Integrating Cloud Technology and Artificial Intelligence for Enhanced Real Estate Investment Trusts (REITS) and Crowdfunding Synergy

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Abstract -The integration of Cloud technology (CT) and Artificial Intelligence (AI) presents significant potential benefits for the real estate industry, particularly in the areas of REITs and crowdfunding. By providing greater transparency, reducing costs, and increasing liquidity, the cloud can make real estate investments more accessible and appealing to individuals. Moreover, AI can assist with decision-making processes and data analysis, leading to better investment strategies and higher returns. To measure individual perspectives on this integration in India, a survey questionnaire involving 236 individuals will be designed using a Likert scale to measure attitudes and opinions on this topic. This will be followed by data collection through a convenient sampling method and analysis using the SPSS tool. The survey aims to identify the level of awareness and adoption of integrating cloud and AI among real estate professionals and investors, intending to enhance REITs and Crowdfunding Synergy (CS). The findings of the study revealed that the use of CT can enhance transparency in real estate investments, making it easier for investors to understand how their money is being used and what returns they can expect.

Keywords: Crowdfunding Synergy, Real Estate Investment Trusts, Cloud Technology, Artificial Intelligence, Likert scale, Investment.

I. INTRODUCTION

REITs and crowdfunding have emerged as powerful tools in the realm of real estate investing, offering opportunities for both institutional and individual investors to participate in lucrative ventures [1] [2]. With the rapid advancements in technology, particularly cloud computing and artificial intelligence (AI), these investment vehicles are undergoing a transformative integration that promises enhanced synergies and opportunities for investors. Cloud technology has revolutionized the way businesses operate by providing scalable and cost-effective infrastructure, storage, and computational power [3][4][5][6]. It has empowered the real estate industry by enabling efficient data management, seamless collaboration, and enhanced accessibility. Similarly, AI has brought about a paradigm shift in various sectors, leveraging its capabilities in data analysis, pattern recognition, and predictive modeling. When applied to real estate investment, AI holds the potential to unlock valuable insights, automate decision-making processes, and optimize investment strategies. The integration of cloud technology and AI in the context of REITs and crowdfunding presents a compelling opportunity to enhance the efficiency, transparency, and profitability of real estate investments [7][8][9]. By leveraging the vast amounts of data generated in these domains, cloud-based platforms can provide investors with real-time market trends, property analytics, and investment performance metrics [10][11][12]. These insights enable more informed decision-making, reduce risks, and increase the overall effectiveness of investment strategies.

Moreover, AI algorithms can analyze vast datasets to identify patterns, predict market trends, and assess the viability of investment opportunities. Machine learning models can analyze historical data to identify factors that influence real estate prices, forecast rental income, and evaluate the potential return on investment. This AI-driven approach allows investors to make data-backed decisions, optimize portfolio diversification, and identify hidden opportunities that may have otherwise been overlooked. In the context of crowdfunding, cloud-based platforms provide a centralized hub for investors and project sponsors to connect, collaborate, and streamline investment processes. With the integration of AI, these platforms can leverage natural language processing and sentiment analysis to automate due diligence, assess project risks, and perform investor profiling [13][14][15]. This not only accelerates the investment cycle but also enhances the transparency and accountability of crowdfunding campaigns. This paper aims to explore the integration of cloud technology and AI in the context of REITs and crowdfunding, highlighting the potential synergies, benefits, and challenges associated with this convergence. By examining real-world examples and emerging trends, we aim to shed light on the transformative

impact of these technologies on the real estate investment landscape.

The contribution of the paper is:

- Provides a comprehensive overview of the current state of CT and AI in the real estate investment industry
- Helps investors and industry professionals better understand the potential applications of these technologies and the opportunities for enhanced investment performance

The paper consists of five sections, starting with a thorough literature review in Section 2. Section 3 outlines the research hypotheses and describes the data collection and analysis methodology. The findings of the investigation are presented and discussed in Section 4. Finally, Section 5 concludes the research.

II. LITERATURE REVIEW

Gupta *et al.* 2020 [16] Market liquidity and transparency might be greatly increased thanks to CT, thereby rendering it more approachable for average investors. Due to the simplicity and adaptability of creating Security Tokens backed by genuine assets, real estate became liquid. Investors could buy ERC 777 tokens, which were also listed on secondary exchanges and represented partial ownership of the property. The reliability of Smart Contracts allowed for the smooth distribution of profits among investors and the efficient transfer of tokens.

Belgaum 2021 [17] discussed the role of artificial intelligence (AI) along with issues and opportunities confronting all communities for incorporating the integration of these technologies in terms of reliability and scalability. This paper puts forward the future directions related to scalability and reliability concerns during the integration of the above-mentioned technologies and enables the researchers to address the current research gaps.

Gill *et al.* 2019 2020 [18] proposed a conceptual model for cloud futurology to explore the influence of emerging paradigms and technologies on the evolution of cloud computing.

Kang *et al.* 2020 [19] aimed to create representations for predicting real estate auction prices employing a combination of AI and statistical techniques. Three models were developed – "a regression model, an artificial neural network, and a genetic algorithm". The authors used data from Seoul apartment auctions between 2013 and 2017 to test the accuracy of the models. The genetic algorithm model was found to perform the best, and the accuracy of predictions was further improved by segmenting regions based on auction appraisal prices.

Qureshi *et al.* 2021 [20] proposed a Software-Defined Network-based Anomaly Detection System (SDN-ADS) for edge computing-based system architecture for IoT networks. Afterward, we proposed an anomaly detection system to detect the device's behavior for SDN and edge computing networks. Also, we proposed a Trusted Authority for Edge Computing (TA-Edge) to ensure the trust of edge devices for data forwarding. The edge device is acting as a certificate authority for the specified trusted domain. To overcome the edge devices overhead, in this proposed TA-Edge model, the edge node, only once time, verifies the certificate and when the trust is established, all communication can be done through local certificates.

Behl *et al.* 2021 [21] utilized AI techniques to improve the efficiency of their operations. According to the uses and gratification hypothesis, motivational elements including "symbolic and utilitarian rewards had an impact on how DBC was adopted". However, there were concerns associated with using AI techniques to solicit funding from international donors. A moderating variable was included to better understand DBC's operational performance. 293 responders who were in charge of DBC responsibilities during disaster relief operations provided empirical data.

Yeh and Chen 2020 [22] developed a technique for creating several neural networks using ensemble machine learning and dropout techniques to avoid the overfitting issue. Application and comparison of four machine learning approaches for prediction performance.

Saadat *et al.* 2019 [23] aimed to address these issues by integrating "Ethereum smart contracts with the crowdfunding platform so that the agreements would be fully performed automatically", eliminating fraud and guaranteeing that projects could be delivered within the specified time frame.

Starr *et al.* 2021 [24] examined Industry 4.0 technology to create a framework for Real Estate 4.0. The study also examined how the COVID-19 epidemic spurred the development of prop-tech, particularly concerning reintegrating workers into their conventional work settings.

Yathiraju 2022 [25] explored the perception of IT professionals regarding the integration of AI and S- machine learning into cloud service platforms in the enhancement of the cloud ERP system.

A. Problem Statement

Despite the significant advancements in cloud technology and AI, the integration of these technologies within REITs and crowdfunding platforms for real estate investments face several challenges that hinder their full potential. These challenges arise from various factors, including technological limitations, data management complexities, regulatory concerns, and the need for investor trust and confidence.

a) Technological Limitations

The implementation of cloud-based platforms and AI algorithms require robust infrastructure and technical expertise. Many REITs and crowdfunding platforms may lack the necessary resources to adopt and integrate these technologies seamlessly. Additionally, concerns regarding data security, privacy, and reliability may impede the widespread adoption of cloud technology and AI within the real estate investment domain.

b) Data Management Complexities

The success of cloud technology and AI integration relies heavily on the availability and quality of data. However, real estate investment data is often dispersed, heterogeneous, and unstructured, making it challenging to collect, clean, and analyze. Inadequate data standardization and compatibility across different platforms hinder the seamless integration of cloud technology and AI, limiting the effectiveness of datadriven decision-making and predictive modeling.

c) Regulatory Concerns

The real estate industry is subject to various regulatory frameworks and compliance requirements, which can pose challenges to the integration of cloud technology and AI. Compliance with data protection and privacy regulations, such as General Data Protection Regulation (GDPR) and regional data sovereignty laws, adds complexity to data management and may limit cross-border data utilization. Ensuring compliance while harnessing the full potential of cloud technology and AI remains a critical challenge for REITs and crowdfunding platforms.

d) Investor Trust and Confidence

The success of REITs and crowdfunding relies heavily on investor trust and confidence. The integration of cloud technology and AI introduces concerns about transparency, accountability, and potential biases in automated decision-making processes. Investors may question the reliability and accuracy of AI algorithms and the security of their personal and financial information stored on cloud-based platforms. Building trust and addressing these Addressing these challenges is crucial to unlocking the full potential of cloud technology and AI in enhancing REITs and crowdfunding platforms. Overcoming these obstacles will not only streamline investment processes, improve decision-making, and increase efficiency but also foster investor trust, expand access to real estate investment opportunities, and drive innovation within the industry.

III. PROPOSED METHODOLOGY

The integration of CT and AI has the potential to revolutionize REITs and CS. The data collection strategy for this study used statistical analysis using the SPSS tool. Online surveys were created and distributed among 236 individuals who were interested in investing in real estate, where they can provide their opinions and perspectives on the integration of CT and AI for enhanced REIT and CS. These constructs can be measured using a Likert scale, which allows respondents to rate their agreement or disagreement with statements on a scale of 1-5. To ensure that the questionnaire is validated and reliable, several steps should be taken. The surveys can be distributed through social media platforms or online survey tools.



Figure 1: Framework of the proposed model

B. Research Hypotheses

Null Hypothesis 1 (NH1): There is a positive relationship between the use of CT and EC.

Alternative Hypothesis 1 (AH1): There is a negative relationship between the use of CT and EC.

Null Hypothesis 2 (NH2): The utilization of AI has a positive impact on ET.

Alternative Hypothesis 2 (AH2): The utilization of AI has a negative impact on ET.

Null Hypothesis 3 (NH3): The EM in the real estate industry, such as demand and supply, interest rates, and economic growth, moderates the relationship between CT and EC.

Alternative Hypothesis 3 (AH3): The EMs in the real estate industry, such as demand and supply, interest rates, and economic growth, do not moderate the relationship between CT and EC.

Null Hypothesis 4 (NH4): The relationship between AI and EC is moderated by the EMs in the real estate sector.

Alternative Hypothesis 4 (AH4): The relationship between AI and EC is not moderated by the EMs in the real estate sector.

IV. RESULTS AND DISCUSSION



Figure 2: Resultant Framework of the proposed model

A. Frequency Table

TABLE 1: TABLE ON FREQUENCY AND PERCENTAGE

Category	Frequency	Percent		
Age				
18-24	25	10.6		
25-34	37	15.7		
35-44	46	19.5		
45-54	62	26.3		
55 and above	66	28.0		
Ger	nder			
Male	191	80.9		
Female	45	19.1		
Educ	cation	1.1		
"High school diploma or less	79	33.5		
Bachelor's degree	53	22.5		
Master's degree	88	37.3		
Doctorate"	16	6.8		
Annual	income			
Less than \$30,000	11	4.7		
\$30,000-\$50,000	50	21.2		
\$50,000-\$100,000	69	29.2		
\$100,000-\$200,000	45	19.1		
\$200,000 and above	61 25.8			
Осси	pation			
Professional/Managerial	45	19.1		
Skilled Trades/Services	49	20.8		
Clerical/Administrative	54	22.9		
Sales/Marketing	50	21.2		

Other	38	16.1				
How many years have you b	How many years have you been investing in real estate?					
"0-2 years	31	13.1				
3-5 years	42	17.8				
6-10 years	47	19.9				
11-15 years	64	27.1				
16 years and above"	52	22.0				
How likely are you to invest in a r	eal estate crowdfu	nding project?				
Not at all likely	2	.8				
Somewhat unlikely	4	1.7				
Neutral	6	2.5				
Somewhat likely	125	53.0				
Very likely	99	41.9				
How familiar are you wit	th the concept of R	EITs?				
Somewhat unfamiliar	3	1.3				
Neutral	3	1.3				
Somewhat familiar	132	55.9				
Very familiar	98	41.5				
How likely are you	to invest in REITs?					
Somewhat unlikely	1	0.4				
Neutral	6	2.5				
Somewhat likely	140	59.3				
Very likely	89	37.7				
How important is it for crowdfu	inding platforms to	offer REIT				
investmen	t ontions?					
Not important at all	1	0.4				
Not very important	1	0.4				
Neutral	7	3.0				
Somewhat important	144	61.0				
Very important	83	35.2				
How likely are you to invest in l	REITs through a cu	owdfunding				
nlatfe	orm?	owulululul				
Somewhat likely	134	56.8				
Very likely	102	43.2				
How important is it for REITs	to consider crowdf	inding as a				
source of	funding?	unung us u				
Not important at all	1	0.4				
Not very important	20	8.5				
Neutral	12	5.1				
Somewhat important	124	52.5				
Very important	79	33.5				
How likely are you to invest	in a REIT that has	s utilized				
crowdfunding as a	source of funding?	, uundeu				
Somewhat unlikely	1	0.4				
Neutral	4	1.7				
Somewhat likely	124	52.5				
Very likely	107	45.3				
How much do you think crowdfu	nding can help REI	Ts to diversify				
their fundiu	ng sources?					
Neutral	6	2.5				
Somewhat help	158	66.9				
Greatly help	72	30.5				
How much do you think REITs ca	n benefit from the	ability to offer				
crowdfunding inv	estment options?					
Neutral	5	2.1				
Somewhat benefit	159	67.4				
Greatly benefit	72	30.5				
How likely are you to use a crow	wdfunding platform	n that offers				
REIT investo	ent options?					
Neutral	4	1.7				
Somewhat likely	141	59.7				

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Very likely	91	38.6
How familiar are you	with the concept of	CT?
Somewhat unfamiliar	2	0.8
Somewhat familiar	156	66.1
Very familiar	78	33.1
How likely are you to invest in a	company that has i	ntegrated CT?
Somewhat unlikely	2	0.8
Neutral	5	2.1
Somewhat likely	154	65.3
Very likely	75	31.8
How important do you think	CT is in the future	of business?
Neutral	2	0.8
Somewhat important	153	64.8
Very important	81	34.3
How much do you trust CT a	is a secure means of	conducting
trans	actions?	A CLEAR A
Neutral	3	1.3
Somewhat trust	154	65.3
Completely trust	79	33.5
How likely are you to use a clo	ud-based platform f	or conducting
financial t	ransactions?	1.7
Neutral	4	1./
Somewhat likely	141	59.7
	91	38.0
How much do you timik C1 c	an neip reduce trans	
Neutrai	4	1./
Greatly help	100	12.4
How likely are you to use a clou	id-based platform fo	+2.4
managing vou	r financial data?	or storing and
Neutral		17
Somewhat likely	145	61.4
Very likely	87	36.9
How important do you think it is	s for businesses to in	tegrate CT for
enhance	d security?	lagraa er ior
Neutral	3	13
Somewhat important	142	60.2
Very important	91	38.6
How much do you think CT c	an help increase tra	nsparency in
financial t	ransactions?	
Neutral	5	2.1
Somewhat help	148	62.7
Greatly help	83	35.2
How much do you think CT c	an help reduce frau	d in financial
trans	actions?	
Neutral	3	1.3
Somewhat help	158	66.9
Greatly help	75	31.8
How familiar are you	with the concept of	AI?
Neutral	5	2.1
Somewhat familiar	145	61.4
Very familiar	86	36.4
How likely are you to invest in a	company that uses	AI technology?
Neutral	5	2.1
Somewhat likely	145	61.4
Very likely	86	36.4
How important do you think	AI technology is in t	the future of
bus	iness?	
Not very important	1	0.4
Neutral	3	1.3
Somewhat important	147	62.3

Very important	85	36.0
How much do you trust AI techn	ology as a means o	f automating
business p	processes?	
Somewhat distrust	3	1.3
Neutral	3	1.3
Somewhat trust	141	59.7
Completely trust	89	37.7
How likely are you to use an A	I-based platform for	or customer
service or	support?	
Somewhat unlikely	1	0.4
Neutral	4	1.7
Somewhat likely	159	67.4
Very likely	72	30.5
How much do you think AI techn	ology can help imp	orove business
decision-	making?	
Neutral	4	1.7
Somewhat help	159	67.4
Greatly help	73	30.9
How likely are you to use an AI-h	based platform for	analyzing and
processi	ng data?	
Neutral	5	2.1
Somewhat likely	163	69.1
Very likely	68	28.8
How important do you think it	is for businesses to	integrate AI
technology for enl	nanced efficiency?	
Neutral	10	4.2
Somewhat important	160	67.8
Very important	66	28.0
How much do you think AI teo	chnology can help i	mprove the
accuracy of predict	ions and forecasts?	1
Neutral	4	1.7
Somewhat help	157	66.5
Greatly help	75	31.8
How much do you think AI	technology can help	o increase
productivity in	the workplace?	
Neutral	5	2.1
Somewhat help	163	69.1
Greatly help	68	28.8
How do you think the current den	nand for real estate	e will affect the
industry in the	e next 5 years?	
Somewhat decrease	3	1.3
Neutral	4	1.7
Somewhat increase	167	70.8
Significantly increase	62	26.3
How do you think the current su	pply of real estate	will affect the
industry in the	e next 5 years?	
Somewhat decrease	1	0.4
Neutral	2	0.8
Somewhat increase	172	72.9
Significantly increase	61	25.8
How important do you think in	terest rates are in a	ffecting real
estate marke	t conditions?	
Not very important	1	0.4
Somewhat important	183	77.5
Very important	52	22.0
How likely are you to invest in r	eal estate in the nex	at 12 months,
given the current	economic growth?	0.0
Somewhat unlikely	2	0.8
Somewhat likely	1/0	72.0
very likely	64	27.1

How do you think changes in in	terest rates will im	pact the real		
estate n	narket?			
Somewhat negatively impact	2	0.8		
Somewhat positively impact	172	72.9		
Positively impact	62	26.3		
How do you think economic gr	owth will impact th	e real estate		
mar	ket?			
Negatively impact	1	0.4		
Somewhat negatively impact	1	0.4		
Neutral	4	1.7		
Somewhat positively impact	173	73.3		
Positively impact	57	24.2		
How likely are you to purchase re	al estate in a mark	et experiencing		
high de	emand?			
Not at all likely	4	1.7		
Somewhat unlikely	1	0.4		
Neutral	5	2.1		
Somewhat likely	167	70.8		
Very likely	59	25.0		
How likely are you to purchase re	al estate in a marke	et experiencing		
high s	upply?			
Somewhat unlikely	2	0.8		
Neutral	3	1.3		
Somewhat likely	163	69.1		
Very likely	68	28.8		
How do you think changes in	demographic facto	rs, such as		
population growth, will aff	ect the real estate r	narket?		
Somewhat negatively impact	2	0.8		
Somewhat positively impact	171	72.5		
Positively impact	63	26.7		
How do you think the existing ma	arket conditions in	the real estate		
industry will affect the profitabili	ty of real estate inv	estments in the		
next 5	years?			
Somewhat decrease	3	1.3		
Somewhat increase	168	71.2		
Significantly increase	65	27.5		

Table 1 presents the results of a survey conducted on a sample of individuals to understand their investment preferences and attitudes towards real estate crowdfunding and REITs. The table contains the frequency and percentage of responses to questions related to demographics, investment experience, familiarity with crowdfunding and CT, and the likelihood and importance of investing in real estate crowdfunding and REITs. It indicates that the "majority of respondents were male (80.9%) and aged 35 years and above (73.8%). In terms of education, 37.3% of respondents had a Master's degree, and 22.5% had a Bachelor's degree". Concerning 22.9% occupation, were in skilled clerical/administrative roles, followed by trades/services (20.8%) and sales/marketing (21.2%). When asked about their investment experience, 27.1% of respondents had been investing in real estate for 11-15 years, followed by 22.0% who had been investing for 16 years and above. In terms of the likelihood of investing in a real estate crowdfunding project, 53.0% were somewhat likely, and 41.9% were very likely. Similarly, 59.3% were somewhat

likely to invest in REITs, and 37.7% were very likely. It also shows that 66.9% of respondents believed that crowdfunding could somewhat help REITs diversify their funding sources, while 30.5% thought it could greatly help. Regarding CT, 66.1% were somewhat familiar with the concept, and 33.1% were very familiar. Furthermore, 65.3% were somewhat likely to invest in a company that has integrated CT, and 31.8% were very likely. On the whole, the survey results indicate that respondents are generally open to investing in real estate crowdfunding and REITs, and they recognize the potential benefits of crowdfunding and CT in enhancing investment opportunities and security.

B. Regression Analysis

a) Regression analysis on CT with EC as the dependent variable

TABLE 2: CT WITH EC

(A) DESCRIPTIVE STATISTICS

	Mean	Std. Deviation
EC	4.3250	0.32079
СТ	4.3386	0.29129

Table 2(a) states the mean scores for both EC and CT are relatively close, with EC at 4.3250 and CT at 4.3386. The standard deviation for EC is slightly higher than that of CT, indicating that there is slightly more variability in the scores for EC. The fact that both standard deviations are tiny, however, indicates that the scores are tightly packed around the mean.

(B) CORRELATIONS

Pearson Correlation	EC	СТ	
EC	1.000	0.679	
СТ	0.679	1.000	

The PCCs between the two variables EC and CT are displayed in Table 2 (b). Since EC and CT have a correlation coefficient of 0.679, this suggests that the two variables are positively correlated.

(C) SUMMARY

R	Std. Adjuste Error		Change Statistics					
R	Squa re	d R Square	of the Estimat e	R Square Change	F Change	df1	df2	Sig. F Chan ge
0.679	0.461	0.459	0.23597	0.461	200.302	1	234	0.000

With a PCC of 0.679, which denotes a moderate link between the two variables, Table 2 (c) demonstrates a positive correlation between the variables EC and CT. The variable in EC can account for around 46% of the variance in CT, according to the coefficient of determination, R-squared, which is 0.461. To account for the model's variable count and degrees of freedom, the adjusted R-squared was calculated, and it is equal to 0.459. The standard error of the estimate, which is 0.23597, illustrates the average gap between the observed and projected values. The change statistics table shows that the R-squared change is 0.461, which indicates that the inclusion of EC in the model significantly improves the ability to predict CT. The regression model is significant at the 0.05 level according to the F statistic of 200.302, which has 1 degree of freedom in the numerator and 234 degrees of freedom in the denominator. Therefore, we can conclude that EC is a significant predictor of CT which explains NH1.

(D).	ANOVA
(D)	ANOVA

	Model	SS	df	MS	F	Sig.
	Regression	11.153	1	11.153	200.302	0.000
1	Residual	13.029	234	0.056		
	Total	24.182	235			
	"cc_ !	Cum of Caus	mag M	C- Magu	Caurano"	

'SS= S<mark>um of Square</mark>s, MS= Mean Square"

Table 2 (d) shows the ANOVA table on CT. The SS due to regression is 11.153, indicating that the predictor variable significantly explains the variability in the response variable. The residual SS is 13.029, which represents the unexplained variability in the model. The regression model is a good fit for the data, as shown by the highly significant F-test result of 200.302 for the sample. As a result, we can conclude that the predictor variable and the responder variable have a significant linear connection.

		UC		SC		Correlations			
	Model	В	Std. Err or	Bet a	t	Sig ·	Zer o- Part ord ial er		Par t
	(Const	1.0	0.2		4.70	0.0			
1	ant)	80	30		1	00			
1	CT	0.7	0.0	0.6	14.1	0.0	0.6	0.67	0.6
	CI	48	53	79	53	00	79	9	79

(E) CO-EFFICIENT

UC= Unstandardized Coefficients, SC= Standardized Coefficients

The coefficients of the linear regression model are displayed in Table 2(e). The t-value is 4.701 and the constant term (intercept) is 1.080 with a standard error of 0.230. It can be claimed that the constant term is statistically significant because its p-value is less than 0.05. With a coefficient of 0.748, a standard error of 0.053, and a t-value of 14.153, the

predictor variable CT is statistically significant. The coefficient of CT has a p-value of less than 0.05, meaning it is statistically significant. The standardized coefficient (beta) of CT is 0.679, which means that a one-unit increase in CT is associated with a 0.679 unit increase in the response variable, holding other variables constant. The zero-order correlation (ZOC) between CT and the response variable is 0.679, which is the same as the beta coefficient.

b) Regression analysis on AI with EC as dependent variable

TABLE 3: AI WITH EC

" I KENA	Mean	Std. Deviation
EC	4.3250	0.32079
AI	4.3008	0.29736

(A)

Table 3 (a) displays descriptive statistics for EC and AI variables, including means and standard deviations. The mean for EC is 4.3250, and for AI is 4.3008, with both variables having similar means. Since EC's standard deviation is 0.32079, the values are rather closely packed around the mean. The standard deviation for AI is slightly smaller at 0.29736, also suggesting that the values are closely grouped around the mean.

(B) CORRELATIONS

Pearson Correlation	EC	AI
EC	1.000	0.577
AI	0.577	1.000

Table 3 (b) shows the Pearson correlation coefficient (PCC) between EC and EC is 1.000, which means that EC is perfectly correlated with itself. The coefficient between EC and AI is 0.577, indicating a moderate positive correlation between the two variables. Similarly, the coefficient between AI and EC is 0.577, which is the same as the coefficient between EC and AI due to the symmetric nature of the Pearson correlation.

			Std.		Chang	e Stat	istics	
"R	R Squ are	Adjus ted R Squar e	Error of the Estim ate	R Squa re Cha nge	F Cha nge	df 1	df 2	Sig. F Chan ge"
0.5 77	0.33 2	0.330	0.262 66	0.332	116.5 32	1	23 4	0.000

Table 3 (c) shows the regression analysis results between two variables, EC and AI. The two variables have a moderately favorable linear connection, as indicated by the value of R, which is 0.577. R Square is equal to 0.332, which indicates that changes in EC can account for roughly 33.2% of the variation in AI. The modified R Square, which is 0.330, takes into consideration the number of predictor factors. In this case, the adjusted R Square is very close to the R Square, indicating that adding or removing predictors would not significantly affect the explanatory power of the model. The estimate's standard error, which represents the variability of the regression model's errors, is 0.26266. It displays the average distance, in units of AI, between the observed and anticipated values. The change statistics section shows the change in R Square and the F-test statistics for testing the significance of the change in R Square when EC is added to the model as a predictor variable. The R Square change is 0.332, which indicates that adding EC to the model explains an additional 33.2% of the variation in AI beyond what is already explained by the existing predictors (if any). The Ftest statistic has a "high value of 116.532, 1 degree of freedom for the numerator, 234 degrees for the denominator, and a significance level of 0.000", showing that the model improvement that accounts for NH2 is statistically significant.

(D) ANOVA

	Model	SS	df	MS	F	Sig.
	Regression	8.039	1	8.039	116.532	0.000
1	Residual	16.143	234	0.069		
	Total	24.182	235			

Table 3 (d) summarizes the results of a regression model with EC and AI. The Regression SS (8.039) represents the variation in AI that can be explained by the regression model. The Residual SS (16.143) represents the variation in AI. The F-statistic (116.532) indicates that the variation explained by the regression model is significantly larger than the variation, with a p-value (Sig.) of 0.000, which is less than the typical threshold of 0.05, indicating that the regression model is significant. Overall, the model explains 33.2% of the variance in the AI scores (as shown by the R Square value of 0.332), and the standard error of the estimate (0.26266) represents the average difference between the observed and predicted values of AI.

	(E) CO-EFFICIENT								
		U	C	SC			Co	orrelatio	ns
	Model	Bet a	Std. Err or	Bet a	t	Si g.	Zer o- ord er	Part ial	Par t
	(Const	1.6	0.24		6.64	.0			
1	ant)	50	8		2	00			
1	ΔŢ	0.6	0.05	0.5	10.7	.0	0.5	0.57	0.5
	AI	22	8	77	95	00	77	7	77

Table 3 (e) presents the results of a regression analysis with EC and AI. The unstandardized coefficient (Beta) for the constant term (i.e., intercept) is 1.650. This represents the expected value of AI when EC is equal to zero. The unstandardized coefficient (Beta) for AI is 0.622, indicating that for every one-unit increase in EC, the expected value of AI increases by 0.622 units. The standardized coefficient (Beta) for AI is 0.577, indicating that a one standard deviation increase in EC is associated with a 0.577 standard deviation increase in AI. The t-value of 10.795 for AI indicates that the regression coefficient is significantly different from zero, with a p-value (Sig.) of 0.000, which is less than the typical threshold of 0.05, suggesting that the independent variable is a significant predictor of the dependent variable. The correlations section shows the ZOC between the two variables (0.577), as well as the partial correlation (0.577) and part correlation (0.577) for AI, which is equivalent to the standardized coefficient (Beta) for AI.

c) Regression analysis on CT and EM with EC as dependent variable

TABLE 4: CT AND EM WITH EC

(A) DESCRIPTIVE STATISTICS

	Mean	Std. Deviation
EC	4.3250	0.32079
СТ	4.3386	0.29129
EM	4.2305	0.31971

Table 4 (a) presents the descriptive statistics for three variables: EC, CT, and EM. The mean for EC is 4.3250, representing that the average value of EC for the sample is around 4.3250. The standard deviation for EC is 0.32079, which suggests that the values of EC are relatively tightly clustered around the mean. The mean for CT is 4.3386, indicating that the average value of CT for the sample is slightly higher than that of EC. The standard deviation for CT is 0.29129, which is smaller than that of EC, suggesting that the values of CT are even more tightly gathered around the

mean. The mean for EM is 4.2305, demonstrating that the average value of EM for the sample is slightly lower than that of EC. The standard deviation for EM is 0.31971, which is similar to that of EC, suggesting that the values of EM are also relatively tightly clustered around the mean.

(B) CORRELATIONS

Pearson Correlation	EC	СТ	EM
EC	1.000	0.679	-0.090
СТ	0.679	1.000	-0.110
EM	-0.090	-0.110	1.000

Table 4 (b) presents the PCCs between three variables: EC, CT, and EM. Since EC and CT have a correlation coefficient of 0.679, there is a somewhat positive link between the two variables. This implies that the values of CT tend to grow as the values of EC increase, and vice versa. Since EC and EM have a correlation coefficient of -0.090, there is only a weakly negative link between the two variables. This implies that the values of EM tend to somewhat drop when the values of EC rise, and vice versa. Since CT and EM have a correlation coefficient of -0.110, there is only a weakly negative link between the two variables. This suggests that as the values of CT increase, the values of EM tend to decrease slightly, and vice versa.

(C) SUMMARY

			Std.	Change Statistics				
"R	R Squ are	Adjus ted R Squar e	Error of the Estim ate	R Squa re Cha nge	F Cha nge	df 1	df 2	Sig. F Chan ge"
0.6 79	0.46 1	0.457	0.236 42	0.461	99.81 9	2	23 3	0.000

Table 4 (c) shows the regression analysis with one dependent variable and two independent variables. According to the results, the independent variable can explain about 46.1% of the variation in the dependent variable, with an R square of 0.461. The adjusted R square of 0.457 takes into account the number of independent variables and the sample size, which can be useful in determining if the model is a good fit for the data. The average difference between the estimated values and the actual values is shown by the standard error of the estimate (0.23642). The change statistics show that the R square change is 0.461, which means that the addition of the independent variable significantly improved the model's ability to explain the variation in the dependent variable. The F change statistic of 99.819 with 2 and 233 degrees of freedom indicates that the improvement in the model is

significant with a p-value of less than 0.0001 which proves NH3.

(D) ANOVA

	Model	SS	df	MS	F	Sig.
	Regression	11.159	2	5.579	99.819	0.000
1	Residual	13.024	233	0.056		
	Total	24.182	235			

The results of regression analysis with one dependent variable and two independent variables are displayed in Table 4(d). The model has a significant F-statistic of 99.819 with a corresponding p-value of 0.000, showing that the model's overall performance in fitting the data is good. The regression output also shows that the SS for the regression is 11.159, with 2 degrees of freedom, resulting in an MS of 5.579. This implies that the independent factors can account for the variation in the dependent variable. The remaining SS, which is the sum of the squared differences between the observed and predicted values, is 13.024, with 233 degrees of freedom, and a MS of 0.056.

(E) CO-EFFICIENT

		U	с	SC		3	Co	orrelatio	ons
"	'Model	В	Std Err	Bet a	t	Sig ·	Zer o- ord	Part ial	Par t"
1			or	14			er		
1	(Const	1.1	0.3		3.54	0.0			
	ant)	54	26	12	1	00			
	CT	0.7	0.0	0.6	14.0	0.0	.67		.67
1	CI	46	53	77	05	00	9	.6/6	3
	EM	0.0 16	0.0 49	0.0 16	- 0.32 1	0.7 49	- .09 0	.021	- .01 5

Table 4 (e) provides the regression output for a model with two predictor variables (CT and EM) and one outcome variable. The coefficient for CT is 0.746, and the coefficient for EM is -0.016. The standardized coefficient for CT is 0.677, and the coefficient for EM is -0.016. The t-statistic for CT is 14.005, and the t-statistic for EM is -0.321. Since CT has a p-value of 0.000, the coefficient is statistically significant. With a p-value of 0.749, the coefficient for EM is not statistically significant. The ZOC between CT and the outcome variable is 0.679, and the outcome variable is -0.090, and the partial correlation is -0.090, and the partial correlation is -0.015.

d) Regression analysis on EM and AI with EC as dependent variable

TABLE 5: EM AND AI WITH EC

(A) DESCRIPTIVE STATISTICS

	Mean	Std. Deviation
EC	4.3250	0.32079
EM	4.2305	0.31971
AI	4.3008	0.29736

Table 5 (a) presents the descriptive statistics for three variables: EC, EM, and AI. The sample's average value of EC is around 4.3250, according to the mean for EC, which is 4.3250. Given that EC's standard deviation is 0.32079, likely, the values of EC are closely clustered around the mean. The mean for EM is 4.2305, indicating that the average value of EM for the sample is slightly lower than that of EC. The standard deviation for EM is 0.31971, which is similar to that of EC, suggesting that the values of EM are also relatively strongly clustered around the mean. The mean for AI is 4.3008, indicating that the average value of AI for the sample is slightly higher than that of EC. The standard deviation for AI is 0.29736, which is smaller than that of EC, suggesting that the values of AI are even more tightly clustered around the mean.

(B) CORRELATIONS

Pearson Correlation	EC	EM	AI
EC	1.000	090	.577
EM	090	1.000	055
AI	.577	055	1.000

Table 5 (b) shows the PCCs between three variables: EC, EM, and AI. With a correlation coefficient of 0.577 between EC and AI, there is a relatively favorable relationship between the two variables. This implies that the values of AI tend to grow as the values of EC increase, and vice versa. Since EC and EM have a correlation coefficient of -0.090, there is only a weakly negative link between the two variables. This implies that the values of EM tend to somewhat drop when the values of EC rise, and vice versa. Only a slight negative link exists between EM and AI, with a correlation coefficient of -0.055. This suggests that as the values of EM increase, the values of AI tend to decrease slightly, and vice versa.

(C) SUMMARY								
	1	Adjusted	Std.	Change Statistics				
"R	R Square	R Square	Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change"
0.580	0.336	0.330	0.26255	0.336	58.908	2	233	0.000

The outcomes of multiple linear regression analysis with one dependent variable and two independent variables are displayed in Table 5(c). The two independent variables (EM and AI), which together account for 33.6% of the variance in the dependent variable (EC), are shown to have an R-squared of 0.336. Given the number of independent variables and sample size, the corrected R-squared is 0.330. The standard error of the estimate, which is 0.26255, is the average difference between the dependent variable's actual values and its anticipated values. Indicating that at least one of the independent variables substantially predicts the dependent variable is the F-statistic, which is 58.908 and has a significant level of 0.000.

(D) ANOVA

Model	SS	df	MS	F	Sig.	
Regression	8.121	2	4.061	58.908	0.000	
Residual	16.061	233	0.069			
Total	24.182	235				

Table 5 (d) provided the ANOVA output for a multiple regression model with two predictor variables. Here's what the different components of the output represent: The Regression SS is 8.121, the Residual SS is 16.061, and the Total SS is 24.182. The Regression df is 2, the Residual df is 233, and the Total df is 235. The Regression MS is 4.061, and the Residual MS is 0.069. There is a 58.908 F-statistic. The model, which explains NH4 emissions, has a p-value of 0.000, indicating that it is statistically significant at levels of significance generally accepted.

(E) CO-EFFICIENT

	UC		SC			Correlations			
			Std				Zer		
			•				0-		
			Err	Bet		Sig	ord	Part	Par
"Model		В	or	a	t	•	er	ial	t"
1	(Const	1.9	0.3		5.53	0.0			
	ant)	12	46		0	00			
	EM	-	0.0	-	-	0.2	-	-	-
		0.0	5.0	0.0	1.09	0.2	0.0	0.07	0.0
		59	54	58	1	11	90	1	58
	AI	0.6	0.0	0.5	10.7	0.0	0.5	0.57	0.5
		19	58	73	22	00	77	5	72

Table 5 (e) provided regression output for a model with two predictor variables (EM and AI) and one outcome variable. The coefficient for EM is -0.059, and the coefficient for AI is 0.619. The standardized coefficient for EM is -0.058, and the coefficient for AI is 0.573. The t-statistic for EM is -1.091, and the t-statistic for AI is 10.722. Since the coefficient is not statistically significant, the p-value for EM is 0.277. Since AI has a p-value of 0.000, the coefficient is statistically significant. The ZOC between EM and the outcome variable is -0.090, and the partial correlation is -0.058. The ZOC between AI and the outcome variable is 0.577, and the partial correlation is 0.572.

V. CONCLUSION

In conclusion, integrating CT and AI can provide enhanced opportunities for REITs and crowdfunding. By using the cloud, REITs can improve transparency, reduce costs, and enable greater liquidity in real estate investments. AI, on the other hand, can assist with data analysis and decision-making processes, leading to better investment strategies and higher returns. The combination of cloud and AI can also help to reduce the risk of fraud and increase the efficiency of transactions in the real estate market. Additionally, many real estate transaction processes can be automated with the help of smart contracts on the cloud, eliminating the need for middlemen and accelerating the investing process. Furthermore, integrating cloud and AI in crowdfunding can improve the quality of investments and increase access to investment opportunities, particularly for small investors. The use of the cloud can enable fractional ownership, making it possible for investors to purchase smaller portions of real estate assets, while AI can provide insights into potential investment opportunities.

REFERENCES

- Gibilaro, L. and Mattarocci, G., 2021. Crowdfunding REITs: a new asset class for the real estate industry?. *Journal of Property Investment & Finance*, 39(2), pp.84-96.
- [2] Saiz, A., 2020. Bricks, mortar, and proptech: The economics of IT in brokerage, space utilization and commercial real estate finance. *Journal of Property Investment & Finance*.
- [3] Shayan, J., Azarnik, A., Chuprat, S., Karamizadeh, S. and Alizadeh, M., 2014. Identifying Benefits and risks associated with utilizing cloud computing. *arXiv* preprint *arXiv:1401.5155*.
- [4] Rashid, A. and Chaturvedi, A., 2019. Cloud computing characteristics and services: a brief review. *International Journal of Computer Sciences and Engineering*, 7(2), pp.421-426.
- [5] Dutt, M., 2015. Cloud computing and its application in libraries. *International Journal of Librarianship and Administration*, 6(1), pp.19-31.

- [6] Bhatnagar, R., Prof (Dr.) Paramjeet, R. and Dr Amit, G., 2022. Cloud IoT: An Emerging Computing Paradigm for Smart World. *Emerging Computing Paradigms: Principles,* Advances and Applications, pp.19-40.
- [7] Niaki, M.K., Torabi, S.A. and Nonino, F., 2019. Why manufacturers adopt additive manufacturing technologies: The role of sustainability. Journal of cleaner production, 222, pp.381-392.
- [8] Savolainen, J. and Collan, M., 2020. How additive manufacturing technology changes business models?– review of literature. *Additive manufacturing*, 32, p.101070.
- [9] Sánchez, M.A., 2022. A multi-level perspective on financial technology transitions. *Technological Forecasting and Social Change*, *181*, p.121766.
- [10] Handfield, R., Jeong, S. and Choi, T., 2019. Emerging procurement technology: data analytics and cognitive analytics. *International Journal of Physical Distribution & Logistics Management*, 49(10), pp.972-1002.
- Kwon, M.-S. ., Park, S.-B. ., Kim, D.-B. ., & Hong, S.-D. . (2023). A Study on Effective Color Production of Outdoor Digital Theme Park. International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 146–149. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2581
- [12] Ikegwu, A.C., Nweke, H.F., Anikwe, C.V., Alo, U.R. and Okonkwo, O.R., 2022. Big data analytics for data-driven industry: a review of data sources, tools, challenges, solutions, and research directions. *Cluster Computing*, 25(5), pp.3343-3387.
- [13] Saxena, A., Singh, R., Gehlot, A., Akram, S.V., Twala, B., Singh, A., Montero, E.C. and Priyadarshi, N., 2022. Technologies Empowered Environmental, Social, and Governance (ESG): An Industry 4.0 Landscape. Sustainability, 15(1), p.309.
- Kang, Y., Cai, Z., Tan, C.W., Huang, Q. and Liu, H., 2020. Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics*, 7(2), pp.139-172.
- [15] Perifanis, N.A. and Kitsios, F., 2023. Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. *Information*, 14(2), p.85.
- [16] Drydakis, N., 2022. Artificial Intelligence and reduced SMEs' business risks. A dynamic capabilities analysis during the COVID-19 pandemic. *Information Systems Frontiers*, 24(4), pp.1223-1247.
- [17] Gupta, A., Rathod, J., Patel, D., Bothra, J., Shanbhag, S. and Bhalerao, T., 2020. Tokenization of real estate using cloud technology. In *Applied Cryptography and Network Security:* ACNS 2020 Satellite Workshops, AIBlock, AIHWS, AIoTS, Cloud S&P, SCI, SecMT, and SiMLA, Rome, Italy, October 19–22, 2020, Proceedings 18 (pp. 77-90). Springer International Publishing.
- [18] Belgaum, M.R., Alansari, Z., Musa, S., Alam, M.M. and Mazliham, M.S., 2021. Role of artificial intelligence in cloud computing, IoT and SDN: Reliability and scalability issues.

International Journal of Electrical and Computer Engineering, 11(5), p.4458.

- [19] Gill, S.S., Tuli, S., Xu, M., Singh, I., Singh, K.V., Lindsay, D., Tuli, S., Smirnova, D., Singh, M., Jain, U. and Pervaiz, H., 2019. Transformative effects of IoT, Blockchain and Artificial Intelligence on cloud computing: Evolution, vision, trends and open challenges. Internet of Things, 8, p.100118.
- [20] Prof. Sagar Kothawade. (2020). Scale Space Based Object-Oriented Shadow Detection and Removal from Urban High-Resolution Remote Sensing Images. International Journal of New Practices in Management and Engineering, 9(04), 17 -23. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/95
- [21] Kang, J., Lee, H.J., Jeong, S.H., Lee, H.S. and Oh, K.J., 2020. Developing a forecasting model for real estate auction prices using artificial intelligence. *Sustainability*, 12(7), p.2899.
- [22] Qureshi, K.N., Jeon, G. and Piccialli, F., 2021. Anomaly detection and trust authority in artificial intelligence and cloud computing. Computer Networks, 184, p.107647.
- [23] Behl, A., Dutta, P., Luo, Z. and Sheorey, P., 2021. Enabling artificial intelligence on a donation-based crowdfunding platform: a theoretical approach. *Annals of Operations Research*, pp.1-29.
- [24] Yeh, J.Y. and Chen, C.H., 2020. A machine learning approach to predict the success of crowdfunding fintech project. *Journal of Enterprise Information Management*, (ahead-of-print).
- [25] Saadat, M.N., Halim, S.A., Osman, H., Nassr, R.M. and Zuhairi, M.F., 2019. Cloud based crowdfunding systems. *Indonesian Journal of Electrical Engineering and Computer Science*, 15(1), pp.409-413.
- [26] Starr, C.W., Saginor, J. and Worzala, E., 2021. The rise of PropTech: Emerging industrial technologies and their impact on real estate. *Journal of Property Investment & Finance*, 39(2), pp.157-169.
- [27] Yathiraju, N., 2022. Investigating the use of an Artificial Intelligence Model in an ERP Cloud-Based System. International Journal of Electrical, Electronics and Computers, 7(2), pp.1-26.
- [28] Rodríguez, M., Jovanović, A., Petrova, M., Merwe, M. van der, & Levi, S. Predicting Customer Lifetime Value with Regression Models. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/144
- [29] Hoesli, M. and Malle, R., 2022. Commercial real estate prices and COVID-19. Journal of European Real Estate Research, 15(2), pp.295-306.
- [30] Banka, M., Tien, N.H., Dao, M.T.H. and Minh, D.T., 2022. Analysis of business strategy of real estate developers in Vietnam: the application of QSPM matrix. International journal of multidisciplinary research and growth evaluation, 3(1), pp.188-196.
- [31] Kieltyka, L., Hiep, P.M., Dao, M.T.H. and Minh, D.T., 2022. Comparative analysis of business strategy of Hung Thinh and Novaland real estate developers using McKinsey matrix.

International Journal of Multidisciplinary Research and Growth Evaluation, 3(1), pp.175-180.

[32] Ngoc, N.M., Tien, N.H. and Anh, D.B.H., 2020. Opportunities and challenges for real estate brokers in post Covid-19 period. Journal of Science and Technology, 170(10), pp.203-208.

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