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AI and Business Model Innovation: Leverage the AI Feedback Loops

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Abstract

Purpose: The article analyzes the effects of Artificial Intelligence (AI) on Business Model Innovation (BMI), focusing on the platform business model.

Design/Methodology/Approach: Proposes a CLD (Causal Loop Diagram) model and analyzes the model to discuss insights about the structure and performance of the business model.

Findings: Shows that AI enables key strategic feedback loops that constitute the core structure of the business model.

Practical Implications: Managers and entrepreneurs who seek to leverage AI should invest in the AI feedback loops. An AI strategy for BMI should seek to create, strengthen, and speed-up AI feedback loops in the business model.

Originality/Value: Analyzes the effects of AI on BMI while accounting for dynamic complexity as a business model property to be understood and leveraged. Contributes to our understanding of the business value and impact of AI.

Keywords: AI strategy, Business Model, Platforms, Digital Transformation, Dynamic Complexity.

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Introduction

AI is expected to have a transformative impact on the economy and society (Brynjolfsson and McAfee, 2016). However, companies are struggling to make sense of the business impact of AI and create a coherent AI strategy. This article brings together the concepts of AI and Business Model Innovation, analyzing the effects of AI on Business Model Innovation. BMI can be seen as a process and an outcome, the innovative business model (Foss and Saebi, 2017). To make the analysis specific and useful, the article focuses on the platform business model (Economides and Katsamakas, 2006; Parker and Van Alstyne, 2005), the most innovative business model archetype in the digital economy (Abdelkafi et al., 2019; Parker, Van Alstyne, and Choudary, 2016).

An extensive literature on business models spans across fields such as management, strategy, innovation, and information systems. In early work, (Osterwalder, Pigneur and Tucci, 2005) called for a clarification of the business model concept. In simple terms, a business model is "a blueprint of how a company does business," and it defines "the logic of the firm": how a company creates and delivers value to customers and how it captures value.

Business model innovation (BMI) is crucial to business viability (Demil and Lecocq, 2010). Several authors propose normative frameworks for practitioners, such as the business model canvas (Osterwalder and Pigneur, 2010), a template of nine building blocks: customer segments, value propositions, channels, customer relationships, revenue streams, key resources, key activities, key partnerships, cost structure.

Zott, Amit, and Massa (2011) note the business model concept is emerging as a new unit of analysis, emphasizing a holistic approach to how a firm does business. Moreover, firm activities play an essential role in a business model, "a system of interconnected and interdependent activities that determines the way the company does business with its customers, partners and vendors."

In most recent reviews, (Massa, Tucci and Afuah, 2017) suggest three interpretations of business model (attributes of firms; cognitive schemas; formal representation of how a business functions) and discuss the relationship with the rest of strategy literature. (Foss and Saebi, 2017) identify issues of construct clarity and research gaps and recommend future research related to complexity and entrepreneurship. (Täuscher and Abdelkafi, 2017) review the value of visual tools in BMI. (Wirtz and Daiser, 2017) explore an integrative BMI framework in which technology and firm dynamics are important dimensions. It also discusses BMI at Google as an illustrative example.

The closest article to our approach is (Casadesus-Masanell and Ricart, 2010), which clarifies the difference between strategy and business model, and proposes that Causal Loop Diagrams (CLDs) are a useful representation of business models illustrating an old-economy airline example.

This article contributes to a rigorous understanding of business model dynamics in the digital economy. It provides a framework to understand AI effects on business models, adding to the literature related to the dynamic impact of technology on business (Georgantzas and Katsamakas, 2008). The critical motivating question is: How can we analyze the effects of AI on BMI while accounting for dynamic complexity as a feature of business that needs to be understood and leveraged?

Approach and Model

We build a framework to explore business models using Causal Loop Diagrams (CLDs). A positive link between two variables in a CLD means that an increase of the first variable leads to an increase of the second variable.

The research focuses on key feedback loops that drive business model performance and sheds light on the dynamic complexity of digital business models. We focus on the platform business model, which is the most important new form of business model enabled by the Internet and digital technologies (Bakos and Katsamakas, 2008; Sorri *et al.*, 2019).

The availability of more content, apps, and services on a digital platform attract more users, which in turn attract even more content, apps and services (Eisenmann, Parker and Van Alstyne, 2006; Hagiu, 2014;

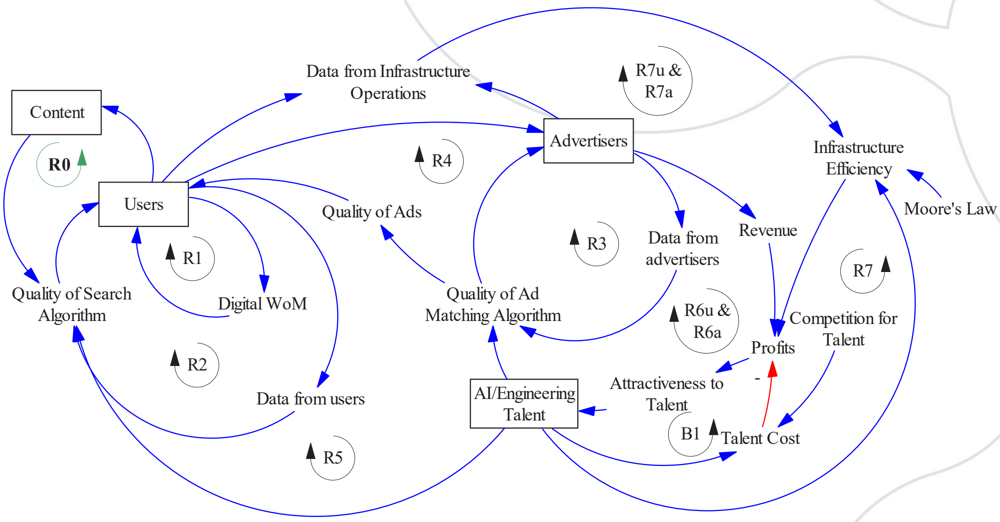

Figure 1: Advertising based digital content and services platform business model (e.g., Google)

Katsamakas and Madany, 2019). This mechanism of two cross-side network effects constitutes a reinforcing feedback loop, depicted at the top left corner of our model (R0 feedback loop in Figure 1). Our model (Figure 1) illustrates the structure of one type of digital platform, an advertising-based content and services platform (e.g., Google). The platform provides users with access to digital content and services and makes revenue from advertisers.

We describe some of the critical feedback loops that constitute the core structure of the business model. *Users* bring more users to the platform through *Digital WoM (Word of Mouth)* (R1 reinforcing feedback loop). This feedback loop is an important mechanism for platform adoption and growth.

More *Users* mean that the platform collects more *Data from users*, which drives higher *Quality of Search Algorithm*, which provides more relevant organic search results, hence attracts more users (R2 reinforcing feedback loop).

Advertisers are attracted by platform *Users*. More *Advertisers* and more *Data from advertisers* help improve the *Quality of Ad Matching Algorithm*. This has two effects: it directly attracts more *Advertisers* (R3 reinforcing feedback loop), and it improves the *Quality of Ads*, which helps attract more *Users*, thus more *Advertisers* (R4 reinforcing feedback loop).

More *Advertisers* raises the platform *Revenue* and *Profits*, which helps attract *AI/Engineering Talent*, which further helps drive a higher *Quality of Search Algorithm*, which brings even more *Users* and more *Advertisers* (R5 reinforcing feedback loop).

AI/Engineering Talent brings improvements to *Quality of Ad Matching Algorithm*, which leads to more *Advertisers* (R6a feedback loop), as well as higher *Quality of Ads* and more *Users* (R6u feedback loop).

AI/Engineering Talent is also crucial for improving *Infrastructure Efficiency*, as they optimize digital infrastructure at scale, aided by Moore's Law. This helps increase *Profits*, which helps attract event more *AI/Engineering Talent* (R7 feedback loop).

Moreover, serving more *Users* and *Advertisers* leads to more *Data from Infrastructure Operations* (e.g., running sophisticated data centers), which is used to further improve *Infrastructure Efficiency* and *Profits*, with associated positive effects on *Users* (R7u feedback loop) and *Advertisers* (R7u feedback loop).

All these reinforcing feedback loops provide the core structure of the ad-based platform business model and drive its performance, growth, and sustainability. The business model performance can be measured by *Profits*, as well as by market-share (number of *Users* and *Advertisers*).

Figure 1 also shows one balancing feedback loop that may moderate the effect of the reinforcing loops. As the platform attracts more *AI/Engineering Talent*, and has to pay higher salaries due to *Competition for Talent*, the *Talent Cost increases* and this hurts *Profits* (B1 balancing loop).

Analysis and Key Insights

AI as a field aiming to build and understand intelligent systems, has a long history and applications, such as expert systems, natural language processing, robotics etc. (Russell and Norvig, 2010). But recent advances in AI, especially in the form of machine learning and neural networks (deep learning), allowed for more innovation and elevated the use of AI in business as a primary concern of business leaders (McKinsey, 2018). For example Google has been using algorithms that learn from data in search since the company's inception.But most recently, Google has substantially improved the quality of search results using deep learning algorithms, such as BERT (Nayak, 2019).

Several researchers have written about the business effect of AI, exploring issues such as the future of work, bias and trust, and the economics of AI (Raj and Seamans, 2019). For example, (Agrawal, Gans and Goldfarb, 2018, 2019) argue that AI lowers the cost of prediction, and this has significant implications for managers. The unique perspective of our article is that it looks at the effect of AI at the level of the business model. We use the proposed framework to understand the effects of AI on business model innovation, focusing on the platform business model.

Figure 1 shows that AI has a crucial effect on a platform business model, because it enables new reinforcing feedback loops that constitute the core structure of the business model and drive its growth and profitability. AI may also strengthen, or speed up, existing reinforcing feedback loops. Table 1 summarizes the effects of AI in a template of three elements: **AI for User Experience**, **AI for Advertiser Experience**, **AI for Efficient Infrastructure at scale**. Each element is a cluster of feedback loops. In all three elements, *Data* is a strategic resource connecting AI with Business Model Innovation. We summarize selected insights from each element.

AI for User Experience: *Data from Users* is a key resource in this cluster of feedback loops that reinforces an improvement of user experience over time. *AI/Engineering talent* leverages *Data from Users* to improve the *Quality of Search Algorithm*, which improves the user experience concerning access to *Content* (R0, R2, R5). *AI/Engineering talent* leverages *Data from Advertisers* to improve the *Quality of Ad-matching Algorithm*, which enhances the user experience for relevant advertising (R4). Other secondary feedback loops that help attract *AI/Engineering talent* (either through more revenues or lower infrastructure costs) also contribute to better user experience (e.g., R6u, R7u).

AI for Advertiser Experience: *Data from Users* is a crucial resource in this cluster of feedback loops that reinforce an improvement of user experience over time. *AI/Engineering talent* leverages *Data from Advertisers* to improve the *Quality of Ad-matching Algorithm* (R3), which improves the targeting of *Users*. Feedback loops, such as R4, that increase the number of *Users* are

AIBM Template Element	Key Feedback Loops	Primary data resources	Other key resources
AI for User Experience	R0, R2, R5, R4	Data from Users, Data from Advertisers	AI/Engineering Talent, Search Algorithm, Ad-Matching Algorithm
AI for Advertiser Experience	R3, R4	Data from Advertisers	AI/Engineering Talent, Ad-Matching Algorithm
AI for Efficient Infrastructure at scale	R7, R7u, R7a	Data from Infrastructure Operations	AI/Engineering Talent, Infrastructure Optimization Algorithms

Table 1: AIBM template – Key effects of AI on business model

crucial to the business model. Other secondary feedback loops that help attract *AI/Engineering talent* also contribute to better advertising experience (e.g., R6a, R7a).

AI for Efficient Infrastructure at scale: *AI/Engineering talent* leverages *Data from Infrastructure Operations* to improve the *Efficiency of Infrastructure*, which increases *Profits* and help attract even more *AI/Engineering talent* in a competitive market for talent (R7). Other secondary feedback loops that help attract more *Users* and more *Advertisers* help the company collect more *Data from Infrastructure Operations,* contributing to improved economies of scale (R7u, R7a).

We can now generalize these mechanisms into two high-level AI-related processes that apply to all business models: data accumulation and data exploitation.

Data accumulation is the process of aggregating data from serving customers and other business processes and operations. Figure 1 shows how *Data from Users, Data from Advertisers*, and *Data from Infrastructure Operations* accumulate in the platform business model. Data from external sources (data acquisition) can support data accumulation when necessary.

Data exploitation is the process of using Artificial Intelligence (AI) to leverage accumulated data to create business value. Data exploitation helps improve the quality of platform services and business processes, as well as the overall performance of the business model. Figure 1 shows how the platform business model exploits data to improve the *Quality of Search Algorithm*, *Quality of Ad Matching,* and *Infrastructure Efficiency*.

Our causal model shows that data accumulation and data exploitation are crucial processes. Most importantly, those two processes reinforce each other: the more data a platform accumulates, the more data it can exploit, which helps collect even more data.

Discussion and conclusion

The unique contribution of this article is that it brings together the BMI and AI concepts, and it analyzes the effects of AI at the level of business model.

This article makes progress towards understanding business models as complex systems (Massa, Viscusi and Tucci, 2018). We focused on the dynamic, not the combinatorial, complexity of a business model. We presented a framework for describing the structure of digital business models using causal loop diagrams (CLD). The framework brings together key platform resources, such as *data*, *algorithms*, *AI talent*, and *infrastructure*. We proposed a three-element template (AIBM), and we showed that the feedback loop concept is critical in understanding the effects of AI at the level of business model. We generalized our discussion into data accumulation and data exploitation processes that reinforce each other.

Our research provides several insights for managers and entrepreneurs. First, mapping the business model using CLDs can be very powerful in the fast-changing digital economy, where platforms and platform ecosystems are prevalent (Jacobides, Cennamo, & Gawer, 2018; Katsamakas, 2014; Parker, Van Alstyne, & Choudary, 2016). A focus on feedback loops can help managers map the core structure of their business model that drives behavior and business performance. Moreover, it supports communication and assists managers and entrepreneurs to refine their mental models (Groesser and Jovy, 2016; Moellers *et al.*, 2019).

Second, managers need to understand and invest in the AI feedback loops in their business model. An AI strategy for BMI should seek to create, rewire, strengthen, and speed-up AI feedback loops in the business model. Managers and entrepreneurs need to ask: *Do the "AI feedback loops" work for our company? Or they work against our company? How can we best leverage the "AI feedback loops" in our BMI initiatives?*

Third, managers need to invest in the reinforcing mechanism of data accumulation and data exploitation to maximize the value of AI in their company.

We call for more research that accounts for the dynamic complexity in the context of BM and AI. Future research could map and analyze the CLDs of more business models, and synthesize that knowledge into generic patterns. Moreover, future work could take the analysis a step forward, building computational models.

References

Abdelkafi, N. *et al.* (2019), Multi-sided platforms, *Electronic Markets*, 29(4), pp. 553–559. doi: 10.1007/s12525-019-00385-4.

Agrawal, A., Gans, J. and Goldfarb, A. (2018), *Prediction Machines: the simple economics of artificial intelligence*, *Harvard Business Review Press*. doi: 10.1016/0166-3615(86)90070-9.

Agrawal, A., Gans, J. S. and Goldfarb, A. (2019), Exploring the impact of artificial Intelligence: Prediction versus judgment, *Information Economics and Policy*, 47, pp. 1–6. doi: 10.1016/j.infoecopol.2019.05.001.

Bakos, Y. and Katsamakas, E. (2008), Design and ownership of two-sided networks: Implications for internet platforms, *Journal of Management Information Systems*, 25(2), pp. 171–202. doi: 10.2753/MIS0742-1222250208.

Brynjolfsson, E. and McAfee, A. (2016), *The Second Machine Age*. New York: W. W. Norton & Company.

Casadesus-Masanell, R. and Ricart, J. E. (2010), From strategy to business models and onto tactics, *Long Range Planning*, 43(2–3), pp. 195–215. doi: 10.1016/j.lrp.2010.01.004.

Demil, B. and Lecocq, X. (2010) Business model evolution: In search of dynamic consistency, *Long Range Planning*, 43(2–3), pp. 227–246. doi: 10.1016/j.lrp.2010.02.004.

Economides, N. and Katsamakas, E. (2006), Two-sided competition of proprietary vs. open source technology platforms and the implications for the software industry, *Management Science*, 52(7) pp. 1057-1071. doi: 10.1287/mnsc.1060.0549.

Eisenmann, T., Parker, G. and Van Alstyne, M. W. (2006), Strategies for two-sided markets, *Harvard Business Review*, 84(10), pp. 92–101.

Foss, N. J. and Saebi, T. (2017) Fifteen Years of Research on Business Model Innovation: How Far Have We Come, and Where Should We Go?, *Journal of Management*, 43(1), pp. 200–227. doi: 10.1177/0149206316675927.

Georgantzas, N. C. and Katsamakas, E. (2008), Information systems research with system dynamics, *System Dynamics Review*, 24(3), pp. 274–284. doi: 10.1002/sdr.420.

Groesser, S. N. and Jovy, N. (2016), Business model analysis using computational modeling: a strategy tool for exploration and decision-making, *Journal of Management Control*, 27(1), pp. 61–88. doi: 10.1007/s00187-015-0222-1.

Hagiu, A. (2014), Strategic decisions for multisided platforms, *MIT Sloan Management Review*, 55(2), pp. 71–80.

Jacobides, M. G., Cennamo, C. and Gawer, A. (2018), Towards a theory of ecosystems, *Strategic Management Journal*, 39(8), pp. 2255–2276. doi: 10.1002/smj.2904.

Katsamakas, E. (2014), Value network competition and information technology, *Human Systems Management*, 33(1–2). doi: pp. 7-17 10.3233/HSM-140810.

Katsamakas, E. and Madany, H. (2019), Effects of user cognitive biases on platform competition, *Journal of Decision Systems*, 28(2), pp. 138–161. doi: 10.1080/12460125.2019.1620566.

Massa, L., Tucci, C. L. and Afuah, A. (2017), A critical assessment of business model research, *Academy of Management Annals*, 11(1), pp. 73–104. doi: 10.5465/annals.2014.0072.

Massa, L., Viscusi, G. and Tucci, C. (2018), Business Models and Complexity, *Journal of Business Models*, 6(1), pp. 59–71. doi: 10.5278/ojs.jbm.v6i1.2579.

McKinsey (2018), *An executive's guide to AI*, *Report*.

Moellers, T. *et al.* (2019), System dynamics for corporate business model innovation, *Electronic Markets*. Electronic Markets, pp. 387–406. doi: 10.1007/s12525-019-00329-y.

Nayak, P. (2019), *Understanding searches better than ever before*, *Google Blog*. Available at: https://www.blog.google/products/search/search-language-understanding-bert/ (Accessed: 1 May 2020).

Osterwalder, A. and Pigneur, Y. (2010), *Business Model Generation*, *Wiley*. Hoboken, NJ: Wiley.

Osterwalder, A., Pigneur, Y. and Tucci, C. L. (2005), Clarifying Business Models: Origins, Present, and Future of the Concept, *Communications of the Association for Information Systems*, 16(1), pp. 1–25. doi: 10.17705/1cais.01601.

Parker, G., Van Alstyne, M. and Choudary, S. (2016), *Platform Revolution*. New York: W.W. Norton & Company.

Parker, G. G. and Van Alstyne, M. W. (2005), Two-sided network effects: A theory of information product design, *Management Science*, 51(10), pp. 1449–1592. doi: 10.1287/mnsc.1050.0400.

Raj, M. and Seamans, R. (2019), Primer on artificial intelligence and robotics, *Journal of Organization Design*, 8, 11 (Note: it is online article so it does not have pages, it is just issue 8, article 11) doi: 10.1186/s41469-019-0050-0.

Russell, S. and Norvig, P. (2010), *Artificial Intelligence: A Modern Approach*. 3rd editio, *Pearson*. 3rd editio. New York: Prentice Hall. doi: 10.1017/S0269888900007724.

Sorri, K. *et al.* (2019), Business Model Innovation with Platform Canvas, *Journal of Business Models*, 7(2), pp. 1–13.

Täuscher, K. and Abdelkafi, N. (2017), Visual tools for business model innovation: Recommendations from a cognitive perspective, *Creativity and Innovation Management*, 26(2), pp. 160–174. doi: 10.1111/caim.12208.

Wirtz, B. W. and Daiser, P. (2017), Business Model Innovation : An Integrative Conceptual Framework, *Journal of Business Models*, 5(1), pp. 14–34.

Zott, C., Amit, R. and Massa, L. (2011), The business model: Recent developments and future research, *Journal of Management*, 37(4), pp. 1019–1042. doi: 10.1177/0149206311406265.

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