A Study to Determine Artificial Intelligence Enablers for Value Creation in Business

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Abstract: Businesses have been applying Artificial Intelligence (AI) tools along with other forms AI in the last decade. While AI offer immense potential to solve issues, they remain a challenge in terms of practical execution and capability and understanding the AI enablers for value creation in business. The purpose of our study is to determine the AI enablers for value creation in business. From the literature review and gaps, we derived four predictor variables Artificial Intelligence (AI) Capability, Organization Culture, Business Integration and Ethics and Governance impacted the outcome variable value creation. An empirical study was conducted using statistical tools, a quantitative type of research was conducted. We collected primary data though the questionnaire tool using a Likert five-item scale and we followed simple random sampling Data from 52 respondents was collected and was statistically analyzed through ADANCO 2.4 software using Structural Equation Model (SEM). The relationships between the predictor variables and outcome variable were found significant and therefore all hypothesis were accepted. Organization culture was the most impactful predictor variable on the outcome variable value creation in the business. The framework will help provide more research publications explore various elements of AI enablers on value creation in business. The paper has contributed in creating new insights and learnings on areas like AI capability , AI ethics and governance and its relationship with value creation in business, that will help policy makers in the ecosystem build awareness and get more insights on skill development, creating AI ethics and governance policy. The findings will provide business leaders with a framework for value creation enabled by AI and focus on getting maximum benefit in the business and achieve value creation. Practitioners will get insight to build strong organization culture that will go a long way in AI implementation, increase productivity and create a competitive advantage in business. While we have collected data across many countries globally, a focused country approach could provide a more detailed view of what is required by a country to deliver value creation from AI interventions.

Keywords: Artificial intelligence, value creation, business strategy, business value, digital transformation

1. Introduction

Businesses are transforming at a fast pace in the digital age to keep up with the fast adoption of emerging technologies. Artificial Intelligence (AI) among the digital advancements, is playing a leading role and is the focus of academicians and leaders in the business segment. In this highly competitive environment, with large amounts of data and scarce resources, there is a necessity for faster decision-making and hence the need for

AI tools. With the advent of AI, other digital tools are getting integrated. There is a lot of interest in this field, researchers are further investigating the influence of AI on business strategy [1].

While there is a huge potential upside in AI-driven applications to enable value creation in business, organizations are still piloting AI, and there are only a few organizations that implement AI in an integrated way within the organization [2, 3]. Given a very futuristic outlook on AI and its influence on the business, and limited studies done in this regard, we have conducted empirical research to determine AI enablers of value creation in the business. The literature was sourced from database such as EBSCO and PROQUEST using keywords Artificial intelligence, Value creation, Digital transformation, Business strategy, and Business Value. Peer-reviewed articles from 2020 onwards were selected. The articles were selected given their significance to the research topic. The four independent variables identified from the literature review are (1) AI Capability, (2) Organizational Culture, (3) Business Integration and, (4) Ethics and Governance. The dependent variable is Value Creation in business.

1.1. Artificial Intelligence (AI)

AI is like a machine that can replicate similar behaviour to human beings as they can recognise, learn, self-regulate and rationalise. Machine Learning [4] is an automatic learning technique understood by analysing data, learning them and making decisions based on what was learned. Deep Learning [4] is another automatic learning technique that incorporates neural network architecture. Neural network solutions refer to the functions done by the human brain by imitating human neurons.

1.2. Value Creation (VC)

Value Creation is the benefit that users will get from some product or service expressed in terms of Willingness to Pay (WTP) minus the cost of various resources required for production. In business, value creation can be achieved in many ways. Some of the ways are through achieving competitive advantage, improving productivity, increasing revenue, optimizing costs, enhancing sustainability of the business, communities and the environment.

2. Research Problem and Research Questions

Given that there is less clarity on the Artificial enablers for value creation in business and limited studies done in this regard leading to slow implementation of AI globally, our study aims to determine AI enablers for value creation. The four research gaps were identified from the literature survey of multiple articles are:

(1) AI Capability

(2) Organizational Culture

(3) Business Integration and

(4) Ethics and Governance.

The research questions are designed based on the gap variables.

- What are the main drivers of creating effective AI capabilities for the organization for value creation?
- Does organizational culture impact value creation?
- What are the factors of business integration that enable value creation?
- Does Ethics and Governance enable value creation?

The context setting for the research has been a global study so that a broad understanding and insights are generated across the globe.

3. Research Objectives

To address the research questions, following research objectives were formulated for further research.

- To determine the factors of AI capabilities for value creation.
- To ascertain the impact of organizational culture on value creation.

- To determine the factor of business integration for value creation.
- To ascertain the impact of Ethics and Governance on value creation.

4. Literature Review

While there is a huge potential in AI-driven business to enable value creation in business and given that companies do not have a clear roadmap to implement AI and deliver value creation, this study will attempt to chart a roadmap and provide leadership in the business where should be the priority be in terms of factors of AI that will enable value creation. The literature review was made given one question in mind initially. What are the factors of AI that enable value creation?

Dr Seetha's patented in 2021 format was used. A research framework was derived based on the gap variable identified and the association that we would like to test further. The study has been planned based on independent variables selected from the gaps in the research, found in the literature having association with the dependent factor.

4.1. AI Capability

The core business organization needs competence building and training during the transformation. Opportunities in the ecosystem need to be evaluated before deciding the nature of the capabilities required. In our study, another independent variable AI infrastructure readiness was considered, however we have combined the same under AI capability for giving a more comprehensive understanding of AI capability and it resulted in higher reliability, validity and significance during our data analysis phase. Training across the organization on AI, project teams and pilot projects may be instituted. Developing human competence and skills is key for driving AI implementation [5]. The study done by Caner *et al.* [6] means that understanding the ecosystem including competence with the functions is critical for AI implementation. Both competencies, internal and external requires to be evaluated and built further for providing the company a competitive edge in the marketplace. Through the study derived from literature surveys [6] mentioned AI capabilities to be included like Machine Learning methods, and Deep Learning. Other capabilities like Natural Language Processing should be included in the capability framework.

From the literature review of the article authored by Cao [7] on how AI enables value creation in retail, factors like Data Management Capabilities are critical given that AI applications require high data processing [8]. Significant development and advancements in the recent period have taken place in the area of generative AI and building capability is key to many AI applications like in marketing and advertising especially in the area of creating content [9]. Digital Servitization is a way that the business leverages the functionality of the product [10]. After reviewing all the articles, the common themes on organization capabilities that need to be built are AI competence in the ecosystem, Generative AI, Data Management and Digital Servitization. Very importantly, the competencies and skills should be evaluated in the entire ecosystem of the organization. The study of the articles though being very informative on AI capability, there was no empirical evidence to create value creation, a quantitative research study is proposed. This brings us to our first research question based on the gap analysis.

a) What are the main drivers of creating effective AI capabilities for the organization for value creation?

The first hypothesis to be tested is as follows:

H1: AI capability plays a critical role in enabling value creation in business.

4.2. Organizational Culture

Cultural Transformation in the organization is an important area for further research to ascertain how businesses change their culture to adopt AI implementation [7]. Decision-making is crucial for value creation as informed choices within organizations can drive business performance. Volkmar *et al.* [11] mentioned autonomy to team members play an important role in success. Managing and coping with failures in AI implementation becomes important in the process. Further discussions on decision making and roles of human and AI were made in the literature. Important questions were raised on how organizations collaborate effectively and manage both inward and goals to achieve success in AI implementation. Organizational transformation is in important element for AI implementation success and requires transformation in culture driven by the senior leadership in the organization. This brings us to our second research question based on the gap analysis.

b) Does organizational culture impact value creation?

The second hypothesis to be tested is as follows:

H2: A robust Organizational Culture enables value creation in business.

4.3. Business Integration

Business Integration is a combination of business function, business process and business model. In business like sales, marketing, and customer service, AI can impact in terms of cost-effectiveness and retention rate of customers. AI has an impact on production, manufacturing, supply chain, finance, human resources, information technology, legal and other functions helping teams to improve on transactional work and freeing time for strategic thinking. Kitsios and Kamariotou [12] explained how AI can play a role in Marketing in terms of decision-making in pricing, promotion and other applications in marketing like product development. Advertising media purchase is given as an example based on consumer demographics, and search behaviour in digital advertising. The essence is to decide which business functions AI can be applied to and how data management, strategic thinking, AI capability and the nature of tasks of each function can be planned. From the studies on the impact of AI in business functions , it was articulated the usage of AI in business functions, especially in Customer service management, wherein customers can benefit from optimised search engines to search for the right product or service for better customer satisfaction and low customer returns, In the retail space, AI assists in merchandising, and category management, in supply chain , order and delivery management bring about both efficiency and productivity.

AI implementation can lead to new business model creation or improvisation of business models, hence opportunity for value-creation for the organization. Business model includes all activities that focuses to satisfy the end consumer. The AI implementation needs to aim at areas that can transform the business model. In this way it can create value addition, value creation and create operational efficiencies to the existing business model. This brings us to our third research question based on the gap analysis.

c) What are the factors of business integration that enable value creation?

The third hypothesis to be tested is as follows:

H3: AI applications play an important role in creating value creation opportunities through Business Integration.

4.4. Ethics and Governance

From the literature review , it is found that AI ethics and governance leads to business sustainability. AI systems can be used to protect people's privacy and protecting data. From a societal point of view, companies need to address the effects of AI in the ecosystem. Social acceptance and trust in AI are important factors to be included in the AI implementation process. It is important to have an effective governance that will ensure compliance of laws and regulations as well as organization policies. This will lead to better security, safety and hence long-term sustainability. Technical Robustness and safety are very important in AI implementation as it helps in operating with reliability in the give conditions and situations. Resourcing and sponsorships of projects to be initiated to ensure transparency, accountability and take into consideration of social and environment well-being. From the literature review, it is clear that there was no empirical study to find evidence of impact of AI ethics and governance on sustainability, hence quantitative research is proposed. This brings us to our fourth research question based on the gap analysis.

d) Does Ethics and Governance enable value creation?

The fourth hypothesis to be tested is as follows:

H4: Ethics and Governance in AI applications is an important enabler for value creation in business.

5. Conceptual Framework

The conceptual framework will help us guide through the research in terms of the various variables identified and the association between them. From literature reviews, we found that empirical study was missing in all the cases. After reviewing the pieces of literature, gaps were identified and the following are the independent variables.

(1) AI Capability (2) Organizational Culture (3) Business Integration and (4) Ethics and Governance.

The dependent variable is Value Creation in business.

The hypotheses given below that emanated from the research questions and are tested in our study:

H1: AI capability plays a critical role in enabling value creation in business.

H2: A robust Organizational culture enables value creation in business.

H3: AI applications play an important role in creating new value-creation opportunities through Business Integration.

H4: Ethics and Governance in AI applications is an important enabler for value creation in business.

Fig. 1 shows the framework of value creation in business. It demonstrates relationship between the predictor and outcome variable with the corresponding hypothesis to be tested.

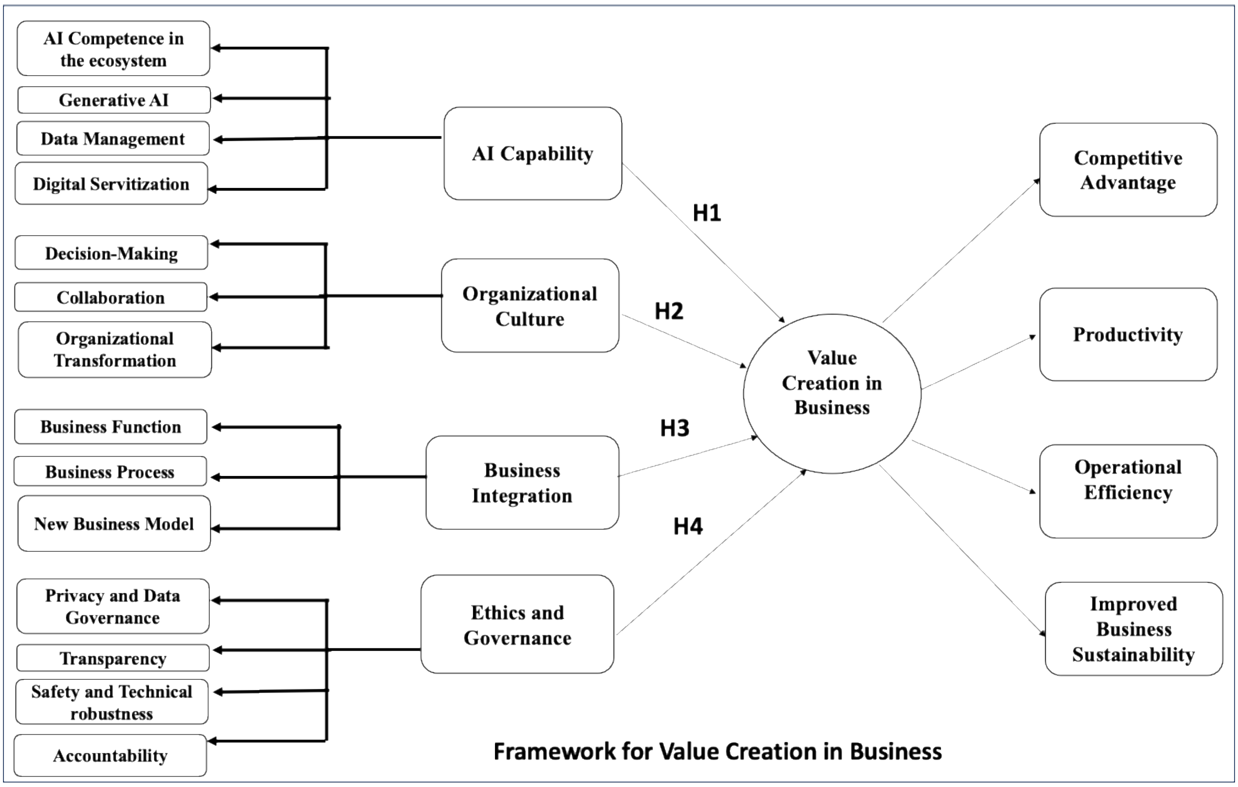

Fig. 1. Provides a framework for value creation in business.

Table 1 demonstrates the specific research questions that emerge from the literature review, the research questions led to research objectives and hypotheses that were tested.

Table 1. The research questions, objectives and hypotheses that was tested

SL no.	Research Questions	Research Objectives	Hypotheses
1.	What are the main drivers of creating effective AI capabilities for the organization for value creation in business?	To determine the factors of AI capabilities for value creation in business.	H1: AI capability plays a critical role in enabling value creation in business.
2.	Does organizational culture impact value creation in business?	To ascertain the impact of organizational culture on value creation in business.	H2: A robust Organizational culture enables value creation in business.
3.	What are the factors of business integration that enable value creation?	To determine the factor of business integration for value creation.	H3: AI applications play an important role in creating new value-creation opportunities through Business Integration.
4.	Does Ethics and Governance enable value creation in business?	To ascertain the impact of Ethics and Governance on value creation in business	H4: Ethics and Governance in AI applications is an important enabler for value creation in business.

6. Research Methodology

The initial process included literature review with research gaps and limitations. The research methodology is aligned with the research objectives. As we are attempting to find a correlation between independent and dependent variables, and quantitative research approach was followed. Primary data was collected through random sampling with 30 questions using the questionnaire tool supported by Likert 5-item scale. Each respondent was sent an email requesting for the survey with key objectives in mind and the purpose of the study. Questions were uploaded on Google Forms and 52 respondents filled up the questionnaire which was the source of data analysis that will be discussed in the next stage. Questions from respondents were handled and clarifications were provided. The demographic profile included people with age 18 years and above, all genders, countries included India, Netherland, Canada, U.S. U.K, Spain, Ivory Coast, Nigeria, Singapore and Dubai. Education qualifications included Bachelor's degree, Master's degree, Ph.D. and Others. The following segments were selected students, employed full-time, self-employed and employed part-time.

7. Data Analysis

In the earlier sections, a clear articulation of the research methodology was provided. The information was gathered via a survey questionnaire instrument, and ethical requirements were followed. For data analysis, we used the Structural Equation Modelling (SEM). SEM being a multivariate technique, helps predict a multiple inter-related dependence relationships at the same time. It helps in assessing intricate connections between predictor and outcome variables.

The ADANCO 2.4 software supported the data analysis. The software helps establish the variance-based structural equation model and reflective and formative measurement model as well. The hypothesis that was considered, was evaluated using the t-value and p-value analysis.

7.1. Measurement Model

ADANCO 2.4 software provides plethora of measurement model indicators. The measurement model examines the link between observed variables and their latent constructs.

7.2. Construct Reliability

Analysis of the internal consistency and reliability are provided by Construct Reliability evaluations. Measurement of Construct reliability provides reliability of the overall construct being measured by a set of indicators and is a part of the reflective measurement model.

"A construct can be taken as internally consistent and reliable", As per [13], "The rho value must be greater than 0.7. Any value above 0.8 is taken as good and above 0.9 is excellent". As per [14] "any of rho value above

0.9 is excellent". "Cronbach's alpha value is 0.6, with values above 0.7 being preferred [15, 16]".

Given the above standards, results of the reliability tests were found to be good and illustrated in Table 2.

Table 2. Construct reliability

Construct	Dijkstra-Henseler's rho (ρ_A)	Jöreskog's rho (ρ_C)	Cronbach's alpha(α)
AC	1.0000	0.8862	0.8277
OC	1.0000	0.8826	0.8002
BI	1.0000	0.8971	0.8276
EG	1.0000	0.9131	0.8730
VC	1.0000	0.9034	0.8571

7.3. Scale Validity

Validity refers to the extent to which a tool or instrument accurately measures what it is designed to measure. A measure may prove to be reliable, but it may not be valid. To test the constructs' validity, it needs to be reliable first. The construct was tested for reliability in the earlier section and was found to be reliable. In this section, confirmation of the validity of the constructs will be proved through various validity tests.

7.3.1. Convergent validity

Convergent validity is the degree to which two measures of constructs that theoretically should be related are, in fact, related [17]. To consider the model is convergent valid or not, Average variance extracted (AVE) data is used. A construct with an AVE value greater than 0.5 is considered to explain a significant amount of the variance in the model.

Table 3. Convergent validity

Construct	Average variance extracted (AVE)
AC	0.6614
OC	0.7149
BI	0.7442
EG	0.7244
VC	0.7008

Table 4. Convergent validity with loadings

Indicator	AC	OC	BI	EG	VC
AC1	0.7566				
AC2	0.8681				
AC3	0.8453				
AC4	0.7778				
OC1		0.8435			
OC2		0.8722			
OC3		0.8200			
BI1			0.8294		
BI2			0.8865		
BI3			0.8710		
EG1				0.8329	
EG2				0.8702	
EG3				0.8377	
EG4				0.8630	
VC1					0.8785
VC2					0.8336
VC3					0.7950
VC4					0.8393

The AVE data below in Table 3 for the constructs is between 0.6614 to 0.7442. All the constructs within the model are therefore convergent valid.

"Convergent validity is also demonstrated with the observations of the loading values of each indicator with respect to its respective construct [18]". The loading value is considered satisfactory provided the indicator be ≥ 0.7. In this case, all the values are ≥ 0.7. Table 4 demonstrates that the factor loadings for all indicators in the measurement model are above 0.7, confirming the convergent validity of the model.

7.3.2. Discriminant validity

"Discriminant validity refers to the degree to which constructs that theoretically should be unrelated are, in fact, unrelated." It could be evaluated through the report criterion [19]. The indicator for evaluating discriminant validity is the "Average Variance Extracted (AVE) should exceed the squared correlations between the latent construct and all other constructs in the model". In each column and row, the highest absolute correlation should be located along the main diagonal. This arrangement indicates that each construct has a stronger correlation with its own indicators than with those of other constructs in the model.

The discriminant validity is established in this case because the "diagonal values (AVEs) exceed the squared correlation values of their corresponding rows and columns". This is demonstrated in Table 5.

Table 5. Discriminant validity (Fornell and Larcker)

Construct	AC	OC	BI	EG	VC
AC	0.6614				
OC	0.4274	0.7149			
BI	0.5167	0.3376	0.7442		
EG	0.4964	0.3873	0.3069	0.7244	
VC	0.6399	0.6580	0.5251	0.5996	0.7008

7.3.3. Discriminant validity using inter-construct correlations

"As per [20], the inter-construct correlations must be less than 1 to prove discriminant validity." This is demonstrated in Table 6 through the ADANCO 2.4 report. It can be seen that all inter-constructs correlations are below 1. Therefore, the model is valid as all inter-construct correlations are below 1.

Table 6. Discriminant validity with inter-construct correlations

Construct	AC	OC	BI	EG	VC
AC	1.0000				
OC	0.6537	1.0000			
BI	0.7188	0.5810	1.0000		
EG	0.7045	0.6224	0.5540	1.0000	
VC	0.8000	0.8112	0.7246	0.7743	1.0000

7.3.4. Validating scale through cross-loadings

The cross-loadings matrix provides insights into how indicators correlate with various constructs, demonstrated in Table 7. The indicators of discriminant validity are manifested through the loadings of the factors, which are expected to surpass the cross-loadings observed across the entirety of construct within the model. It is observed, in this case, that all determinants are higher than the cross loadings across the model. This proves that the instrument is valid without any cross-loading.

Table 7. Cross-loading matrix

Indicator	AC	OC	BI	EG	VC
AC1	0.7566	0.3801	0.4632	0.5339	0.5273
AC2	0.8681	0.6783	0.6261	0.6222	0.7659
AC3	0.8453	0.6113	0.7067	0.6351	0.6987

AC4	0.7778	0.4536	0.5385	0.4971	0.6062
OC1	0.6252	0.8435	0.5272	0.7207	0.7918
OC2	0.5223	0.8722	0.4692	0.4403	0.6761
OC3	0.5102	0.8200	0.4770	0.4172	0.5891
BI1	0.5353	0.4388	0.8294	0.5462	0.5828
BI2	0.6289	0.5414	0.8865	0.4023	0.6671
BI3	0.6954	0.5230	0.8710	0.4846	0.6246
EG1	0.4817	0.4203	0.4605	0.8329	0.6041
EG2	0.6067	0.5357	0.4351	0.8702	0.6169
EG3	0.6828	0.6278	0.4899	0.8377	0.7497
EG4	0.6269	0.5346	0.5001	0.8630	0.6649
VC1	0.6988	0.6435	0.7118	0.6090	0.8785
VC2	0.6432	0.7851	0.5069	0.6662	0.8336
VC3	0.6435	0.6662	0.6092	0.6632	0.7950
VC4	0.6915	0.6198	0.5970	0.6529	0.8393

7.4. Indicator Multicollinearity

Multicollinearity is defined as the presence of correlation between independent variables within a multiple regression model. This suggests that the predictor variables are interrelated and can result in challenges such as unreliable probability values and complexity in understanding the impacts of individual predictors. The prediction of the dependent variable may be inaccurate and the results may be inaccurate should there be multicollinearity among the independent variables. The multicollinearity can be assessed by the "Variance Inflation Factor (VIF) and its reciprocal. A construct should have VIF values below 10 or 5 to avoid issues of multicollinearity in the model. Table 8 illustrates that the Variance Inflation Factor (VIF) values for the various constructs examined are below 2.6671. Consequently, there is no evidence of multicollinearity, as all VIF values fall below 5 [21]".

Table 8. Indicator multicollinearity

Indicator	AC	OC	BI	EG	VC
AC1	1.4851				
AC2	2.5614				
AC3	2.3089				
AC4	1.6280				
OC1		1.7609			
OC2		1.9684			
OC3		1.5711			
BI1			1.6358		
BI2			2.2300		
BI3			2.0826		
EG1				2.3002	
EG2				2.6247	
EG3				2.3214	
EG4				2.5185	
VC1					2.6671
VC2					1.9482
VC3					1.7735
VC4					2.3319
	Variance Inflation Factors (VIF)				

7.5. Structural Model

The structural model encompasses both exogenous and endogenous variables. Exogenous constructs have their attributes determined externally and are integrated into the model. The significance and magnitude of the path coefficients is crucial components.

Fig. 2 Demonstrates the structural model having path coefficients and has been generated by the ADANCO 2.4 software.

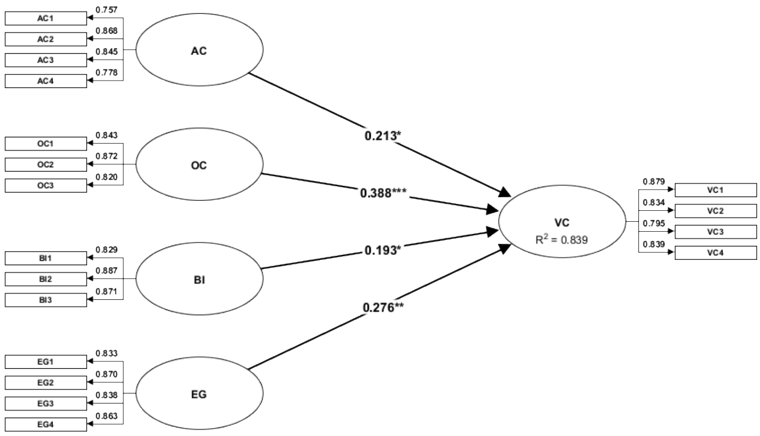

Fig. 2. Structural equation model.

7.5.1. Coefficient of determination (R2)

In Fig. 2, where the structural model is presented, has R2 value 0.839 for the dependent variable "Value Creation" (VC) having four independent variables in the model.

R2 measures the degree to which the variance in the outcome variable can be attributed to or clarified by the predictor variables incorporated within the model. Since variance proportions are bounded between 0 and 1, and "R2 value is 0.839 is considered high as per the PLS regression model [22]".

7.6. Testing of Hypotheses and Path Coefficients

In this research study, four hypotheses were examined within the model, encompassing all direct relationships. "A bootstrapping methodology [23]", was implemented for processing the sample data. the significance of each hypothesis was assessed by examining the t-values associated with both the predictor and outcome variables. "Two-tailed t-tests were used in this research and measured at 10%, 5% and 1% of significance levels. Table 9 demonstrates levels of significance and decision measures of the t-values and p-values [24]".

Table 9. Hypothesis testing using t-values

t-values	Significance	Decision
t<1.65	p>0.10	Not significant
1.65<t<1.96	0.10>p>0.05	Moderate
1.96<t<2.59	0.05>p>0.01	Significant
t>2.59	p<0.01	Very Significant

The ADANCO 2.4 software produced the subsequent figure illustrating the direct effects, used for testing the four direct hypotheses. From Tables 9 and 10, it is observed all the hypothesis is accepted and significant as the t-values >1.96 and therefore the hypothesis mentioned below, are significant, also p values of all hypothesis are also below 0.05 (*p*-value < 0.05).

Table 10. Direct effects interference

Hypothesis	Effect	Original coefficient	Standard bootstrap results					Significance
			Mean value	Standard error	t-value	p-value (2-sided)	p-value (1-sided)	
H1	AC → VC	0.2133	0.2288	0.0948	2.2496	0.0247	0.0123	YES
H2	OC → VC	0.3880	0.3791	0.1158	3.3517	0.0008	0.0004	YES
H3	BI → VC	0.1932	0.1983	0.0965	2.0033	0.0454	0.0227	YES
H4	EG → VC	0.2756	0.2819	0.0919	2.9992	0.0028	0.0014	YES

Table 11. Constructs and determinants with loadings

Predictor Variable	Determinants	Loadings (Path Coefficients)	Inference on the loading
AI Capability	AI Competence in the ecosystem	0.7566	Moderate
	Generative AI	0.8681	Strong
	Data Management	0.8453	Strong
	Digital Servitization	0.7778	Moderate
Organizational Culture	Decision-making	0.8435	Strong
	Collaboration	0.8722	Strong
	Organizational Transformation	0.8200	Strong
Business Integration	Business Function	0.8294	Strong
	Business Process	0.8865	Strong
	New Business Model	0.871	Strong
Ethics and Governance	Privacy and Data Governance	0.8329	Strong
	Transparency	0.8702	Strong
	Safety and Technical Robustness	0.8377	Strong
	Accountability	0.8630	Strong

The loading values range lie between 0.5 and 0.8, then there is a moderate effect. Should the values go beyond 0.8, then it indicates a significant influence of the determinant on the independent variable [25].

7.6.1. Testing of hypotheses associated to Artificial Intelligence Capability (AC)

Based on the literature review, the association between the variable Artificial Intelligence Capability (AC) and Value Creation (VC) was identified for the study. Artificial Intelligence Capability (AC) was evaluated with four determinants, as shown in Table 11. In the analysis, two of the loadings are above 0.8 indicating significant influence of the determinant on the predictor variable and two of the loadings are more than 0.75 indicating moderate effect.

Hypothesis 1 (H1): Assessing the effect of Artificial Intelligence Capability (AC) on Value Creation (VC) in business.

Hypothesis 1: AI capability plays a critical role in enabling value creation in business.

The association between Artificial Intelligence Capability and Value Creation is significant as per Table 10 as the *t*-value >1.96 (*t*-value = 2.2496) and the path co-efficient ßAC-VC =0.2133. The hypothesis (H1) is thus accepted at 95% confidence level. This confirms from the study by Lee [9], that capability building in AI results in AI orientation and value creation.

7.6.2. Testing of hypotheses associated to Organizational Culture (OC)

As per the literature review, relationship between the variable Organizational Culture (OC) and Value Creation (VC) was identified for the study. Organizational Culture (OC) was evaluated with three determinants, as shown in Table 11. In the analysis, loading values are above 0.8 demonstrating significant influence of the determinant on the independent variable.

Hypothesis 2 (H2): Assessing the effect of Organizational Culture (OC) on Value Creation (VC) in business.

Hypothesis 2: A robust Organizational Culture enables value creation in business.

The association between Organizational Culture (OC) and Value Creation (VC) is very significant as per Table 10 as the *t*-value >2.59 (*t*-value = 3.3517) and the path co-efficient ßOC-VC = 0.3880. The hypothesis (H3) is thus accepted at 99% confidence level. This is confirmed from the literature review that organizational culture impacts value creation.

7.6.3. Testing of hypotheses associated to Business Integration (BI)

As per the literature review, relationship between the variable Business Integration (BI) and Value Creation (VC) was identified for the study. Business Integration (BI) was evaluated with three determinants, as shown in Table 11. In the analysis, loading values are above 0.8 demonstrating significant influence of the determinant on the independent variable.

Hypothesis 3 (H3): Assessing the effect of Business Integration (BI) on Value Creation (VC) in business.

Hypothesis 3: AI applications play an important role in creating value creation opportunities through Business Integration.

The association between Business Integration (BI) and Value Creation (VC) is significant as per Table 10 as the *t*-value >1.96 (*t*-value =2.0033) and the path co-efficient ßBI-VC = 0.1932. The hypothesis (H3) is thus accepted at 95% confidence. This supports from the study that application of AI on business model [26], business function and business process enable value creation.

7.6.4. Testing of hypotheses associated to Ethics and Governance (EG)

As per the literature review, relationship between the variable Ethics and Governance (EG) and Value Creation (VC) was identified for the study. Ethics and Governance (EG) was evaluated with four determinants, as shown in Table 11. In the analysis, loading values are above 0.8 demonstrating significant influence of the determinant on the independent variable.

Hypothesis (H4): Assessing the effect of Ethics and Governance (EG) on Value Creation (VC) in business.

Hypothesis 4: Ethics and Governance in AI applications is an important enabler for value creation in business.

The association between Ethics and Governance (EG) and Value Creation (VC) is very significant as per Table 10 as the *t*-value >2.59 (*t*-value =2.9992) and the path co-efficient ßEG-VC = 0.2756. The hypothesis (H4) is thus accepted at 99% confidence level. This is confirmed from the earlier studies made by that ethics and governance lead to value creation and sustainability mentioned in the literature review.

7.7. The Positive Outcomes Resulting from Value Creation as Part of Research Outcomes

There were four predictor variables and one outcome variable in the research. AI Capability, Organization Culture, Business Integration and Ethics and Governance were part of the exogenous variables. Value creation in business was the endogenous variable.

Al predictor variables have significant effect on the outcome variable "Value Creation in business". The structural model reported R2 value 0.839 for the dependent variable "Value Creation" (VC) having four independent variables in the model.

Since variance proportions are bounded between 0 and 1, and R2 value is 0.839 is considered high as per the PLS regression model.

From the literature review, four positive outcomes of Value Creation, each associated to an independent variable. The significance of each of these four positive outcomes was assessed and was demonstrated in the construct's loading values and with the t-values.

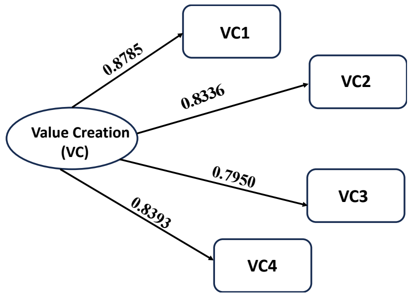

Fig. 3. Loading estimates for outcome measure -value creation positive outcomes.

The Positive Outcome of Value Creation were measured with four Outcomes as shown in Fig. 3. In the analysis shown in Fig. 3, the loading values are above 0.8 demonstrating significant effect except VC3 at 0.7950 demonstrating moderate effect.

Value Creation Positive Outcomes were used to assess the research outcomes. Each outcome variable identified is related to the independent variable. All four results of value creation positive outcomes demonstrated strong influence

- Competitive Advantage

This output measure is associated to AI Capability. The fact that AI Capability results in competitive advantage in the process of enabling Value Creation is accepted with a loading value of 0.8785 and *t*-value 15.99. Competitive advantage is a strong outcome of value creation and is associated to AI Capability. This is also verified from Krakowski *et al.* [27], that demonstrates AI capability impacts competitive advantage.

- Productivity Improvement

This output measure is associated to Organizational Culture. The fact that organizational culture results in productivity improvement in the process of enabling Value Creation is accepted with a strong loading value of 0.8336 and *t*-value 10.70. Productivity improvement is a strong outcome of value creation and is associated to Organizational Culture. This is also verified from Mohammadi [28] who reported that Organizational Culture had a potential impact on productivity improvement.

- Operational Efficiency

This output measure is associated to Business Integration. The fact that Business Integration results operational efficiency is accepted with a loading value of 0.795 and *t*-value 10.71.

Here, Business Integration is associated with operational efficiency, a form of value creation. This is also verified from Mohapatra *et al.* [29], reported that there is a synergy between Business Integration (Business function) and operational efficiency, a measure of value creation.

- Sustainability

This output measure is associated to Ethics and Governance in AI. The fact that Ethics and Governance results in Business Sustainability in the process of enabling Value Creation is accepted with a loading value of 0.8393 and *t*-value 11.88. Business Sustainability is a strong outcome of value creation and is associated to Ethics and Governance in Stahl *et al.* [30] clarified that Ethics and Governance had a potential impact on business sustainability.

7.8. Summarizing the Hypotheses Tested

There were four hypotheses tested. The structural equation model was processed, with four predictor variables and one outcome variable. All had direct relationships. All four hypotheses were found significant.

The relationships between the predictor variables and outcome variable were found significant.

1. AI Capability (βAC-VC = 0.2133; *t*-value = 2.2496)

2.Organization Culture (βOC-VC=0.03880; *t*-value = 3.3517)

3. Business Integration (βBI-VC = 0.1932; t-value = 2.0033)
4. Ethics and Governance (βEG-VC = 0.2756; *t*-value = 2.9992)

Organization Culture was identified as the most impactful factor on value creation, followed by Ethics and Governance, AI Capability and Business Integration.

8. Research Contributions

This study has contributed to the enablers of AI to capture value creation in business, and solve real business challenges and contribute to the theory and literature on value creation frame work related to AI interventions in business.

8.1. Contribution to the Literature

The literature review has some very relevant articles on AI enablers value creation from researchers like [31, 32]. Research on AI enablers on value creation is rare and use of the Structural Equation Model (SEM) to being a multivariate technique, helps predict a multiple inter-related dependence relationships at the same time. This has helped provide deep understanding of various variables interacting at the same time. This study will help provide more research publications exploring various elements of AI enablers on value creation in business.

8.2. Contribution to Theory

Given that there were very few studies with empirical evidence on AI enablers for value creation in business, this study created a clear framework to determine the AI enablers on value creation in business based on a methodical literature review. This framework should support the understanding AI enablers in many markets globally.

8.3. Contribution to Practice

The study was based on real need of the business as AI can be implemented and value captured in many parts of the business. While many organizations have invested in AI, they are not clear on the enablers that will help create value in business. This study provides a holistic view on the organization and the ecosystem and provides a strategic view to capture value on AI implementation. The strong relation between the organization culture and value creation (*t*-value 3.3517), has a strong implication to business. The business leaders and top management has an important role in creating a conducive culture for AI implementation, that will go on enable value creation.

9. Limitations and Future Scope of Research

While we have collected data across many countries globally and this study based on multiple countries, a focused country approach could provide a more detailed view of what is required by a country to deliver value creation from AI interventions. This will also help understand the ecosystem in the particular country that is critical in resourcing, building AI capability and understand the government policies in AI related implementations. While this research was based on quantitative research method, the scope of future research could be implemented based on a mixed method to understand other AI enablers that may be missing in this study. An area of future research could be on genetic programming [33] capability and its application in business.

10. Conclusion

We initiated our study, after observing a huge potential upside in AI-driven business to enable value creation in business. We found organizations were still piloting AI, and there are only a few organizations that implement AI in an integrated way within the organization [3]. Given that the futuristic outlook on AI and its impact on the business, and limited studies done in this regard, this study aimed to fill this void by conducting empirical research on factors of AI enabling value creation in the business. We developed our research questions, research objectives and hypothesis to be tested. We conducted quantitative research using the questionnaire tool. Four predictor variables and one outcome variable were considered in the research. AI Capability, Organization Culture, Business Integration and Ethics and Governance were part of the exogenous variables. Value creation was the endogenous variable.

The ADANCO 2.4 software supported the data analysis. The software helps establish the variance-based structural equation model and reflective and formative measurement model as well. The hypothesis that was considered, was evaluated using the *t*-value and *p*-value analysis.

All had direct relationships. The relationships between the predictor variables and outcome variable were found significant and therefore all hypothesis were accepted. Among all the independent variables, Organization Culture was identified as the most impactful factor on value creation, followed by Ethics and Governance, AI Capability and Business Integration.

This study has the potential to provide a strategic framework to the industry players, researchers to understand AI enablers on value creation in a holistic way. We have taken into consideration all parts of the organization that includes business functions, business processes and even creating and reinventing the business model to create value creation through AI intervention. We looked at key enablers like AI capability, Organization culture, Business Integration and Ethics and Governance that can go a long way in value creation in business.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Arijit Mitra, being the research scholar conducted the research, analyzed the data and wrote the paper. Dr. A Seetharaman provided the concept of literature review and analysis, and Dr. K. Maddulety provide understanding various concepts in Data Analytics and understanding of the Structural Equation Modelling (SEM) and the software ADANCO 2.4. All authors had approved the final version.

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