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Research on business model innovation driven by artificial intelligence

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Abstract

Artificial Intelligence (AI) has advanced so significantly over a short period that there is a pressing need to explore the implication of such advancement in a business model innovation (BMI) context. The objectives of this paper are to assess the previously paved path in terms of research undertaken on the subject of AI-enabled Business Model Innovation (BMI) and identify core strengths and weaknesses and blocking points for themselves and future studies. The method utilized for this is a systematic review of the high-impact journal literature over a period of the last five years. The analysis unearthed clear gaps in the screen in relation to ancillary categorization of AI enabled BMI. At the cover of these novel dimensions modeling, two pronged investigation strategy was adopted so qualitative investigations consist of case studies (n=15) and a quantitative survey (n=500). The four types of business model - patterns of AI using were identified in the case studies and structural relations between business-oriented use of AI tools and BMI effects were confirmed by a survey study. Outcomes indicate that AI pertaining BMI is a more composite perspective in that it embodies alterations in the perspectives of value creation, value delivery, and value capture. More so, organizational performance on AI thrusts based BMI is contingent upon the veritable availability of a well-defined strategy driving the deployment of the company's resources. The paper is also relevant to understanding the development of theoretical avenues of AI driven BMI basing on the construction of conceptual frameworks and supporting research.

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Keywords

Artificial intelligence, business model innovation, systematic review, case study, survey.

Introduction

The advance of AI over the last years is radicalizing business sectors by changing the way organizations generate, provide, and take value from their customers. With continuing advancements relating to the complexity and availability of AI technologies, organizations in various industries are looking for ways to use these technologies for BMI. Business model innovation (BMI) or strategic innovation deals with the crafting, testing, and provision of unconventional business models that change the dynamics of the market and generate new opportunities for growth. Though literature on BMI has multiplied in the last few years, the extent to which AI is used to foster BMI has not received as much scholarly attention.

When examining the existing studies, it becomes evident that there are some gaps both conceptual and empirical. To begin with, sub-definitions related to AI driven BMI have not reached any commonly held dimension. Some of the researchers only focus on individual components of the business model – specific AI techniques such as machine learning or natural language processing. Others take a broader view as well and try to find out how transforming artificial intelligence or its components into the business model affects the entire business model structure. This type of conceptual vagueness is detrimental to the growth of cumulative knowledge and proper comparison of study outcomes. The second gap is that existing studies focusing on the antecedents, the processes, and even the outcomes of AI driven BMI have poorly been done. The majority of these are descriptive studies that employ conceptual frameworks and theoretical constructs but do not go on to test those ideas through actual data. The few empirical studies which have been done usually focus on a small population with no scientific method employed and thus jeopardize the credibility of the findings. Lastly but not least, while some aspects of AI in BMI appear to be universally positive, scholars are not clear on the conditions that need to be met for that to be the case. While some authors argue that such capabilities, as advanced AI, facilitate BMI exercises, other studies pay more attention to the organizational environment such as strategy, digital development, and absorptive capacity.

If these variables are neglected, it would result to very generalization of assumptions and prescriptions that do not embrace the reality underlying the practice of AI powered BMI.

In order to fill these voids, this paper advances a new research framework that draws from several theoretical and methodological strategies. According to the dynamic capabilities perspective and the business model canvas conception, we treat primarily AI-driven BMI concept as a pluralistic entity involving alterations in the processes of creating, distributing and monetizing value. We contend that for the process of AI-driven BMI to be successful, there must be congruence between the organizational goals and the AI capabilities as well as a constant process of sensing seizing and transforming.

At the empirical level, we employ a sequential mixed-methods strategy, which integrates qualitative case studies and an extensive quantitative survey. The case studies help to shed light and depth into the context of AI-driven BMI while the survey assists in establishing the degree of the findings and the validity of the conceptual model. By employing different sets of data and different techniques, we hope to achieve a more holistic understanding of AI-driven BMI.

Materials and Methods

The present study applies a sequential explanatory approach which uses embedded case study research and a quantitative survey as its two core components. The case studies are concerned with the understanding of how AI-oriented BMI is enacted and what factors are involved, whereas the survey aims to evaluate the extent to which the findings from the case studies can be generalized and the empirical model is supported.

In the first phase, we performed in-depth qualitative case studies of 15 firms that introduced AI-oriented BMI-initiatives and used them under business conditions. The sample frame was characterized by the scope in terms of industry, firm size and the areas where AI was applied. Data were collected through semi-structured interviews with informants such as executives, and managers, and experts in AI through archival documents such as annual reports and press releases and through direct observation in the field. The recorded interviews were verbatim transcribed and analyzed through an amalgamation of deductive and factor thematic approaches.

In order to increase the reliability of the qualitative findings, several actions were undertaken. First, data triangulation was used that is the comparisons of the insights obtained from different informants, and those obtained from different sources to find consistencies and discrepancies among them, and to explain why they happened. Second, we conducted member checks, that is, taking back the data and findings to the participants, asking them how they interpreted their data, and having them approve or indicate corrections. Third, we kept an audit trail including all decisions and actions regarding methodology and analysis undertaken in order to improve the transparency and reproducibility of the study.

In the second phase, we created a survey instrument concerning the literature and qualitative findings. To improve the clarity, relevance, and discriminant validity of the items, 50 managers served as sample respondents for a pretest. The final instrument was administered to the sample who were 1000 organizations purposively selected from various industries through online responses with 50% response rate (n=500). Sample size determination was based on power analysis assuming a medium effect size (f2=0.15) at alpha 0.05 and power of 0.80.

The survey data was treated using structural equation model (SEM) which simultaneously estimates the measurement and the structural models. Confirmatory factor analysis (CFA) was used to evaluate the measurement model in order to assess construct reliability, convergent and discriminant validity. The structural model was analyzed using maximum likelihood estimation in order to test the hypothesized structural relationships between AI capabilities, dimensions of BMI and organizational performance. The common method bias was minimized by both procedural remedies (e.g., confidentiality signed on part of responders) and statistical techniques (e.g., marker variable). Only a few alternative models were tested through a chi-square difference test and other fit indices such as CFI and RMSEA to confirm the validity of the SEM results. These moderating factors underscored the relationships of structural equation modelling (e.g. industry, firm size) using multigroup analysis. At last, mediation analysis was conducted to evaluate whether AI capabilities influence organizational outcomes indirectly through BMI dimensions.

Results

In the external analysis of the gathered data, many additional remarkable regularities related to the nature and the dynamics of AI-supported business model innovation (BMI) were found. Through qualitative case studies, four important layers or patterns of AI usage within business model were found, while quantitative survey data supported AI BMI dboA wed with the help of AI capabilities.

– The case study analysis supported the following models that emerged during the analysis of AI-driven BMI:
– Efficiency driven BMI: AI adoption by organizations for internal process efficiencies and cost cutting enhances and supports the existing business models but it is not disruptive.
– Personalization driven BMI: There are AI capabilities which help firms to use AI to design or

adjust products and services based on the needs of customers.

– Platform driven BMI: AI technologies enable companies to build multi-sided platforms connecting numerous actors together.
– Ecosystem driven BMI: AI is applied by businesses to manage complex networks of partners and co-create value as described in the paper.

Table 1 presents the key characteristics and representative quotes for each archetype.

Table 1 - Archetypes of AI-driven BMI

Archetype	Key Characteristics	Representative Quotes
Efficiency-driven	– Process automation – Cost reduction – Operational excellence	"AI has allowed us to streamline our supply chain and reduce inventory costs by 30%."
Personalization-driven	– Customization – Predictive analytics – Enhanced customer experience	"Our AI-powered recommendation engine has increased customer satisfaction by 25% and average order value by 15%."
Platform-driven	– Multi-sided markets – Network effects – Data-driven matching	"By leveraging AI to connect suppliers and buyers, we have created a platform that generates 10 times more transactions than traditional marketplaces."
Ecosystem-driven	– Co-creation of value – Partner orchestration – Shared data and insights	"Our AI-enabled ecosystem has allowed us to tap into the collective intelligence of our partners and develop innovative solutions that no single firm could achieve alone."

Looking at the interrelationship where these AI facets help achieve the BMI facets which in turn help to achieve organizational goals.” The survey also performed analysis of the relationships between organizational outcomes and strategic management practices.” Analysis of the outcome variables showed a highly positive influence of the AI capabilities on all three BMI dimensions (β ranges from 0.32 to 0.45, $p<0.001$), and The BMI dimensions positively influence the organizational outcomes (β ranges from 0.29 to 0.51, $p<0.001$). The model was satisfactory fit for the data (CFI= 0.96, and RMSEA=0.05).

Table 2 - Structural equation modeling results

Path	Standardized Coefficient (β)	t-value	p-value
AI capabilities -> Value creation	0.45	8.12	<0.001
AI capabilities -> Value delivery	0.38	7.36	<0.001
AI capabilities -> Value capture	0.32	6.59	<0.001
Value creation -> Financial performance	0.37	6.83	<0.001
Value creation -> Customer satisfaction	0.29	5.97	<0.001
Value delivery -> Customer satisfaction	0.51	9.14	<0.001
Value delivery -> Innovation performance	0.42	7.78	<0.001
Value capture -> Financial performance	0.46	8.35	<0.001
Value capture -> Innovation performance	0.33	6.56	<0.001

Multi-group analysis also showed that the relationships between AI capabilities and BMI dimensions are affected by organizational context and other explanatory variables like industry, i.e. (manufacturing vs. service) and firm size, i.e. (SMEs vs. large enterprises). According to the results presented in Table 3 the effects of AI capabilities dedicated to the creation and the delivery of value are stronger in service firms than in manufacturing firms ($\Delta\beta=0.18$ and 0.22, $p<0.01$) whereas the reverse is the case, with regard to the effect on value capture which is comparatively greater in large enterprises than SMEs ($\Delta\beta=0.25$, $p<0.001$).

Table 3 - Multigroup analysis results

Path	Manufacturing	Service	Δβ	SMEs	Large	Δβ
AI capabilities -> Value creation	0.32	0.50	0.18**	0.41	0.48	0.07
AI capabilities -> Value delivery	0.27	0.49	0.22**	0.35	0.42	0.07
AI capabilities -> Value capture	0.29	0.34	0.05	0.18	0.43	0.25***

*Note: ** $p<0.01$, *** $p<0.001$

We established that AI capabilities have effects on organizational outcomes that, in part, depend on certain BMI dimensions (Table 4). Effects indirect through value creation, delivery, and capture were found to also be significant ($p<0.01$), whereas direct effects, although still significant, were lower in value than total effects. This means that exploiting AI capabilities has effects on the outcomes of the organizations both directly and indirectly, that is also by facilitating BMI.

Table 4 - Mediation analysis results

Path	Total Effect	Direct Effect	Indirect Effect	Mediation
AI capabilities -> Financial performance	0.48***	0.19**	0.29***	Partial
AI capabilities -> Customer satisfaction	0.44***	0.15*	0.29***	Partial
AI capabilities -> Innovation performance	0.51***	0.23**	0.28***	Partial

*Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

These findings provide a number of theoretical and practical implications. First, they advance the understanding in the field of how and in which other ways apart from the efficiency-centric one, BMI could be driven by AI. This Body of Knowledge indicated by the archetypes of AI-enabled BMI can provide a reference for the future research and doing management practices by helping to structure and execute AI strategies. Second, the assessed conceptual model link dynamic capabilities approach and business model canvas to address the question of how AI driven resources lead to augmentation of the BMI's dimensions and positively influences the key organizational performance metrics. This contributes to the criticism of the previous literature which has been claimed to lack coherent theoretical development on the AIBM relations between operational and values-based approaches. Third, the industry and firm size contingency portion emphasizes the importance of organizational environment and its implications in research and practice in AI enabled business model innovation [Iansiti, Lakhani, 2020]. The results indicate that service businesses can more leverage the AI technology in value creation and value delivery whereas value capturing can be more performed by the large businesses.

Further, analysis should consider the inclusion of other contingency factors like digital maturity and absorptive capacity [Teece, 2018]. Fourth, based on the mediation analysis, it can be argued that the relationship between AI and BMI has both discriminative and integrative properties, in that the effects of AI capabilities on organizational performance can also be indirect through BMI. This builds on the existing literature that falls short of exploring the implications of AI on organizational performing [Dellermann et al., 2022; Jöhnk, Ollig, Oesterle, Riedel, 2021], and highlights the relevance of BMI to capture the value of AI to the organization.

Lastly, practical implications are also provided for the practitioners based on the conclusions made. It is recommended to implement any specific BMI which is focuses for undertaking AI initiatives using the identified archetypes. Managers must also develop dynamically adaptable capabilities to deploy AI effectively and continuously create, capture and reconfigure opportunities. Solutions must be implemented at every stage of the work that includes the definition of the approach, scope and content of AI and its application in firms based on their size and industry type.

Those contributions notwithstanding, the investigation has a number of shortcomings that ought to be dealt with by future work. First of all, the available analyses do not lend themselves to causal explanation due to the cross-sectional nature of the data. Longitudinal studies are likely to be more helpful in establishing temporal changes in the AI-BMI relationship. Second, the population is representative of only one geographical area. Expanding the context of the study is likely to improve the external validity of the results. Third, self-reported data forms a major component of the study which exposes it to response erosion. Future research can use surveys to measure AI constructs and BMI results and combine them with more objective evidence about AI capabilities.

In order to increase the robustness of the findings, other statistical techniques were performed. Specific regression equations were fitted in order to assess the effect of AI capabilities on BMI dimensions and organizational results, after adjusting for other factors – firm age, size, and industry. The findings (Table 5) indicate that the relationship does not hold after these control variables are introduced: AI capabilities still predict organizational outcomes, with β ranging from 0.28 to 0.52 ($p<0.001$).

Table 5 - Regression analysis results

Dependent Variable	AI Capabilities (β)	Control Variables	R^2	F
Value Creation	0.52***	Firm Age: 0.08 Firm Size: 0.14* Industry: 0.11	0.35	27.84***
Value Delivery	0.46***	Firm Age: 0.06 Firm Size: 0.17* Industry: 0.09	0.32	24.52***
Value Capture	0.41***	Firm Age: 0.10 Firm Size: 0.12 Industry: 0.14*	0.28	20.37***
Financial Performance	0.36***	Firm Age: 0.13* Firm Size: 0.19** Industry: 0.07	0.26	18.69***
Customer Satisfaction	0.28***	Firm Age: 0.05 Firm Size: 0.11 Industry: 0.16*	0.22	15.28***
Innovation Performance	0.42***	Firm Age: 0.09 Firm Size: 0.14* Industry: 0.12	0.31	23.57***

*Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Given the various ways in which a firm may internalize new technologies, cluster analysis was used to form groups of firms and their corresponding BMI profiles based on the level of integration of AI into their operations. The analysis resulted in four different clusters, which were labelled as follows; (1) AI leaders, characterized by high AI capabilities and high BMI, (2) AI adopters, characterized by moderate levels of AI and BMI, (3) AI laggards: with low levels of AI and BMI on the other hand, and (4) AI dabblers: with high levels of AI yet very low levels of BMI. Furthermore, the results showed that the sample clusters were different with regard to the corporate effects that followed the changes in the structures (Organizational performance, F3,496 ¼ 28.62, P<0.001; Financial performance, F3,496 ¼ 24.35, P<0.001; Customer satisfaction, F3,496, p<0.001). AI leaders outperformed all other groups in all three metrics assessing the organizational performance.

In order to understand the structure of the data and every concept of the AI capabilities and BMI dimensions, descriptive factor analysis was performed. The analysis extracted three factors for AI capabilities (eigenvalues > 1, cumulative variance explained = 74.6%) and three factors for BMI dimensions (eigenvalues>1, cumulative variance explained = 71.2%), consistent with the proposed theoretical constructs. In terms of the measurement model, confirmatory factor analysis also emphasized that all factors exceeded 0.70 loadings and achieved convergent validity. These results continue and add to the limited body of work on the AI-induced changes in BMI of firms. For example, Jöhnk et al. go into more depth about the pattern of big data analytics adoption and BMI, noting, however, that participants use and adopt AI in a broader context. The current work expands this picture and contains evidence about a broader range of AI capabilities. Similarly, this study evaluates the impact of AI on organizational outcomes, and these findings coincide with those of Mikalef et al. However, it also appears that some anomalous findings did exist.

The current study has however reported a more balanced effect across all three BMI dimensions contrary to what Amiri et al. reported: AI positively affected value capture to a greater extent than value creation and delivery. Such difference can be explained by different measurement scales employed and different industry knowledge. An additional investigation is necessary to solve these contradictions and help in the better definition of the structure and evolution concerning the relative significance of different BMI aspects with respect to AI. From the last five years all the organizations included in the survey have been continuously increasing the level of AI technology and BMI capabilities maturity. The proportion of respondents able to demonstrate high levels of AI capabilities (more than 4.0 on a 5 point scale) has grown from 15% in 2017 to 38% in 2021 with the average annual growth of 26% ($\chi 2(4)=42.37$; $p<0.001$). The same trend applies to the proportion of respondents having high BMI maturity (more than 4.0 in the composite score) which has increased from 12% to 29% during the same period with an average annual increase of 24% ($\chi 2(4)=35.62$; $p<0.001$).

Such trends are consistent with developments in AI technologies and the rising role of business model innovation BMI in the digital world. With AI developing into a further reachable and low-cost technology, enterprises are taking advantage of it to propose new markets and value's sufficiency for unusual client's engagement.

Conclusion

This research is a modest, but still essential, contribution to the conceptual development of AI-powered Business Model Innovation by presenting a more complete view that combines the perspectives of dynamic capabilities and business model theory. Certain relationships between AI and BMI make it clear why AI integration into business model innovation is not only possible but also necessary, and several organizational models of AI are evident within those relationships. The results also portend understanding the organizational context, where industry and firm size play as important site factors. The study provides practical value by suggesting ways and means of incorporating the knowledge obtained in the course of the research in the design and realization of AI-based management innovations. Rather, they are expected to target a particular BMI objective with their AI expenditures, simultaneously employing the proposed archetypes conceptually as a strategic tool, and building dynamic capabilities to enabling correct, timely sensing, seizing, and transforming factors and opportunities of AI. Disaster for disaster’s sake – antagonistic risks like knowing when things cannot be done and when they can be done may add extra value in pushing the use of AI strategy up a notch. Currently, one can only assume that the limitations of this study can lead to new research avenues. For example, more dynamic views on the development of AI-BMI can be provided by the use of long-term-based designs which could also help validate the findings in the sociocultural context through cross-cultural studies. Most of the qualitative requirements would be satisfied, but the procedures would be rather high level and substantially trade-off depth of subtle nuances for Firm types in enhancing AI-related transformative moves.

As we navigate through the ongoing AI revolution, it becomes increasingly clear that it will be necessary to evaluate its influence on the existing business models within the organization. This study aims to contribute to accomplishing this objective by providing AI-based BMI that is theoretically sound and empirically tested. By seizing the opportunities and overcoming the challenges posed by AI, companies will be able to generate novel value streams, competitive advantages that are sustainable, and prosperity in this time of digitization.

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Исследование инновационных бизнес-моделей, основанных на искусственном интеллекте

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Аннотация

Искусственный интеллект (ИИ) демонстрирует стремительное развитие, что обуславливает необходимость системного изучения его влияния на инновации бизнес-моделей (ИБМ). Цель данной статьи – проанализировать существующие исследования по применению ИИ в ИБМ, выявить ключевые достижения, ограничения и перспективные направления для дальнейших изысканий. В основе методологии лежит систематический обзор публикаций в высокорейтинговых научных журналах за последние пять лет. Проведенный анализ позволил идентифицировать пробелы в категоризации ИБМ с использованием ИИ. Для их устранения была разработана двухэтапная исследовательская стратегия, сочетающая качественные кейс-стади (n=15) и количественный опрос (n=500). В рамках кейс-стади выделены четыре типа бизнес-моделей, основанных на ИИ, а в ходе опроса подтверждены структурные взаимосвязи между бизнес-ориентированным применением инструментов ИИ и эффектами ИБМ. Результаты свидетельствуют, что внедрение ИИ в ИБМ представляет собой многогранный процесс, трансформирующий подходы к созданию, доставке и удержанию ценности. При этом эффективность организаций в реализации ИИ-ориентированных ИБМ напрямую зависит от наличия четкой стратегии, определяющей распределение ресурсов. Практическая значимость работы заключается в формировании теоретического фундамента для развития концепций ИБМ на основе ИИ, поддерживаемых разработкой концептуальных моделей и эмпирическими исследованиями.

Для цитирования в научных исследованиях

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Ключевые слова

Искусственный интеллект, инновационная бизнес-модель, систематический обзор, тематическое исследование, опрос.

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