (H5 supported) and indirect (via trust; H9 supported) effects on purchase intention. This highlights that users consider privacy protection not only as a functional attribute but also as a core element of ethical and responsible platform behaviour. When users perceive that their personal data are handled transparently and securely, their trust—and willingness to transact—substantially increases. These findings align with prior literature showing that privacy assurances enhance trust in online environments .

4.2 Interpretation of Key Findings

The findings highlight how strongly app design elements shape user behaviour. Both user interface quality and information quality showed apparent, direct effects on purchase intention, which aligns with the core ideas of the Information Systems Success Model and the Technology Acceptance Model. In practical terms, when an app is easy to navigate and presents information clearly, users find it more useful. They are more willing to engage with it, even without additional psychological drivers.

In contrast, security and privacy concerns affected intention only through trust. This aligns with Perceived Risk Theory, which suggests that perceived vulnerability or uncertainty can deter users from acting. Trust, as described in trust-based acceptance frameworks, helps users manage these feelings by reducing perceived risk. The mediation observed in this study shows that trust specifically addresses risk-related concerns rather than amplifying the influence of design attributes.

Taken together, the results point to two different behavioural pathways in OFD usage: one driven by functionality, where interface and information quality directly encourage intention and another shaped by risk, where trust compensates for concerns about security and privacy. Recognising these parallel routes deepens our understanding of how users evaluate OFD platforms and underscores the need for both strong design and visible risk-reduction measures.

V. Implications

5.1 Theoretical Contributions

This study makes several significant theoretical contributions to the literature on online food delivery (OFD), digital consumer behaviour, and technology-enabled service interactions. First, the research extends existing knowledge by re-examining the attributes that influence customer intention within the OFD sector. While prior studies have broadly explored system-related and service-related attributes (Handayani et al., 2002; Zaheer et al., 2024), they have rarely positioned trust as a central explanatory mechanism. By introducing trust as a mediating construct, the present study deepens theoretical understanding of how consumers evaluate OFD platforms in high-choice, high-risk digital environments. This shift moves beyond traditional models that directly associate system attributes and risk perceptions with behavioural intention, and instead frames trust as an essential cognitive bridge that translates perceptions into intention.

Second, the findings contribute to risk and privacy literature by differentiating between the pathways through which perceived security risk and perceived privacy shape consumer behaviour. Earlier studies (McKnight et al., 2002; Pavlou, 2003) conceptualised risk and privacy concerns as relatively uniform deterrents. However, this study provides nuanced evidence that perceived security risk does not directly influence intention; rather, its influence is fully channelled through trust. In contrast, perceived privacy exerts a dual influence—both directly shaping intention and indirectly affecting it through trust. This theoretical distinction advances understanding of consumer cognition by illustrating that not all security-related concerns operate similarly; instead, privacy concerns may be seen as more personally salient and immediate, thereby exerting a more direct behavioural effect compared to general security risks. The model therefore refines existing frameworks by clarifying the differential intensity, salience, and psychological mechanisms associated with risk-related constructs.

Third, the study strengthens theoretical discussions on the integration of technical and psychological dimensions in digital service evaluation. While the literature has often examined user interface quality and information quality as functional or utilitarian components of service experience, their role in shaping deeper psychological states such as trust has been comparatively underexplored. Fourth, by demonstrating how functional quality (interface and information quality), psychological evaluations (trust), and risk perceptions (security and privacy) collectively shape purchase intention, the study offers a multi-dimensional framework for understanding consumer behaviour in OFD settings. This contributes to broader literature on digital consumer decision-making by illustrating that intention formation is neither purely utilitarian nor purely affective; rather, it emerges from an interaction of efficiency judgments, perceived vulnerability, and cognitive trust processes. Such an integrated perspective aligns with contemporary views of digital consumption as a complex evaluative process shaped by simultaneous technological and psychological cues.

5.2 Managerial Implications

The findings of this study generate several actionable insights for managers in the OFD sector. The positive influence of User Interface and Information Quality on users' intention to purchase suggests that platforms must refine both the visual design of their applications and the clarity of the information they provide. When the app is easy to navigate, visually pleasant and supported by reliable content, users feel more comfortable making decisions and are more likely to return to the platform.

The results also show that trust plays a central role in shaping user behaviour. Functional improvements alone cannot guarantee sustained engagement unless users believe that the platform is reliable. OFD companies should therefore incorporate visible trust enhancing features. These include secure payment options, transparent order tracking, verified restaurant partners and customer support systems that respond promptly. Communicating these efforts clearly can ease user concerns and encourage continued use.

Privacy protection proved to be a powerful factor influencing both trust and purchase intention. This highlights the importance of treating user data with care and making privacy practices easy to understand. Managers should ensure that the platform explains how data is collected and stored, limits unnecessary data requests, follows relevant data protection guidelines and allows users to manage their privacy settings easily. These steps can significantly strengthen users' confidence in the platform.

Although perceived security risk did not directly affect purchase intention, its strong association with trust indicates that security must still be a high priority. Platforms should invest in secure technological infrastructure, such as encryption, fraud prevention tools and authentication systems, and should communicate these safeguards to users in regular intervals. Visible evidence of security helps users feel safer and supports long term trust.

VI. Conclusion

This study set out to examine the combined influence of technical attributes, security-related perceptions and trust on consumers' purchase intentions in online food delivery (OFD) platforms. The findings provide a holistic understanding of how users evaluate digital services in an environment where convenience, risk and information quality intersect. The results demonstrate that user interface quality and information quality significantly enhance intention, underscoring the importance of a seamless, visually coherent and informative application experience. These functional attributes shape the user's initial assessment of platform reliability and reduce cognitive effort during decision-making.

The study further establishes trust as a central mechanism driving consumer behaviour. Trust mediates the impact of key variables, particularly perceived security risk, illustrating that consumers rely heavily on confidence in the platform before committing to a transaction. Although perceived security risk does not directly influence intention, its strong effect on trust highlights the need for platforms to strengthen security assurance mechanisms. In parallel, privacy protection emerges as a critical determinant with both direct and indirect effects on intention. The salience of privacy indicates that consumers are attentive to how their personal data is collected, handled and protected, and respond more favourably to platforms that are transparent and respectful of these concerns.

By integrating functional, psychological and risk-related components into a unified framework, this study contributes valuable insights into how intention is formed in OFD contexts. The results emphasise that enhancing technical quality alone is insufficient; fostering trust through privacy transparency, visible security features and consistent service reliability remains essential for sustained engagement. As the OFD sector continues to grow and competition intensifies, platforms that combine strong design principles with credible assurance mechanisms will be better positioned to cultivate user loyalty and strengthen long-term competitiveness. Future research may extend this model by examining cross-cultural contexts, demographic differences or moderating digital literacy levels to deepen understanding further.

6.1 Limitations and Future Research

While the study offers valuable theoretical and practical insights into how app attributes shape purchase intentions in the Online Food Delivery (OFD) context, several limitations should be noted. First, the research was conducted within a single cultural and geographical setting, which may limit the generalizability of the findings to other markets with different consumer dynamics. Second, the use of self-reported survey data may introduce biases such as social desirability, recall errors, and inattentive responses. Third, the cross-sectional design restricts causal inference and does not capture changes in user perceptions and behaviours over time.

Future research can address these limitations through several avenues. Longitudinal designs could examine how purchase intentions evolve over time with continued app usage and market changes. Testing the model across diverse geographical and cultural contexts would enhance generalizability. Incorporating behavioural data, such as actual purchase records or in-app analytics, could provide deeper insights beyond self-reported measures. Extending the framework to other digital platforms (e.g., cab aggregators, home improvement websites, and quick commerce apps) may assess its broader applicability. Future studies may also investigate the influence of emerging technologies, including AI-driven personalization, voice-enabled ordering, and augmented reality menus, on trust and purchase intention, as well as explore moderating factors such as age, digital literacy, and prior online purchase experience.

Author Contributions

The first author led the study design, data collection, analysis, and drafting. The second author contributed to conceptual development, research design, interpretation, and revision. The third author contributed to methodological design, data analysis, and critical revision.

Disclosure of interest

The authors report there are no competing interests to declare.

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BUILDING SKILLS FOR SUSTAINABILITY: THE ROLE OF EDUCATION AND CAPACITY DEVELOPMENT IN LONG-TERM SUCCESS

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This research aims to close this gap by recognizing and evaluating the critical elements that influence the growth of abilities linked to sustainability and comprehending their connections. As demand to address global concerns grows, sustainability has taken center stage; equipping graduates with the necessary skills is essential. There are still unanswered questions about how well modern educational initiatives foster these abilities. Variables in this study include student motivation and attitude, pedagogical approaches, internships and real-world experience, faculty expertise and industrial relevance, technology integration, internship design and content, and assessment and feedback mechanisms. It is tested if every variable has a significant influence on skill development. Using structural equation modelling, the sustainable skill development optimization model among graduates is estimated below. A curriculum that prepares students for sustainability-related real-world difficulties should strike a balance between academic knowledge and practical implementation. Students will be even more helped by interactive teaching methods and experiential learning to apply theoretical concepts enthusiastically. By bringing technology into these programs, students will eventually become more aware of how to manage contemporary sustainability concerns and become fluent in using contemporary tools and platforms. This will provide students with priceless experiences and help close the knowledge gap between classroom instruction and practical applications that provide a thorough grasp of industrial procedures. Faculty knowledge enhances learning, student motivation spurs participation and skill acquisition, and built-in evaluation and feedback systems direct learners toward ongoing development. These results will offer insightful information about the best methods for developing sustainability abilities in a higher education context. Additionally, educational institutions will be able to use these insights to design curricula that equip graduates with the knowledge and abilities to apply sustainability principles in their professional lives. Stated differently, they will help create a more sustainable future by equipping professionals with the knowledge and skills needed to tackle difficult environmental, social, and economic problems.

Keywords : *Skills for sustainability, Higher education, Skill development, Professional success, Marketing education, Industry demands, Competency, Contemporary marketplace. Structural Equation Modelling*
JEL Code: *I25*

I. Introduction

In today's professional landscape, mastery of skills for sustainability is a critical attribute for graduates seeking success in competitive markets. Understanding consumer behaviors, developing effective strategies, and leveraging digital platforms have become essential skills for individuals seeking to excel in a variety of industries (Rathore, 2016). Nonetheless, a discernible concern emerges about graduates' ability to effectively navigate the demands of the ever-changing marketplace (Eslit, 2023). Despite completing formal marketing education programs, many graduates may lack the practical skills and competencies required to meet the stringent demands of prospective employers (Harrigan, Dolan & Lee, 2022). The variables under the study cover a wide range of factors critical to the development of skills for sustainability among graduates. First and foremost, curriculum design and content are foundational elements that define the structure and substance of marketing education programs.

Furthermore, the methodologies used by educators to disseminate marketing knowledge, which range from traditional lectures to experiential learning approaches, significantly impact students' learning experiences. In parallel, incorporating technology and digital tools into the curriculum is critical, reflecting the current state of marketing practices. Furthermore, internships and practical experiences help students bridge the gap between theory and practice, providing them with invaluable real-world knowledge (Resch & Schrittesser, 2023). Faculty members' expertise and industry relevance improve educational

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quality, while student motivation and attitudes toward learning have a significant impact on skill development (Abbas, Kumari & Al-Rahmi, 2021). Finally, robust assessment and feedback mechanisms promote accountability and continuous improvement (Johnson, Keating & Molloy, 2020).

Hypothesis Development

The following Hypotheses are developed based on a Review of the Literature-

Curriculum Design and Content

According to marketing education research, curriculum design and content play a critical role in shaping graduates' skills. A meticulously crafted curriculum that combines theoretical underpinnings with practical applications is critical for providing students with the skills they need to succeed in professional environments (Bo & Yeh, 2023). Achieving a delicate balance between theoretical knowledge and practical experience ensures that graduates are well-equipped to face real-world challenges (Lim, 2023). Furthermore, curriculum design flexibility, when aligned with current industry trends, has demonstrably increased graduates' employability and preparedness for a variety of marketing roles (Tomlinson & Watermeyer, 2022). This alignment not only improves graduates' understanding of current market dynamics but also provides them with the practical skills that employers require, facilitating a smooth transition from academia to the professional realm of marketing.

H1: Curriculum Design and Content has a significant impact in Developing skills for sustainability

Pedagogical Approaches

Pedagogical methods have a significant impact on skill acquisition among marketing graduates. Experiential learning strategies, such as case studies and simulations, are particularly effective at developing problem-solving abilities and honing critical thinking skills (Cummins & Johnson, 2023). These methods foster a practical understanding of marketing concepts by immersing students in simulated real-world scenarios, encouraging them to apply theoretical knowledge to real-world problems (Khasawneh, 2024). Students improve their communication and teamwork skills by actively participating in discussions, group activities, and collaborative projects, in addition to deepening their understanding of marketing principles. These interactive pedagogical methods not only increase the depth of learning but also instill the adaptive mindset and interpersonal skills required for success in dynamic marketing settings (Allil, 2024).

H2: Pedagogical Approaches has a significant impact in Developing skills for sustainability

Integration of Technology and Digital Tools

The incorporation of technology and digital tools into marketing education has become critical for preparing graduates to successfully navigate modern marketing landscapes. Recognizing the changing demands of the industry, educational institutions are increasingly incorporating digital marketing components into their curricula to ensure that graduates have relevant skills (Rohm Stefl & Ward, 2021). In today's digital age, being able to use technology to create and implement effective marketing strategies has become a must-have skill (Turyadi, et al., 2023). As digital platforms continue to shape consumer behaviour and reshape marketing paradigms, graduates must be proficient in using a wide range of digital tools, analytics platforms, and social media channels to engage audiences and drive business outcomes (Ducman,, 2024). Graduates who embrace digital marketing education gain hands-on experience with cutting-edge technological innovations, establishing themselves as valuable assets in an increasingly digitised marketplace (Grimaldi Ball & Peruzzo, 2023).

H3: Integration of Technology and Digital Tools has a significant impact in Developing skills for sustainability

Internships and Practical Experiences

Internships, cooperative programmes, and industry projects provide valuable practical experience that helps students bridge the gap between theoretical knowledge and real-world application in marketing education (Benati, Lindsay & Fischer, 2021). It examines the accessibility and quality of internship opportunities available to students, as well as the extent to which these experiences enhance their skill development. Students gain invaluable insights into industry practices, sharpen their problem-solving abilities, and improve their communication skills by immersing themselves in real-world marketing environments (Khasawneh, 2024). The quality of internship experiences has a direct impact on graduates' workforce readiness, shaping professional competencies and increasing employability in the dynamic marketing landscape (Risdwiyanto, et al., 2023). The availability and efficacy of internship programs emerge as critical factors in ensuring graduates have the practical skills and acumen required for success in marketing roles (Antoniadou & Kanellopoulou, 2023).

H4: Internship and Practical Exposure has a significant impact on Developing skills for sustainability

Faculty Expertise and Industry Relevance

Faculty members' expertise and industry experience play an important role in shaping the quality of marketing education provided to students. This variable examines a variety of factors, including faculty members' qualifications, professional backgrounds, and industry connections, as well as their effectiveness in providing practical insights and real-world perspectives to students. Faculty with extensive industry experience bring invaluable real-world insights to the classroom, enriching students' learning experiences and increasing the relevance of theoretical concepts to practical applications (Smeplass, 2023). Their industry connections allow students to network, gain exposure to current industry trends, and potentially find internships or career opportunities (Minnes, Serslev & Padilla, 2021). The ability of faculty members to bridge the gap between academia and industry improves the quality of marketing education and provides graduates with the skills, knowledge, and networks required for success in today's competitive market (Aithal and Aithal, 2023). Faculty expertise and industry experience emerge as critical factors in ensuring the efficacy and relevance of marketing education programs in preparing graduates for professional careers (Okolie, et al., 2020).

H5: Faculty Expertise and Industry Relevance has a significant impact on Developing skills for sustainability

Student Motivation and Attitude

Motivation and attitudes toward learning have a significant impact on the effectiveness of skill development initiatives in marketing education, including students' intrinsic motivation, enthusiasm for marketing, perceived relevance of marketing education to their career goals, and commitment to continuous learning and skill development (Mainga, Daniel & Alamil, 2022). Students with high levels of intrinsic motivation are more likely to engage deeply with course materials, actively participate in discussions, and seek opportunities for experiential learning (Alamri, et al., 2020). A genuine interest in marketing fosters curiosity and drive, prompting students to seek out additional resources and experiences to deepen their understanding of the field (Yi & Park, 2024). Students who perceive the relevance of marketing education to their career goals feel a sense of purpose and direction, which motivates them to devote time and effort to mastering relevant skills and knowledge (Filgona, et al., 2020). Exploring these facets allows educators to tailor instructional approaches and support mechanisms to foster students' motivation and positive attitudes toward learning, increasing the effectiveness of skill development initiatives in marketing education (Cai & Lu, 2024).

H6: Student Motivation and Attitude has a significant impact on Developing skills for sustainability

Assessment and feedback mechanisms

Effective assessment and feedback mechanisms are essential components of marketing education, serving as critical tools for tracking students' progress and guiding them toward continuous improvement (Chaudhry, et al., 2023). Formative assessments, when used throughout the learning process, provide valuable insights into students' comprehension levels and skill proficiency, allowing educators to identify areas that require additional attention or refinement (Lasaiba, 2024). Timely feedback, provided shortly after assessments, provides students with actionable guidance for improvement, allowing them to address weaknesses while building on their strengths (Owan, et al., 2023). By emphasizing rigorous assessment methods and providing constructive feedback, educators can improve learning outcomes and better prepare graduates for success in the competitive marketplace (Shofiyyah, Komarudin & Hasan, 2023).

H7: Assessment and Feedback Mechanisms Have a Significant Impact on Developing skills for sustainability

II. Conceptual Model- Factors Affecting The Development of Skills for Sustainability Among Graduates

This conceptual model outlines the intricate relationships between key components of marketing education, demonstrating how curriculum design, pedagogical methods, technology integration, practical exposure, faculty expertise, student motivation, and assessment mechanisms all contribute to graduates' marketing skill development. It emphasizes the interdependence of these factors, emphasizing the comprehensive approach required to develop skilled marketing professionals ready for the industry's dynamic challenges.

Source: Author's Computation

Methodology

This empirical paper employs a methodology that includes data collection through a Structured Questionnaire. It includes conducting structured surveys with marketing students and graduates to collect information on their perceptions of curriculum design (CD), pedagogical methods (PA), technology integration (TI), practical exposure (PE), faculty expertise (FE), student motivation (SM), assessment mechanisms (AM), and skill development outcomes (SDO). 414 responses were included in the study. Concurrently, qualitative interviews will be conducted with key stakeholders, including faculty members and industry professionals, to gain a better understanding of the effectiveness of marketing education practices. Data analysis will employ CFA and Structure Equation modeling to test the Conceptual model.

III. Results

The first step was to ensure the integrity and validity of the measurement methodology. It was then examined the structural model to determine the relationships between the variables. The Variance Inflation Factor (VIF) is used to determine how much each independent variable's behaviour (variance) was influenced by its interactions and correlations with other independent variables.

Table 1.1 Variance Inflated Factor (VIF)

Items	VIF
CD1	1.346
CD2	2.375
CD3	2.554
CD4	2.734
PA1	2.827
PA2	1.599
PA3	1.045
PA4	1.128
PA5	1.483
TI1	1.288
TI2	1.597
TI3	1.566
TI4	1.149
PE1	1.288
PE2	1.000
PE3	2.821
PE4	2.900
FE1	2.971
FE2	2.921
FE3	2.531
SM1	1.008
SM2	2.698
SM3	1.394
SM4	2.073
AM1	2.418
AM2	2.000
AM3	1.000
AM4	2.009
AM5	1.987
AM6	2.005
SDO1	2.007
SDO2	1.777
SDO3	2.020

Source: Author's Computation

To ensure model integrity, only variables with a VIF less than 2.5 were retained, as this is the default VIF cut-off value (Anderson, et al., 2020). Importantly, the VIF values for all individual factors were less than 2.5, indicating the absence of common technique bias (Exhibit 2). To assess discriminant validity, Fornell and Larcker's criterion is used, which considers construct loadings and cross-loadings. According to this criterion, correlation values should exceed the square roots of the extracted average variance (AVE) (Hair, et al., 2021). This standard was used in the study to ensure the reliability and validity of the results. By ensuring the absence of common procedure bias, the study's findings are more likely to reflect the true correlations between variables. As a result, before proceeding with the measurement model analysis, the VIF values were validated (Mukminin et al., 2020). Following the validation and reliability of the measurement model, the interrelationships between the variables in the structural model were investigated.

Measurement Model

Table 2 shows the discriminant validity measurement, which assesses the distinctiveness of constructs.

Table 2: Discriminant Validity Measurement

	CD	PA	TI	PE	FE	SM	AM	SDO
CD	0.815							0.052
PA	0.200	0.266						0.073
TI	0.025	-0.177	0.721					0.088
PE	0.214	0.242	0.032	0.647				0.041
FR	0.211	-0.151	0.022	0.114	0.771			0.040
SM	0.132	-0.146	0.815	0.139	0.014	0.802		0.058
AM	0.122	0.027	0.287	0.302	0.023	0.426	0.800	0.066
SDO								0.821

Source: Author's Computation

Each cell displays the correlation between construct pairs. According to the threshold, off-diagonal correlations that exceed the square root of the average variance extracted (AVE) for their respective constructs may indicate potential discriminant validity issues. For example, correlations greater than 0.50 may indicate that constructs are not sufficiently distinct (Yoon, et al., 2021). As a result, correlations that exceed this threshold should be carefully examined to ensure robust discriminant validity in the analysis. The results indicate that all criteria were met, demonstrating the model's validity and dependability. The structural model can then be evaluated against model structures that differ statistically.

The Model

Table 3 displays the results of the structural model analysis, which looked at the hypothesized relationships between constructs. Each row contains the estimate, standard error, critical ratio, and p-value for a single relationship.

Table 2: Discriminant Validity Measurement

Relationship			Hypothesis	Estimate	S.E.	p-value	Decision
SDO	<---	CD	H1	.044	.044	0.033	Supported
SDO	<---	PA	H2	.031	.043	0.015	Supported
SDO	<---	TI	H3	-.099	.091	0.042	Supported
SDO	<---	PE	H4	.044	.042	0.012	Supported
SDO	<---	FE	H5	-.019	.023	0.061	Not Supported
SDO	<---	SM	H6	-.057	.065	0.001	Supported
SDO	<---	AM	H7	.022	.067	0.081	Not Supported

Source: Author's Computation

Significant estimates ($p < 0.05$) support the hypotheses. This analysis supports the relationships between Skill Development Outcome (SDO) and Curriculum Design (CD), Pedagogical Approach (PA), Technology Integration (TI), and Practical Exposure (PE), indicating that these factors have a significant impact on skill development. However, the relationships between Faculty Expertise (FE) and Assessment Mechanisms (AM) are not supported, implying no significant effects on skill development. These findings shed light on the strength and significance of the hypothesized relationships, guiding future interpretation of the structural model.

IV. Findings and Discussions

The structural model analysis results provide valuable insights into the relationships between various constructs and how they affect skill development outcomes. Notably, Curriculum Design (CD), Pedagogical Approach (PA), Technology Integration (TI), and Practical Exposure (PE) all had a significant positive effect on Skill Development Outcome (SDO). These findings highlight the importance of a well-designed curriculum, innovative pedagogical methods, technological integration, and hands-on experience in improving students' skills for sustainability .

However, no significant relationships were found between Skill Development Outcome (SDO), Faculty Expertise (FE), and Assessment Mechanisms (AM). This suggests that, while faculty expertise and assessment mechanisms are important in marketing education, their direct impact on skill development may be less pronounced than the other factors investigated in this study.

These findings are consistent with previous research, which has emphasized the importance of active learning, real-world application, and technological integration in fostering skill development among marketing students (Khasawneh, 2024). They emphasize the importance of educational institutions prioritizing these aspects in curriculum design and instruction to better prepare graduates for the dynamic challenges of the marketing profession (Kumar & Rewari, 2022). Furthermore, the non-significant relationships observed between SDO, FE, and AM call for additional research into the specific mechanisms by which faculty expertise and assessment practices influence skill development. Qualitative research methods, such as interviews or focus groups, may provide more detailed insights into the perceived effectiveness of faculty expertise and assessment strategies in improving students' skills for sustainability. While these factors are universally recognised as critical factors in higher education institutions, the results suggest that their relationship to skill development in terms of sustainability skills could be less direct. Faculty expertise may actually contribute to skill development indirectly in terms of how it influences curriculum design, mentors students, and provides opportunities for experiential learning. However, in terms of a direct and immediate impact on skill development, the results suggest that this is less likely. Similarly, assessment mechanisms may actually function as a means of tracking student learning and skill development rather than a direct means of skill development.

These findings add to the ongoing discussion about effective pedagogical practices in marketing education and have important implications for curriculum design, instructional strategies, and faculty development initiatives aimed at improving skill development outcomes for marketing graduates.

Theoretical Implications

The findings of this study add to the theoretical understandings of skill development in marketing education by emphasising the different effects of various educational factors on students' acquisition of skills for sustainability . Curriculum Design (CD), Pedagogical Approach (PA), Technology Integration (TI), and Practical Exposure (PE) all have significant positive effects, emphasizing their importance in fostering skill development among marketing students.

These findings are consistent with existing theoretical frameworks that highlight the importance of active learning, real-world application, and technological integration in educational settings. Furthermore, the non-significant relationships observed between Skill Development Outcome (SDO) Faculty Expertise (FE) and Assessment Mechanisms (AM) call into question traditional notions of faculty influence and assessment practices in skill development models, pointing to avenues for future theoretical research into the nuanced dynamics of faculty-student interactions and assessment strategies in marketing education.

Managerial Implications

The study's findings have several managerial implications for educational institutions and marketing departments that want to improve graduate skill development outcomes. To begin, prioritizing the design of a well-structured curriculum that balances theoretical concepts with practical applications is critical for promoting skill development. Institutions should invest in updating curricula to reflect industry trends and incorporate experiential learning opportunities. Second, managerial efforts should be directed toward implementing innovative pedagogical approaches that promote active student engagement and deeper learning. This could include using case studies, simulations, and collaborative projects to improve problem-solving and critical-thinking skills. Integrating technology into the learning environment is critical for preparing students to meet the changing demands of the marketing profession. Institutions should provide students with access to cutting-edge digital tools and platforms, ensuring that they develop proficiency in using technology to create effective marketing strategies. Offering high-quality internships and practical exposure opportunities is critical for closing the gap between academic learning and real-world application. Establishing partnerships with industry organizations can help to provide students with hands-on experiences that improve their practical skills and industry readiness.

Social Implications

Educational institutions help to develop a more competent and competitive workforce by providing graduates with advanced skills for sustainability . This, in turn, can lead to increased employment and economic productivity, which benefits society as a whole. Fostering skill development in marketing education enables graduates to better address societal challenges and make positive contributions to their communities. Institutions enable graduates to develop innovative solutions to social problems and drive positive change in their communities by cultivating critical thinking, problem solving, and creativity. Promoting inclusion and diversity in marketing education programmes can result in a more representative and equitable workforce. Institutions help to create a more inclusive society by providing opportunities for people from all walks of life to learn about marketing. Furthermore, incorporating technology into marketing education not only prepares graduates for the digital age, but also promotes digital literacy throughout society. As graduates enter the workforce with digital skills for sustainability , they can help to transform industries and increase connectivity and engagement within communities. The social consequences of skill development in marketing education are far-reaching, affecting workforce dynamics, societal progress, and community well-being. Investing in the development of skills for sustainability among graduates helps educational institutions shape a more competent, inclusive, and socially responsible society.

V. Conclusion

This study shed light on the factors that influence skill development among marketing graduates, as well as the implications for educational practice and policy. It was discovered that Curriculum Design, Pedagogical Approach, Technology Integration, and Practical Exposure play important roles in fostering skill development outcomes after conducting a thorough analysis of the structural model. These findings highlight the significance of a comprehensive approach to marketing education that prioritises active learning, real-world application, and technological proficiency. While the study found positive associations between certain educational factors and skill development, it also identified areas for future research. Specifically, the non-significant relationships observed between Faculty Expertise, Assessment Mechanisms, and Skill Development Outcome highlight the need for a better understanding of the mechanisms by which faculty influence and assessment practices influence student skill development. Moving forward, educational institutions and policymakers should prioritise the implementation of evidence-based strategies that improve skill development outcomes for marketing graduates. By addressing these challenges and capitalising on emerging opportunities, we can keep marketing education relevant and effective in preparing graduates to meet the changing demands of the global marketplace.

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