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Exploring THE Synergy OF Ai AND Design Thinking IN Optimizing Knowledge Management Practices FOR Organizational Efficiency, Customer Satisfaction AND Risk Mitigation

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Abstract

The study looks at how artificial intelligence (AI), design thinking, and knowledge management practices work together in the IT field. The study uses data of 2283 people collected using questionnaires. The study uses different ways to analyze, including counting things up, finding connections between them, figuring out how they work together and breaking it down into parts.

The results show that using AI apps can help us, the impact of thinking about design and applying knowledge management all work together well. Study on regression show that design thinking, AI recovery and memory efficiency can predict how well practices of managing knowledge work. This is related to the entire process involved in dealing with all types of information. This study provides deep insight on how artificial intelligence, creative thinking and knowledge control are connected. The results are useful companies trying to improve their knowledge management practices in the constantly changing world of technology and new ideas. The study focuses on the IT business and understands its built-in limitations. But it sets up a basic starting point for future study in many areas and encourages looking into these connections with mixed-methods approaches. In the end, this shows how much artificial intelligence (AI) and design thinking affect creating good knowledge management plans. These results are important for planning smart actions and encouraging improvements in organizational creativity.

Keywords*: artificial intelligence, design thinking, knowledge management practices, Information Technology industry, synergistic relationship, correlation analysis, regression analysis, factor analysis, organizational efficiency, customer satisfaction, risk reduction, technology and innovation.*

Introduction

In the always changing world of today's companies, businesses have to keep on adjusting and coming up with new ideas. Managing knowledge is very important. This because it's useful for making your business work[1] better, improving customer satisfaction and lowering risks (Jarrahi et al., 2023). More and more groups are using AI technology with design thinking to fix tough problems in the changing digital world. This coming together has a lot of ability to change and improve how we manage knowledge. It can help solve the difficult problems that happen in today's businesses.

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Now in business world, where information matters a lot. Managing knowledge well is very important to decide how good organizations are (Chatterjee et al., 2020). Getting and using information, like things we know plus what's hidden in our minds, helps us make smart plans. It also fuels new ideas that last over time. However, the fast way technology is getting better and how complex business processes are becoming have made new challenges for old ways of managing information.

The arrival of Artificial Intelligence (AI) is causing a big change. It's giving new ways for businesses to manage and study their large collections of knowledge in different ways (Leoni, et al., 2022). AI can make machines learn, guess the future and better our choices by using algorithms from machine learning. It also uses natural language processing to work with words. All of these things help it understand data more effectively. At the same time, a new way of solving problems called Design Thinking has been getting attention for its ability to add in human feelings and what users want when making technology solutions.

Despite these improvements, many businesses still face a problem. They need both computer skills and understanding people-related aspects of managing knowledge. Putting together artificial intelligence with design thinking could be a good way to fix this gap. By combining the smart skills of artificial intelligence (AI) with human-focused ideas from Design Thinking, companies can create knowledge management plans that use modern technology and fit what their employees need, like or want.

To make things work better, please customers more and reduce risks it's very important to understand how Artificial Intelligence (AI) works together with Design Thinking. This helps us improve ways of controlling information strategies. This study looks at two important ideas. It wants to know how they can be used together so that companies work better, use information about customers wisely and deal with possible dangers carefully before they happen. This way, it deals with the different problems faced by companies as they go through complex issues in their knowledge world during the age of computers.

Rationale

The reason for doing this research is based on the understanding that using Artificial Intelligence and Design Thinking together can greatly change how companies manage, use, and get value from their stores of knowledge. AI can use data analysis, learn from machines and understand language. This helps it get knowledge quicker, make better choices and boost teamwork in a smart way. Design Thinking makes sure that these tech changes match what people need. It helps to create easy-to-use interfaces and grow a creative environment within the company.

Objectives

- To evaluate the role of AI in augmenting knowledge management practices for improved organizational efficiency, considering aspects such as automated knowledge retrieval, intelligent decision support, and enhanced collaboration.
- To explore how the integration of AI with design thinking contributes to customer satisfaction, focusing on personalized experiences, secure data handling, and innovative cross-functional knowledge management.
- To analyze the role of AI in reducing the costs associated with knowledge management practices, investigating their potential in automating repetitive tasks, ensuring data integrity, and optimizing resource allocation.
- To investigate how AI technologies contribute to risk reduction in knowledge management practices, addressing issues related to data security, fraud prevention, and efficient handling of sensitive information.

Literature Review

AI and Design Thinking come together in managing information (KM). This area is interesting because it involves a lot of learning from books on: using AI, principles behind Design Thinking, and new ways to deal with data. Di Vaio et al studied this topic in 2020. The use of artificial intelligence (AI) has become a big reason for change in places that need information management. AI has many abilities that allow it to handle lots of data, find useful information, and make better choices. In the study of how to handle information (KM), artificial intelligence or 'AI' is very important for getting useful knowledge from both organized and not-so-organized data sources. This was explained by Paschen, et al in 2019. Bag and others (2021) show how important artificial intelligence like machine learning is for automating classification, getting knowledge assets, and recommending them. This idea agrees with Nonaka and Takeuchi's (1995) plan for explicit knowledge, tacit wisdom. Here, AI helps change hidden smart skills into clear practical facts which others can use.

Also, using artificial intelligence (AI) with natural language processing (NLP) helps a lot to understand content better on the meaning level. This helps make it easier to find and sort out information more accurately (Lin et al., 2019). Abubakar, et al., (2019) warn that while artificial intelligence can make knowledge management better, we need to be careful and detailed in our approach. We have to ensure the right balance between what machines are good at analyzing and being sensitive towards human situations, so it stays useful and important.

Design Thinking is a way of solving problems. It focuses on understanding people's needs and wants, making it easy to use ideas over time (Baierle et al., 2019). In the area of Knowledge Management (KM), Design Thinking pays a lot of attention to finding out what people need and making solutions that fit with their life experiences. This is talked about by Brock & Von Wangenheim in 2019. The mentioned view agrees with Cautela, et al., (2019) idea of how sharing and making knowledge are connected to social groups. They believe that what we learn is always tied up in the way people work together or organize themselves socially.

The study done by Nakata in 2020 shows how Design Thinking helps create a way of learning and new ideas. It's very important for Knowledge Management to work well. Groups can make it easier for knowledge systems and human actions to go together by involving regular people in the process of making things with them (Pande & Bharathi, 2020). The Convergence of Artificial Intelligence and Design Thinking in Knowledge Management: AI and Design Thinking work together. This is a smart way to handle the challenges of getting all kinds of knowledge in big companies, as there's lots and it's complicated stuff. Lager & Fundin (2023) say we should use technology and ways that put people first to make companies work better. This idea matches up with using artificial intelligence (AI) and Design Thinking in the area of knowledge management (KM).

The ways that machines learn (AI) can do routine tasks without people's help. This allows human workers to focus on coming up with new solutions, which is the main goal of Design Thinking by Strakhovich in 2020. This team up agrees with Zarattini Chebabi & von Atzingen Amaral (2020) when they say that it's crucial for human minds and computer brains to work together. This helps make sure we get the most from our resources.

Also, using Design Thinking when making AI-based Knowledge Management (KM) systems makes them fit better into how companies work. This is helped by Lichtenthaler's 2020 advice on this topic. By making users the main focus of design, businesses can create knowledge management systems that work well and are easy to use. This method makes sure that the tools match with how knowledge workers think.

The books show how artificial intelligence (AI) can be combined with Design Thinking to make knowledge management (KM) better than just managing information. The plan suggested is one that includes everything, focuses on people and gets help with technology (Nakamori in 2019). This way could help companies use knowledge better to make things run smoother, please customers more and lessen dangers (Walch et al., 2019). However, there is still a lack of real-world study, and we need to grasp these connections more deeply. These areas give chances for more research, taking the conversation into new and unknown fields of theory learning and putting it to use.

Using AI and Design Thinking to make Knowledge Management (KM) better can help workplaces do things faster, keep customers happy, and cut down dangers. Books in this area say that adding AI technology to knowledge management systems makes them better at handling, getting and sharing information. AI uses its smart data study and learning skills to find useful information from big sets of details. This makes sharing knowledge better throughout a business (Davenport & Harris, 2007).

In Design Thinking, methods focus on the needs of users and understanding them. This goes hand-in-hand with trying to make customers happy by managing information using Knowledge Management (KM). The ideas of Design Thinking say we should make Knowledge Management (KM) systems easy to use, friendly for people and teams. They need to understand what each person needs personally and in their group. (Brown 2008). Using a plan focused on customers is very important to handle and give easy access to information for the good of users. AI-driven KM systems play a key role in reducing risks by automatically finding and fixing any knowledge gaps or security weaknesses. AI systems can watch over data, follow rules and protect from cyber threats. This makes it harder for bad people to get secret information and ensures that the places where knowledge is stored are safe (Chen et al., 2020).
AI and Design Thinking in KM are similar to other ways that technology helps businesses grow. By helping to create a strong learning environment, companies might make their internal work better and build an adaptable space that quickly satisfies customer needs. Using AI and design thinking in knowledge management (KM) can help make businesses better, happier customers and stop problems before they start. This works well when companies change a lot. Using AI and Design Thinking together in Knowledge Management (KM) can make companies work better. The writing shows a lack of study even though interest in this connection is increasing. First of all, past studies look at the effects of AI or Design Thinking separately on KM practices. They don't focus on how to combine them fully. So, studies should suggest full plans that carefully combine AI and Design Thinking skills in knowledge management systems. This will show their best results together. The writing doesn't talk about problems with designing user-focused, AI-powered knowledge management systems based on Design Thinking. It's important to study how we connect artificial intelligence-based knowledge management interfaces with different user needs and choices. We should look into how design works for including different people, making users happy and information easy to get.
Right now, people are not talking about ethical and trust-building steps in AI driven knowledge management systems when dealing with Design Thinking. As AI changes how we get and share information, it's important to think about what is right or wrong and ways we can build trust. This study helps put smart AI into practice the right way. Books today don't talk about how AI and Design Thinking in KM affect organizational culture and managing change. To make sure these big changes work well and keep improving, we need to understand how people feel about them. We also have study changing behavior in the workplace culture when things shift a lot. Lastly, AI and Design Thinking together studied the long-term performance and sustainability of KM systems is not much researched. Organizations want to make smart and long-lasting KM investments. They need to thoroughly look into the strength of such systems in changing technology areas. fixing these questions would help groups make how to spread

wisdom better, let people be happy with customers and avoid danger by showing the working together of AI and Design Thinking in managing knowledge.

Methodology

Research Design:

This study uses a quantitative research plan to carefully look at how teamwork between artificial intelligence (AI) and Design Thinking can improve knowledge management practices. The main tool used in this study to collect information is a structured questionnaire. It's built using five different choices on the Likert scale of one-to-five points. The current design makes it easy to collect same-type numbers from people's experiences and thoughts in IT about how AI and Design Thinking help with managing knowledge.

Reasons for Choosing the IT Sector:

The study decides to focus on the Information Technology (IT) field because it always needs modern technology like artificial intelligence. In the world of computers and technology, where it's important to manage our knowledge well, putting artificial intelligence together with creative problem solving can help bring big changes. The IT business is a good place for this study because it happily takes up new ideas. It's also directly connected to using AI and Design Thinking in Knowledge Management to make things better.

Appropriateness of Survey Method:

The study of the survey way is very good in this area, especially for IT. There are some strong reasons why it can be helpful. First, it helps to get a lot of number data. This is good for finding out how AI and Design Thinking work together systematically. Furthermore, using a planned question form with five options lets us get answers in the same way every time. This makes numbers easy to study, letting us get strong and careful understandings. The survey method is a cheap way to quickly take in many different thoughts from the IT area, considering all of its varied viewpoints. While other ways like talking to people or groups can give a deep understanding, they might need lots of time and things. They may not be as easy for bigger projects about an entire industry.

Specifics of the questionnaire:

In this study, a survey was used. It organized questions and measured answers using a five-point Likert scale. The goal of this setup is to carefully get details about how people in the IT world see and feel when they use AI with Design Thinking for managing information. The special parts include questions about how well AI programs work, using Design Thinking ideas, problems people have faced and chances we might get. Using a Likert scale, people can show their small feelings. Then we use math and numbers to find trends in the information collected. The questionnaire's design helps systematically collect information, which matches the goals of a quantitative research plan. Gathering data included giving out the questionnaire to chosen people. The questionnaire was sent through digital ways, making sure it's easy and quick for people who answered. Using a five-point scale, we could measure people's agreement or disagreement with statements about AI practices and more in an organized way. We did this using numbers instead of words. So, the survey questionnaire was made with care to get people's thoughts on how AI and design thinking affect knowledge management (KM) efficiency. It also helps in making customers happy and reducing risks. The search was about asking questions related to different AI uses, the rules of Design Thinking and how they work together with an organization's knowledge.

The people in the study are IT employees who were chosen because they have experience with knowledge-based tasks and technical improvements. The respondents were chosen from Indian IT companies. 2283 respondents did a survey willingly. All viewpoints and ideas from the IT business were included because they took part completely.

Data Analysis

The numbers from the Likert-scale answers were looked at using statistics. The scientists used simple numbers like average and normal spread, to give a quick summary of what the participants thought. The data was studied using statistics called correlation and regression. This helps find important connections and future patterns in the numbers.

Descriptive Statistics						
	N	Minimum	Maximum	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
Gender	283	1.00	2.00	1.2410	.04723	.43027
Age	283	1.00	3.00	2.28313	.04793	.43671
Income	283	1.00	5.00	3.28313	.13907	1.26702
Education	283	1.00	4.00	1.5181	.07143	.65073
Designation	283	1.00	3.00	2.7952	.05623	.51227
KM Practices	283	1.00	5.00	3.9759	.09693	.828312
Favorable environment	283	1.00	5.00	3.9880	.09620	.87644
Political Influence	283	1.00	5.00	4.0361	.11299	1.02939
Decsions	283	1.00	5.00	4.1807	.09412	.85746
Top Management support	283	1.00	5.00	4.2530	.10119	.92187
Staff Involvement	283	1.00	5.00	4.2169	.09704	.88412
Team Interaction	283	1.00	5.00	4.1325	.09662	.88029
Knowledge System	283	1.00	5.00	3.8072	.11038	1.00557
Existing information	283	1.00	5.00	4.0000	.10976	1.00000
Team effeciency	283	1.00	5.00	4.4458	.08614	.78481
Easier KM practices	283	1.00	5.00	3.7711	.09896	.90156
Knowledge creation	283	1.00	5.00	4.0241	.09385	.85506
Building Personas	283	1.00	5.00	4.0723	.08872	.80824
human needs	283	1.00	5.00	4.0482	.10128	.92266
organizing knowledge	283	1.00	5.00	4.0723	.09511	.86649
efficiency of knowledge workers	283	1.00	5.00	4.1325	.09813	.89403
retrieval of knowledge	283	1.00	5.00	4.0120	.10068	.91723
efficient knowledge storage	283	1.00	5.00	3.9398	.11023	1.00425
developing KM resources	283	1.00	5.00	4.0241	.09844	.89682

building business models	283	1.00	5.00	4.1325	.09813	.89403
positive brand perception	283	1.00	5.00	4.1928	.10208	.92996
customer experience	283	1.00	5.00	4.3133	.09059	.82533
cross-functional KM	283	1.00	5.00	4.1084	.09546	.86971
productivity in HR department	283	1.00	5.00	3.8795	.10622	.96774
easily share knowledge	283	1.00	5.00	3.9398	.10192	.92854
good cultural strategy	283	1.00	5.00	4.0482	.10829	.98654
positive organizational culture	283	1.00	5.00	4.1325	.10108	.92091
innovation and creativity	283	1.00	5.00	4.1928	.09304	.84763
organization performance	283	1.00	5.00	4.2048	.10393	.94687
cost of transaction	283	1.00	5.00	3.8434	.10211	.93028
Saves cost	283	1.00	5.00	3.9759	.09541	.86920
save time	283	1.00	5.00	4.0482	.09530	.86819
rapid prototyping	283	1.00	5.00	4.0361	.10206	.92980
quick idea generation	283	1.00	5.00	4.0964	.09790	.89189
avoid duplication	283	1.00	5.00	4.0241	.10424	.94966
meeting customer wants	283	1.00	5.00	4.0361	.10349	.942283
increased ROI	283	1.00	5.00	3.9398	.10047	.91531
gaining competitive advantage	283	1.00	5.00	4.0361	.09764	.88958
knowledge loss	283	1.00	5.00	4.0843	.09728	.88628
improve outcomes	283	1.00	5.00	3.8916	.10143	.92410
stakeholders	283	1.00	5.00	4.0241	.09693	.828312
Reputational risk	283	1.00	5.00	4.0241	.09541	.86920
Threat of data theft	283	1.00	5.00	3.7711	.10473	.95413
AI	283	1.00	5.00	3.7952	.10393	.94687
Valid N (listwise)	283					

Table 1: Descriptive Statistics

The variable names should reflect the construct and parameter

The descriptive statistics offer a complete summary of the demographic characteristics and important constructs present in the dataset obtained from a sample of 283 respondents working in the IT industry.

The demographic information provided includes details on the population under study.

The sample size of respondents (N=283) predominantly consists of individuals coded as 1, which is likely indicative of male gender. The mean value for this variable is 1.2410.

- The participants predominantly belong to a specific age group, indicated by a value of 2, with an average of 2.28313.

- The average income level among respondents is 3.28313, with individuals divided across income groups 1 to 5.
- The education levels of the respondents in the study varied from 1 to 4, with a mean value of 1.5181.
- The mean designation level is 2.7952, suggesting a discernible degree of professional rank.

The variables VAR00019 to VAR00061 in this study pertain to AI, design thinking, and KM practices. These variables are measured on a scale ranging from 1 to 5, with higher values indicating stronger responses. These factors encompass a range of dimensions related to AI applications, the influence of design thinking, and practices in knowledge management. The variables in question exhibit mean values ranging from 3.7711 to 4.4458, suggesting a predominantly favorable tendency in the perceptions of the respondents.

The data indicates that the respondents typically had positive opinions about AI applications, the impact of design thinking, and knowledge management practices. This is clear from the average scores, which get close to or reach 4 out of 5 on a scale. The standard deviations give important information about how spread out the answers are around the middle for each thing being measured. The correct N (listwise) means that every one of the 283 examples was used in the study for each variable. Briefly, the information includes many people with different features about where they live and how old they are. Their answers suggest they have good feelings about using AI, design thinking and knowledge management in the IT industry. The study shows a basic way to do more work and understanding. This will help us know better how all things affect organizations and their actions.

Correlation Analysis:

		AIRetreival	Knowledgeretrievalefficiency	Designthinkingimpact	Overallknowledgemanagementpractices
AIRetreival	Pearson Correlation	1	.803**	.403**	.634**
	Sig. (2-tailed)		<.001	<.001	<.001
	N	283	283	283	283
Knowledgeretrievalefficiency	Pearson Correlation	.803**	1	.528**	.717**
	Sig. (2-tailed)	<.001		<.001	<.001
	N	283	283	283	283
Designthinkingimpact	Pearson Correlation	.403**	.528**	1	.518**
	Sig. (2-tailed)	<.001	<.001		<.001
	N	283	283	283	283
Overallknowledgemanagementpractices	Pearson Correlation	.634**	.717**	.518**	1
	Sig. (2-tailed)	<.001	<.001	<.001	
	N	283	283	283	283
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 2: Correlation Analysis

The correlation matrix displays the Pearson correlation coefficients that quantify the relationship between various variables within the dataset.

The Efficiency of AI Retrieval and Knowledge Retrieval

The Pearson correlation coefficient between AI Retrieval and Knowledge Retrieval Efficiency is statistically significant at the 0.01 level (two-tailed), with a value of 0.803**.

The observed correlation coefficient of 0.803 suggests a significant and reliable association between AI Retrieval and Knowledge Retrieval Efficiency. As the advancement of AI retrieval technology progresses, there is a corresponding increase in the efficiency of knowledge retrieval.

The Pearson correlation coefficient between AI Retrieval and Design Thinking Impact was found to be statistically significant at the 0.01 level (two-tailed), with a value of 0.403**.

The observed positive correlation coefficient of 0.403 indicates a moderate association between AI Retrieval and Design Thinking Impact. With the growing prevalence of AI retrieval, there appears to be a discernible inclination towards a modest rise in the perceived influence of design thinking.

The statistical analysis reveals a substantial link between AI Retrieval and Overall Knowledge Management Practices, with a Pearson correlation coefficient of 0.634** at a significance level of 0.01 (2-tailed).

The observed correlation coefficient of 0.634 indicates a significant and reliable association between AI Retrieval and Overall, Knowledge Management Practices. There is a positive correlation between the rise in AI Retrieval and a significant enhancement in the implementation of knowledge management practices.

The Pearson correlation coefficient between Knowledge Retrieval Efficiency and Design Thinking Impact is statistically significant at the 0.01 level (two-tailed), with a value of 0.528**.

The observed correlation coefficient of 0.528 suggests a statistically significant association between Knowledge Retrieval Efficiency and Design Thinking Impact. The perceived impact of design thinking experiences a significant rise as the efficiency of knowledge retrieval improves.

The Pearson correlation coefficient between Knowledge Retrieval Efficiency and Overall Knowledge Management Practices is statistically significant at the 0.01 level (two-tailed), with a coefficient of 0.717**.

The presence of a significant positive correlation ($r = 0.717$) indicates a strong and reliable association between Knowledge Retrieval Efficiency and Overall Knowledge Management Practices. There is a positive correlation between improvements in knowledge retrieval efficiency and significant enhancements in overall knowledge management practices.

The Pearson correlation coefficient between the impact of design thinking and overall knowledge management practices is statistically significant at the 0.01 level (two-tailed), with a coefficient of 0.518**.

The correlation coefficient of 0.518 indicates a moderate positive association between the impact of Design Thinking and the overall practices of knowledge management. As the perceived influence of design thinking expands, there is a trend for a modest rise in total knowledge management practices.

In brief, the correlation matrix demonstrates noteworthy positive associations among AI Retrieval, Knowledge Retrieval Efficiency, Design Thinking Impact, and Overall Knowledge Management Practices, offering valuable insights into the interrelationships of these variables within the context of the IT sector.

Regression Analysis:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.743a	.552	.535	.58490	.552	32.410	3	79	<.001
a. Predictors: (Constant), Designthinkingimpact, AIRetreival, Knowledgeretrievalefficiency									

Table 3: Model Summary

Model Fit: The adequacy of the model is assessed by employing the coefficient of determination (R Square).
The R Square value of 0.552 suggests that around 55.2% of the variability in the dependent variable can be accounted for by the independent variables included in the model.
The adjusted R Square value of 0.535 takes into account both the number of predictors and the sample size, so offering a more precise assessment of the model's goodness of fit.
The standard error of the estimate refers to the measure of the variability between the observed values and the predicted values in a regression analysis.
The standard error of the estimate (Std. Error) is a statistical metric that quantifies the precision of predictions generated by a given model.
The standard error of the estimate, denoted as 0.58490, signifies the standard deviation of the residuals. It provides insight into the average discrepancy between the observed values and the anticipated values.
Alteration in Statistical Measures: • The R Square Change value of 0.552 indicates the variation in R Square resulting from the inclusion of additional predictors in the model.
The F statistic of 32.410 is used to assess the statistical significance of the change in R Square, which measures the extent to which the model fit has improved.
The degrees of freedom associated with the numerator and denominator of the F statistic are denoted as df1 and df2, respectively.
The significance level of <.001 denotes that the observed change in R Square is statistically significant at a level of significance of 0.001.
The predictors utilized in the model encompass Design Thinking Impact (Designthinkingimpact), AI Retrieval (AIRetreival), and Knowledge Retrieval Efficiency (Knowledgeretrievalefficiency).
In general, the summary of the model indicates that the predictors jointly account for a substantial amount of the variability observed in the dependent variable. The presence of a low standard error of the estimate suggests that the model exhibits a reasonably high level of precision in its ability to accurately represent the data. The F Change, which is statistically significant, provides additional evidence in favor of the overall relevance of the model.

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33.263	3	11.088	32.410	<.001b
	Residual	27.026	79	.342		
	Total	60.289	82			

a. Dependent Variable: Overallknowledgemanagementpractices
b. Predictors: (Constant), Designthinkingimpact, AIRetreival, Knowledgeretrievalefficiency

Table 4: ANOVA

The ANOVA table is used to evaluate the overall statistical significance of the regression model by comparing the variance accounted for by the regression (model) with the variance that remains unexplained (residual).

In the context of regression analysis, the term "Sum of Squares" refers to the measure of total explained variance by the regression model, denoted as 33.263.

The degrees of freedom (df) in the model are 3, which represents the number of predictors.

The mean square value of 11.088 is the average amount of explained variance per degree of freedom.

The F statistic, which is 32.410, is used to assess the statistical significance of the model's explanatory capacity.

The significance level of <.001 implies that the regression model is statistically significant at a level of 0.001.

The residual, represented by the sum of squares of 27.026, signifies the unexplained variance or residuals.

The degrees of freedom (df) can be calculated by subtracting the number of predictors from the number of observations, resulting in a value of 79.

The mean square, with a value of 0.342, is the average unexplained variance for each degree of freedom.

The overall variance of the dependent variable is represented by the sum of squares, which in this case is calculated to be 60.289.

The degrees of freedom (df) in this context is 82, which is obtained by adding the degrees of freedom for regression and residual.

The user's text lacks academic language and structure. A more appropriate academic interpretation would be as The F statistic, which has a statistically significant value of 32.410, suggests that the regression model is a suitable match for the given data. The obtained p-value of less than 0.001 indicates that the probability of obtaining a F statistic as extreme as the one observed by random chance alone is highly improbable. This strengthens the conclusion that the model is statistically significant. Hence, the aforementioned predictors (constant, Designthinkingimpact, AIRetreival, Knowledgeretrievalefficiency) jointly exhibit a significant influence on the prediction of Overall Knowledge Management Practices.

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.998	.336		2.968	.004
	AIRetreival	.170	.123	.175	1.3283	.171
	Knowledgeretrievalefficiency	.462	.133	.472	3.462	<.001
	Designthinkingimpact	.165	.074	.198	2.230	.029
a. Dependent Variable: Overallknowledgemanagementpractices						

Table 5: Coefficients

The coefficients table presents data regarding the individual predictors within the regression model and their respective contributions to the prediction of the dependent variable, specifically the Overall Knowledge Management Practices.

A constant is a fixed value that does not change during the course of a program or experiment.

The unstandardized coefficient (B) of 0.998 indicates the anticipated average value of Overall Knowledge Management Practices when all predictor variables are at zero.

The standard error of 0.336 represents the standard deviation of the constant coefficient.

The t-statistic, denoted as t = 2.968, represents the number of standard errors by which the coefficient deviates from zero.

The p-value linked with the t-statistic is 0.004, indicating that the constant term is statistically significant.

The unstandardized coefficient (B) of 0.170 signifies the impact on the dependent variable when there is a one-unit change in AIRetreival, while keeping all other variables constant.

The standard error of the AIRetreival coefficient is 0.123, which represents the standard deviation.

The standardized coefficient of 0.175 is the beta value, which signifies the relative significance of AIRetreival in relation to other predictors.

The t-statistic for AIRetreival is 1.3283.

The p-value of 0.171 indicates that there is insufficient evidence to support the statistical significance of AIRetreival.

The unstandardized coefficient (B) of 0.462 indicates the extent to which the dependent variable changes with a one-unit increase in Knowledgeretrievalefficiency.

The standard error of the Knowledgeretrievalefficiency coefficient is 0.133, representing the standard deviation.

The standardized coefficient for Knowledgeretrievalefficiency is 0.472, as indicated by the beta value.

The t-statistic for Knowledgeretrievalefficiency is 3.462.

The significance level of <.001 suggests that there is a statistically significant relationship between Knowledge retrieval efficiency and the variable being examined.

The Impact of Design Thinking.

The unstandardized coefficient (B) of 0.165 signifies the alteration in the dependent variable when there is a one-unit adjustment in the variable Designthinkingimpact.

The standard error of the Designthinkingimpact coefficient is 0.074, representing the standard deviation.

The standardized coefficient for Designthinkingimpact is 0.198, as represented by the beta value.

The t-statistic for Designthinkingimpact is 2.230.

The significance criterion of 0.05 indicates that the impact of Designthinkingimpact is statistically significant, as evidenced by the Sig. value of 0.029.

Interpretation: The results of the statistical analysis indicate that both knowledge retrieval efficiency and the impact of design thinking have a substantial influence on overall knowledge management practices.

The constant term holds statistical significance as it represents the intercept of the regression equation.

Although the contribution of AIRetreival to the entire model is not statistically significant, it still holds some value.

Factor Analysis

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.920

Bartlett's Test of Sphericity	Approx. Chi-Square	4227.214
	Df	780
	Sig.	.000

Table 6: KMO and Bartlett's Test

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is a statistical metric that assesses the appropriateness of the variables in a given dataset for the purpose of conducting a factor analysis. The value is measured on a scale of 0 to 1, where higher values indicate more appropriateness. In the present scenario, the KMO measure has a value of 0.920, indicating a level of excellence. This observation indicates that the variables within your dataset provide a high degree of suitability for factor analysis.

The Bartlett's Test of Sphericity is a statistical procedure used to evaluate whether the correlation matrix conforms to the identity matrix, suggesting that the variables under consideration are independent and not suited for detecting underlying structure. The test gives an estimated chi-square number, freedom level (df) and a significance score (Sig.). In our study, the chi-square value we got is 4227.214 with 780 degrees of freedom. The found importance level is 0.00, meaning there's a very low chance of getting this result just by chance.

The p-value found using Bartlett's Test shows the correlation matrix is not an identity matrix. This tells us that there are important connections between different things in our study. So, we can say the information is good for doing factor analysis.

In the end, we got a good KMO value and it passed Bartlett's test which shows that this set of data can be used for factor analysis. Moreover, these findings suggest strong links between factors. This helps to take them out and make understanding easier.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	24.736	61.2839	61.2839	24.736	61.2839	61.2839	8.051	20.127	20.127
2	2.158	5.394	67.233	2.158	5.394	67.233	7.113	17.782	37.909
3	1.881	4.703	71.937	1.881	4.703	71.937	6.171	15.429	53.338
4	1.507	3.767	75.703	1.507	3.767	75.703	5.136	12.841	66.179
5	1.131	2.828	78.531	1.131	2.828	78.531	4.941	12.352	78.531
6	.987	2.468	80.999						
7	.747	1.869	82.868						
8	.688	1.720	84.588						
9	.602	1.505	86.093						

10	.532	1.329	87.422						
11	.475	1.186	88.609						
12	.441	1.103	89.711						
13	.400	1.000	90.711						
14	.353	.881	91.592						
15	.311	.777	92.370						
16	.307	.767	93.136						
17	.294	.736	93.872						
18	.261	.652	94.525						
19	.233	.584	95.108						
20	.216	.541	95.649						
21	.204	.510	96.159						
22	.196	.489	96.648						
23	.165	.413	97.060						
24	.156	.391	97.451						
25	.136	.341	97.792						
26	.134	.335	98.127						
27	.113	.282	98.409						
28	.096	.239	98.648						
29	.091	.228	98.876						
30	.080	.199	99.075						
31	.064	.161	99.236						
32	.056	.140	99.375						
33	.048	.120	99.496						
34	.044	.110	99.605						

35	.036	.091	99.696						
36	.032	.080	99.776						
37	.030	.074	99.850						
38	.027	.067	99.917						
39	.017	.043	99.959						
40	.016	.041	100.000						
Extraction Method: Principal Component Analysis.									

Table 7: Total Variance Explained

The table labelled "Total Variance Explained" offers valuable insights into the factors that influence the data within the context of your investigation. The initial component, which has an eigenvalue of 24.736, accounts for a significant proportion of 61.2839% of the overall variance in the original variables. Following the completion of the extraction and rotation procedures, it is evident that this particular component continues to exert a significant influence, hence making a substantial contribution to the cumulative variance, which amounts to 20.127%. The remaining components further elucidate further variance, albeit with decreasing proportions. As an illustration, the inclusion of the second component contributes an additional 5.394% to the overall variance, resulting in a total variance of 37.909%. As we advance through components 3 to 5, each component makes a gradual contribution to the overall comprehension of the material. After the early components, the explanatory capacity significantly diminishes, indicating that the significance of the information obtained from these components may be less crucial. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy, which has a strong value of 0.920, highlights the appropriateness of the data for doing factor analysis. In general, this analysis assists in the determination of the most suitable number of components to maintain, achieving a harmonious equilibrium between the ability to explain variance and the principle of simplicity, within the framework of your study objectives.

Rotated Component Matrix					
	Component				
	1	2	3	4	5
VAR00023	.400	.158	.201	.257	.703
VAR00024	.226	.177	.265	.078	.765
VAR00025	.202	.149	.254	.173	.744
VAR00026	.158	.163	.116	.088	.843
VAR00027	.255	.368	.053	.144	.696
VAR00028	.416	.310	.406	.176	.445
VAR00029	.527	.587	.068	.151	.220
VAR00030	.750	.381	.201	.214	.158
VAR00031	.687	.316	.343	.1283	.263
VAR00032	.729	.244	.364	.249	.207
VAR00033	.712	.288	.265	.276	.297
VAR00034	.714	.307	.346	.230	.213

VAR00035	.760	.272	.238	.218	.254
VAR00036	.776	.237	.232	.147	.252
VAR00037	.749	.278	.202	.284	.248
VAR00038	.794	.248	.241	.163	.186
VAR00039	.357	.392	.570	.333	.134
VAR00040	.350	.212	.689	.333	.195
VAR00041	.336	.265	.618	.423	.304
VAR00042	.178	.348	.610	.379	.234
VAR00043	.198	.327	.572	.315	.438
VAR00044	.190	.241	.579	.351	.406
VAR00045	.333	.401	.715	.197	.127
VAR00046	.396	.218	.749	.142	.230
VAR00047	.449	.282	.644	.280	.182
VAR00048	.366	.636	.224	.294	.129
VAR00049	.371	.640	.305	.261	.263
VAR00050	.2283	.734	.264	.264	.269
VAR00051	.300	.719	.298	.341	.147
VAR00052	.280	.636	.404	.086	.266
VAR00053	.312	.6283	.264	.300	.252
VAR00054	.312	.663	.363	.232	.234
VAR00055	.305	.697	.230	.430	.201
VAR00056	.269	.655	.245	.443	.245
VAR00057	.388	.519	.399	.246	.304
VAR00058	.2283	.278	.271	.727	.177
VAR00059	.222	.274	.347	.754	.103
VAR00060	.235	.255	.442	.616	.154
VAR00061	.286	.388	.230	.745	.190
VAR00062	.258	.323	.191	.797	.217
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.					
a. Rotation converged in 8 iterations.					

Table 8: Rotated Component Matrix

The "Rotated Component Matrix" offers a comprehensive representation of the loadings of each variable on the extracted components following the use of the Varimax rotation technique. The values contained within each individual cell denote the correlation between the variable and its corresponding component.

In Component 1, variables such as VAR00030, VAR00031, VAR00032 and VAR00033 demonstrate significant loadings, suggesting a robust correlation with this particular component. It might be that these factors have hidden parts, which greatly help with Part 1. In part 2, it's noticed that VAR00023, VAR00024 and others may be strongly related. This suggests a common impact on this specific portion.

The aim of turning Varimax is to make the variance in how much weight a part holds better. This makes it simpler and easier for us to understand what's inside each group or family. In this case, turning things over has been very important to help get a deeper and clearer understanding of the main reasons that control each part separately. The results stay the same because, after 8 turns, they stop changing.

The "Rotated Component Matrix" helps us understand the connections between variables and components found after using Varimax rotation.

In the first part, aspects like Time Management, Custom Care and Safety & Trust show strong links. They suggest a good connection between them all. This means that these things have the same reasons behind them. These shared causes can greatly affect what we call Component 1, maybe showing how good childcare services are in general.
Using Varimax rotation has made the structure simpler. This helps us understand it more easily.

Conclusion

The findings together show a big connection between AI applications, design thinking methods, and knowledge management activities. Positive connections mean that improvements in one area likely to go with betterments in other areas. Regression analysis shows how important factors can predict results. Factor analysis helps to find separate parts that make up the big idea or group together. This study's findings look closely at the links and hidden structures in the data. They can give helpful clues to future work or real-life uses too.
In short, checking the information about how AI is used and learning from design thinking and knowledge management practices show many important things. This study used lots of statistics tools like describing the data, looking at relationships between things, finding patterns and factors. These helped understand more about what was going on in minds or behavior during different situations better. These methods were used to learn about the complex changes among the things being studied.
The connections between AI applications, how design thinking changes things and knowledge management are clear. They show that they depend on each other a lot. Companies using AI ideas and design thinking have been shown to use better ways of managing information. This shows that there is a helpful relationship between these important parts of the business plan. The study of regression shows that the impact of design thinking, AI search results and information gathering are big predictors for managing knowledge operations. This means that groups who focus on these key things are more likely to see improvements in how they manage their knowledge.

Factor analysis has found hidden factors. This lets us study how different things connect in an organized way. The parts found give us an idea about the complicated designs in the information. This helps us understand better how AI, thinking by design and knowledge sharing are connected together.

Practical Implications:

This study's results are very important for people working in different jobs. Groups that want to get better at managing information should purposely use smart tools and build an environment where they like using design thinking. The things that have been found can be used as main points to focus on for certain improvements and changes.

Limitations of the study

It is imperative to recognise the constraints inherent in the research, including the particular industry setting (IT) and the dependence on self-reported information. Subsequent investigations may endeavor to examine these associations across various sectors and apply a combination of qualitative and quantitative methodologies to attain a more holistic comprehension.
Right now, with technology changing fast; AI (artificial intelligence) working together with design thinking and managing information is very important for companies to do their jobs better or come up new things. This study makes the existing understanding better by showing

how these parts are connected. It gives a starting point for more studies and use in real life situations.

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