

How generative AI drives business model innovation: evidence from Chinese manufacturing firms

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Article

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Abstract

Generative artificial intelligence (GAI), as a groundbreaking technology in the field of artificial intelligence, is gradually permeating business model innovation (BMI) within firms. This study, grounded in the Resource-Based View (RBV) and Attention-Based View (ABV), explores the role and mechanisms of GAI in BMI and examines the moderating effect of managerial digital concern. Through a survey of executives in manufacturing firms in the Yangtze River Delta region of China, this research validates the proposed hypotheses. Empirical analyses indicate that GAI adoption significantly fosters both novelty and efficiency business model innovations. Additionally, managerial digital concern plays a significant moderating role, substantially enhancing the positive impact of GAI on BMI. This study not only enriches the theoretical research on GAI and BMI by providing new theoretical perspectives and empirical evidence but also offers practical guidance for firms on effectively leveraging GAI to drive BMI.

1. Introduction

- With the advancement of artificial intelligence (AI) providing new tools and opportunities for firms, generative AI (GAI), as an emerging technology, is gradually gaining attention from firms. GAI refers to computational methods that produce fresh and meaningful material (such as text, graphics, or audio) from training data (Feuerriegel et al., 2024). It has been demonstrated as a new technological paradigm driving organizational innovation and enhancing efficiency (Mariani & Dwivedi, 2024), showing extensive application potential in various functional areas like marketing, operations, and R&D. For example, GAI tools such as DALL-E and ChatGPT greatly boost output, enhance the caliber of the work, and encourage creativity in product design (Akhtar et al., 2024). ChatGPT, through its conversational style resembling multi-round prompts, engages users more effectively compared to traditional large-scale language models (Talaie-Khoei et al., 2024). Furthermore, ChatGPT can be utilized by customer service departments to automate customer interactions and generate rapid, highly accurate natural language responses. This can help uncover potential customers, boost sales, and pinpoint areas where products or services need to be improved (Holmström & Carroll, 2024). This not only has a substantial impact on firm productivity but also acts as a powerful driver of business model transformation (Kanbach et al., 2024).

Within the field of innovation research, business model innovation (BMI) has increasingly emerged as a critical topic, centering on how firms systematically construct, strengthen, and extend mechanisms for value creation, delivery, and capture (Vaska et al., 2021). With the rise of next-generation digital technologies, firms are experiencing profound changes in their external environment, necessitating adaptive adjustments and structural innovations in their business models (Amit & Zott, 2020). Against this backdrop, firms are no longer confined to incremental optimization of products, services, and business processes; rather, they increasingly rely on cutting-edge digital technologies to drive fundamental transformations in their business models, thereby pursuing sustainable competitive advantages (Zare & Persaud, 2024). Existing studies have shown that artificial intelligence, as a key enabling technology, significantly accelerates the process of business model innovation and compels firms to redesign their operational logic (Lee et al., 2019). In particular, the rapid advancement of GAI is facilitating firms' transition from traditional product-oriented models toward more sophisticated digital business models (Paiola & Gebauer, 2020; Gebauer et al., 2020). For example, GAI can create virtual assistants that offer customers rapid and personalized service responses (Gupta et al., 2024). Additionally, it may be utilized to create customized marketing materials that let firms interact with clients in novel ways (Aydin et al., 2023). Although existing research widely recognizes the importance of GAI, the literature remains unclear on its specific impacts and mechanisms in BMI. Therefore, we consider the impact of GAI on firm business models and pose the question: How does GAI influence BMI? What are the specific mechanisms at play?

Firms' innovation activities and research objectives require organizational resources and capabilities to achieve BMI (Teece, 2010). As key decision-makers in firms, executives' experiences and behaviors significantly impact BMI. Existing research indicates that the actions of executives are crucial to the success of BMI (Zhu et al., 2023). Managerial digital concern, as a scarce and valuable resource, directly determines the strategic direction and priority of resource allocation within firms (Yao et al., 2023). In the context of current digital transformation, the extent of executives' concern for GAI will directly influence the intensity of investment, depth of R&D, and scope of application of this technology within firms. As firms increasingly focus on

GAI, this study further explores whether executives' digital concern can alter the extent of GAI application in firms. Therefore, we propose the second research question: Under the influence of managerial digital concern, how does GAI affect BMI?

To empirically examine the proposed hypotheses, data were gathered through a structured questionnaire administered to top executives from manufacturing enterprises located in China's Yangtze River Delta region. The empirical results indicate that GAI promotes novelty BMI (NBMI) by enhancing business model creativity and customer demand analysis. Concurrently, GAI fosters efficiency BMI (EBMI) by improving decision-making efficiency and optimizing resource management. Furthermore, managerial digital concern moderates the relationship between GAI and BMI, amplifying the positive impact of GAI on BMI.

Our study offers several important contributions to the current literature. First, this study extends the application research on GAI. Previous studies primarily focused on the broad applications of GAI across various fields, including healthcare, law, business, and entertainment (Sundberg et al., 2024; Gupta et al., 2024; Feuerriegel et al., 2024). However, research on GAI within business models is still in its infancy. By exploring the relationship between GAI and BMI, our study extends the understanding of GAI in business and organizational contexts.

Second, this study enriches the theoretical understanding of BMI. In a rapidly evolving digital environment, business model transformation is imperative. While previous studies have recognized that GAI plays a major influence in BMI, the precise processes by which it affects BMI are still not well understood. Through empirical analysis and theoretical argumentation, we delve into the specific mechanisms of how GAI impacts BMI, providing targeted insights for firms to implement BMI.

Third, our research expands the study of the moderating effect of managerial digital concern. Existing research has insufficiently emphasized the importance of managerial digital concern, an essential internal factor that decisively influences the application of GAI. From an attention-based perspective, managerial digital concern is a critical capability that fosters an organizational climate conducive to leveraging GAI for BMI. This study examines how GAI impacts BMI under the influence of managerial digital concern, thereby enriching the body of research on managerial digital concern.

2. Theory and hypothesis

2.1 theoretical basis

The relationship between GAI and BMI can be effectively interpreted through the Resource-Based View (RBV) theoretical lens. From this perspective, sustainable competitive outcomes arise when firms possess and leverage strategically distinctive assets and organizational capabilities that are difficult for competitors to replicate or replace. Within this framework, GAI is distinguished as a new kind of digital asset that can generate useful and creative outputs on its own, including ideas, content, and solutions (Singh et al., 2024). By producing distinctive and creative resources, this feature enables firms with sophisticated GAI capabilities to have a competitive edge (Nayak et al., 2023).

According to RBV, the uniqueness of GAI lies in its ability to enhance organizational efficiency and adaptability through innovation, including accelerating decision-making processes and providing advantages in solving complex problems (Hsu & Ching, 2023). Additionally, GAI exhibits strategic relevance due to its high degree of alignment with firms' existing technological infrastructures and its capacity to enhance analytical precision, accelerate managerial decision processes, and strengthen competitive positioning within dynamic markets (Abrokwah-Larbi, 2023). Consequently, in order to achieve more effective operations and increased competitiveness, firms must successfully incorporate GAI into their business processes (Singh et al., 2024).

The ability of GAI to autonomously produce new content or solutions can greatly boost a firm's creativity, efficiency, and adaptability (Hsu & Ching, 2023). Strategic implementation of GAI can enhance internal collaboration, optimize operational processes, and bolster decision-making capabilities, thereby increasing overall competitiveness (Abrokwah-Larbi, 2023). Firms that effectively integrate GAI into their B2B procedures show improved decision-making, operational effectiveness, and competitive advantage (Chen et al., 2022). From the perspective of RBV, we can better understand the strategic importance of

GAI in firms and how it serves as a unique resource driving BMI and optimization. By effectively leveraging GAI, organizations can achieve BMI, thereby improving overall performance and market competitiveness.

However, the successful application and integration of GAI depend not only on the technology itself but also significantly on the digital concern of the firm's top executives. Based on the Attention-Based View (ABV) theory, executives play a crucial role in guiding and allocating organizational resources. ABV posits that organizational decision-makers, particularly the top management team, shape the strategic direction and behavioral patterns of the organization through their focus of concern (Cho & Hambrick, 2006; Tuggle et al., 2010). In the context of digital transformation, the extent to which GAI is promoted and applied within an organization largely depends on the concern of executives (Yao et al., 2023). Managerial digital concern not only influences their decisions regarding technology investments but also determines the allocation of organizational resources, thereby impacting the research, development, and application of GAI.

The concern of executives is a scarce resource, and they tend to allocate it to areas critical to the firm's survival and success. Top executives engage in environmental scanning to identify and evaluate the potential of GAI in organizational operations, dedicating time and effort to support and drive the application of this technology (Hambrick & Mason, 1984). A strong managerial concern for digital technology enhances the effective deployment of GAI and enables firms to leverage its innovative potential for long-term competitiveness in dynamic market conditions.

GAI, as a unique digital resource, combined with the digital concern of executives, constitutes a critical driving force for BMI. By effectively integrating these two resources, firms can enhance their innovation capabilities and market responsiveness, seizing the initiative in the wave of digital transformation and leading new industry trends. Given the accelerating pace of digitalization, firms should prioritize executives' concern for GAI and actively explore how to incorporate this emerging technology into BMI to achieve sustainable competitive advantage.

2.1 GAI and NBMI

NBMI hinges on the development and application of new ideas. NBMI is exhibited by creating new transaction mechanisms or by establishing new connections between actors in the business model (Zott & Amit, 2007, 2008). GAI significantly drives NBMI by generating new ideas, products, and services, and analyzing customer feedback.

First, GAI has the ability to independently generate novel ideas and solutions (Garbuio & Lin, 2021; van Dun et al., 2023), aiding firms in achieving innovative business practices. By analyzing data, GAI produces new ideas and content, demonstrating its significant potential to enhance various value creation mechanisms such as knowledge generation, task improvement, and autonomous decision-making (Akhtar et al., 2024). The combined effect of these mechanisms will drive the development of new business concepts and spawn new products and services, ultimately forming entirely new business models. Within the marketing domain, GAI serves as an enabling technology that supports ideation, uncovers latent patterns from large-scale datasets, anticipates market dynamics, and delivers highly tailored content aligned with organizational communication strategies, thereby reshaping how marketing decisions are formulated and executed (Verma et al., 2023; Dwivedi et al., 2023). For example, ChatGPT can quickly produce emails, articles, and social media postings for marketing purposes (Rivas & Zhao, 2023). Moreover, it is highly effective in data analysis, aiding marketers in extracting valuable insights and offering strategic guidance (Gupta et al., 2024). Firms utilize GAI to analyze data and offer insights, supporting them in refining ideas and developing more effective products and services to meet customer needs.

Second, GAI drives NBMI by understanding customer preferences and feedback, enabling the provision of personalized products and services. Market research may be automated by GAI, which can provide comprehensive data on customer behavior, competitive environments, and industry trends (Arman & Lamiyar, 2023). According to Gupta et al. (2024), firms may enhance their offerings by using this technology to evaluate client feedback and discussions via chatbots, emails, and social media platforms. For example, clients may communicate with chatbots powered by ChatGPT, expressing their requirements, wants, and problems, and getting prompt and efficient assistance. Additionally, marketers find that leveraging GAI helps gain deeper insights into consumer behavior and preferences, fostering closer connections with customers (Echeberria, 2022). By offering individualized and tailored services, GAI is also essential in improving the client experience (Singh et al., 2024). For

example, ChatGPT-enabled chatbots may process and reply to client inquiries instantly, providing prompt service and enhancing the user experience. In summary, the application of GAI demonstrates great potential in generating new ideas and understanding customer needs, leading us to propose:

H1: The application of GAI positively promotes NBMI.

2.2 GAI and EBMI

Efficiency BMI (EBMI) relies on the reflection and optimization of existing business models. Its main goal is to use innovation to lower transaction costs and boost transaction efficiency (Zott & Amit, 2007, 2008). GAI significantly drives EBMI by enhancing decision-making efficiency, improving market responsiveness, and managing resources and time effectively.

GAI facilitates EBMI by streamlining data-driven decision-making procedures, offering real-time insights, and improving organizational response to changing market circumstances (Olan et al., 2022; Prasad Agrawal, 2023). GAI can process large datasets and plays a crucial role in supporting both repetitive and creative tasks (Singh et al., 2024). By automating routine processes, GAI boosts creativity and efficiency across various business operations (Mariani & Dwivedi, 2024). For example, ChatGPT can analyze customer conversation data, enabling customer-facing employees to respond more comprehensively to customer needs. Firms can leverage GAI to collect and process conversation data, improving future response capabilities through fine-tuning and iterative training, thereby managing new types of issues more effectively and providing rapid responses (Talaie-Khoei et al., 2024).

Second, GAI significantly advances EBMI by optimizing resource and time management (Qureshi et al., 2023). The application of GAI in content creation introduces new capabilities that can greatly improve efficiency when leveraged effectively. Rather than replacing human effort, AI-enabled content creation reallocates employee attention toward higher-value activities, allowing individuals to focus on customization, refinement, and strategic alignment, which in turn leads to noticeable gains in labor efficiency and organizational output quality (Kanbach et al., 2024). Firms may easily integrate ChatGPT into their current operations while looking at creative ways to get the most out of it. Marketers may benefit greatly from ChatGPT and other AI solutions (Gupta et al., 2024), which streamline tasks like ideation, research, and content creation and save a ton of time and effort (Lund & Wang, 2023). In summary, the application of GAI demonstrates great potential in enhancing decision-making efficiency and resource management, leading us to propose:

H2: The application of GAI positively promotes EBMI.

2.4 Moderating role of managerial digital concern

2.4.1 Moderating role of managerial digital concern on GAI and NBMI

First, managerial digital concern enhances the impact of GAI on knowledge creation and service innovation by emphasizing digital trends and technological advancements. From a managerial perspective, executives with heightened awareness and concern for digital technologies are better positioned to recognize the strategic potential embedded in GAI applications (Yao et al., 2024). Such cognitive orientation increases the likelihood that firms will leverage GAI to pursue novel market opportunities and to experiment with new product or service offerings. Managerial digital concern increases the organization's investment and support for GAI, allowing it to be more deeply integrated into the innovation process. The prioritization by executives accelerates the integration of GAI with the existing knowledge system, enhancing its effectiveness in knowledge creation, task augmentation, and autonomous agency, thereby promoting NBMI. Second, managerial digital concern drives market research and customer demand analysis (Heller Baird & Gonzalez-Wertz, 2011), facilitating the application of GAI in products and services, thereby enhancing customer experience and satisfaction. Managerial digital concern encourages the organization to actively utilize GAI to analyze customer preferences and feedback. Through resource allocation and strategic guidance (Adner & Helfat, 2003), executives can ensure a more extensive and profound application of GAI in market research and customer demand analysis. Executives leverage the feedback provided by GAI to better meet customer needs, fostering NBMI.

In summary, higher managerial digital concern enhances the role of GAI in generating new ideas and optimizing marketing strategies, thereby driving NBMI. As a result, we advance the following hypothesis:

H3: Managerial digital concern enhances the positive impact of GAI application on NBMI.

2.4.2 Moderating role of managerial digital concern on GAI and EBMI

First, managerial digital concern ensures that GAI can efficiently process data, provide real-time insights, and enhance decision-making efficiency and market responsiveness. Managerial digital concern signifies a greater focus on digital technology and data-driven decision-making processes (Teece, 2016). This focus encourages the organization to leverage the real-time insights and data analysis results provided by GAI, thereby increasing their sensitivity to and insight into new technologies and trends. Executives can promote the construction of data infrastructure and the enhancement of data analysis capabilities to ensure that large datasets may be effectively processed and analyzed by GAI, which improves an organization's response to changing market circumstances and offers real-time insights. Managerial digital concern also drives investment in automation and intelligence (Brock & von Wangenheim, 2019), making GAI more effective in supporting both repetitive and creative tasks, thereby improving overall operational efficiency. Second, managerial digital concern helps identify bottlenecks and inefficiencies in processes and introduces GAI technology to achieve process automation and intelligence. This automation and intelligence not only improve operational efficiency but also reduce labor and time costs, providing robust support for the formation of efficient business models. Through strategic planning and resource allocation (Besson & Rowe, 2012), executives can ensure that GAI effectively supports business operations, saving significant time and effort, and enhancing productivity and competitiveness.

In summary, elevated levels of managerial digital concern amplify the capacity of generative artificial intelligence to stimulate idea generation and refine market-facing activities, thereby reinforcing firms' EBMI. Based on this reasoning, we advance the following hypothesis:

H4: Managerial digital concern enhances the positive impact of GAI application on EBMI.

The conceptual framework underpinning this study is illustrated in Fig. 1.

3. Data and methods

3.1 Data sources

The data for this study were collected through the distribution of questionnaires. The primary sources of the survey were manufacturing firms in the Yangtze River Delta region, and the respondents were mid-to-senior-level managers within these firms. As one of China's most industrially intensive and technologically advanced regions, the Yangtze River Delta occupies a strategic position in national manufacturing development and has emerged as a frontrunner in the adoption and diffusion of artificial intelligence-driven digital transformation. Numerous firms and organizations in this area are exploring and practicing new business models and innovative methods. The region boasts robust policy support and a well-developed industrial ecosystem, which collectively drive the cross-sector integration and innovative application of AI technology. Therefore, it was selected as the sample source for this study. To ensure the accuracy and applicability of the questionnaire items, a preliminary survey was conducted. The designed questionnaire was distributed to 20 part-time MBA students who completed it, followed by discussions and feedback sessions. The questionnaire was also reviewed by experts in relevant fields within academic institutions. Based on feedback from both the experts and the respondents, the questionnaire items were refined. The formal survey underpinning this study was implemented over a five-month interval, spanning from March 2024 to July 2024. To avoid common method bias, we employed multi-source data collection and a split-questionnaire design. Two separate questionnaires were created: Questionnaire 1 included the explanatory variables of this study—GAI, managing digital concern, and some control variables. Questionnaire 2 contained the dependent variables—NBMI, EBMI, and additional control variables. Both questionnaires were distributed within the same firms. Questionnaire 1 was distributed in paper form in the first week, and

Questionnaire 2 was sent three weeks later via online survey or email. Different mid-to-senior-level managers completed each questionnaire, and the responses were matched using firm codes.

A total of 800 questionnaires were distributed throughout the four-month survey period, and 649 of them were returned, yielding an 81.1% response rate. 514 genuine and complete questionnaires were obtained, producing an effective response rate of 64.25%, after invalid questionnaires were eliminated and the remaining replies were matched by business codes.

3.2 Variable measurement

To test the hypotheses proposed in this study, we adopted well-established scales from existing research, refining the items through a pilot study, and then divided them into Questionnaire 1 and Questionnaire 2. A 5-point Likert scale was used in the surveys, with 1 denoting "strongly disagree" and 5 denoting "strongly agree." The particular items created for each variable in the surveys are listed in Appendix Table A1.

3.2.1 Independent variable: generative AI

In this study, GAI is conceptualized as a class of intelligent systems capable of producing novel outputs in response to human prompts. By leveraging sophisticated learning architectures and pattern-recognition algorithms, these technologies generate original artifacts across multiple modalities, including written language, visual imagery, audiovisual material, and sound-based content. By utilizing extensive data sets (e.g., big data) and emulating human intelligence through trained models and algorithms, these systems can generate outputs like text responses, visual content, audio clips, and videos. Drawing from Singh et al. (2024), we used four items to measure GAI, including statements like "Adopting generative AI in my position would significantly increase firm productivity."

3.2.2 Dependent variable: business model innovation

BMI is the dynamic process by which businesses purposefully change and modify their fundamental components and business logic to respond to the always shifting external environment (Bucherer et al., 2012). Two essential characteristics of business models are novelty and efficiency (Zott & Amit, 2007). In practice, novelty and efficiency orientations are two important ways that BMI is expressed (Pati et al., 2018; Liu et al., 2022). EBMI involves actions aimed at improving transaction efficiency, with the goal of reducing systemic costs caused by uncertainty, complexity, and information asymmetry in transactions. NBMI refers to the creation of new economic exchange methods among participants, aiming to generate new value through developing new products, offering new services, exploring new markets, and creating new transaction methods. Building on the research of Zott and Amit (2007) and Zhu et al. (2023), we used five items each to measure NBMI and EBMI. Items for NBMI included statements like "New ways can bring new partners to firms," while items for EBMI included statements like "Firms are committed to improving the efficiency of the use of existing resources."

3.2.3 Moderating variable: managing digital concern

Managing digital concern can be understood as the degree to which firm managers prioritize the application of digital technologies and methods in firms' management and operations (Wang et al., 2023). Based on the studies by Yao et al. (2023), we measured managing digital concern using three items, with example items including "Our firm regards digital technology innovation as a key component of digital management."

3.2.4 Control variables

Following the research of Zhu et al. (2023), Xie et al. (2023), and Zhang et al. (2023), we controlled for several factors that could influence BMI. These included firm age, firm size, firm ownership, profitability, R&D expenditure intensity, and environmental dynamism. Firm age was measured by the number of years the firm had been in operation (1 = "less than 3 years," 2 = "3–10 years," 3 = "10–20 years," 4 = "more than 20 years"). Firm size was measured by the number of employees (1 = "fewer than 50," 2 = "50–200," 3 = "200–500," 4 = "more than 500"). Firm ownership was measured using two dummy variables: domestic and private. Sales revenue was measured by the average annual sales over the past three years (1 = "less than 10 million RMB," 2 = "10–20 million RMB," 3 = "20–30 million RMB," 4 = "30–50 million RMB," 5 = "more than 50 million RMB").

R&D intensity was measured by the changes in R&D expenditures over the past three years (1 = "significantly decreased," 2 = "decreased," 3 = "remained the same," 4 = "increased," 5 = "significantly increased"). Environmental dynamism was measured based on the market environment changes faced by the firm, using a well-established scale developed by Jansen (2006), with representative items like "The market and customer demands of this firm change rapidly." We measured this using the average of five items.

3.3 Sample distribution and reliability and validity test

The distribution of the survey sample is shown in Table 1. Male respondents made up 59.92% of the sample. In terms of age, 39.49% of the participants were between the ages of 36 and 45. 62.73% of the respondents had a bachelor's degree or above. 75.48% of the respondents had more than five years of work experience. In terms of their positions, the majority of the respondents were senior executives other than CEOs and board members. Most of the surveyed firms were non-state-owned (68.29%), with a majority having been in operation for over 10 years (55.06%), and most had between 50 to 500 employees (82.84%). Overall, the sample is fairly representative and aligns well with the research context.

Table 1
Descriptive statistics of the sample.

Classification	Items	Number	Percentage (%)
Gender	Male	308	59.92
	Female	206	40.08
Age (years old)	< 25	35	6.81
	26–35	171	33.27
	36–45	203	39.49
	46–55	75	14.59
	> 55	30	5.84
Education	Below college	142	27.63
	Bachelor's degree	319	62.06
	Master's degree	21	4.09
	Doctor's degree	32	6.23
Working experience (years)	<3	63	12.26
	3–5	63	12.26
	6–10	141	27.43
	10–15	121	23.54
	> 15	126	24.51
Position	General Manager/Vice General Manager	54	10.51
	President/Vice President	48	9.34
	CEO	31	6.03
	Chairman/Executive Director	16	3.11
	Other Directors	365	71.01
Firm ownership	State owned	163	31.71
	Private owned	351	68.29
Firm age (years)	<3	18	3.5
	3–10	213	41.44
	10–20	224	43.58
	> 20	59	11.48
Firm size (number of employees)	< 50	170	13.07
	50–200	284	55.25
	200–500	39	27.59
	> 500	21	4.09

The validity and reliability of the questionnaire have to be evaluated before to conducting the analysis. The analytical results for the research variables' validity and reliability are shown in Table 2. The findings show that all variables have Cronbach's alpha

values more than 0.8 and composite reliability (CR) values, indicating strong reliability. The average variance extracted (AVE) for each variable was larger than 0.6 and all factor loadings were greater than 0.8, indicating good convergent validity. To reduce the common method bias, a split-questionnaire design and Harman's single-factor test were used. After dimensionality reduction, the variance described by the first unrotated component was 26.62%, which is less than the 40% limit, suggesting that common method bias is not a significant issue.

Table 2
Reliability and validity tests.

Variable	KMO	Bartlett's test	Factor loading	AVE	CR	Cronbach's alpha
GAI	0.884	0.000	0.817–0.842	0.678	0.913	0.881
MDC	0.717	0.000	0.844–0.866	0.733	0.892	0.818
NBMI	0.886	0.000	0.812–0.847	0.698	0.920	0.892
EBMI	0.882	0.000	0.813–0.855	0.691	0.918	0.888

3.4 Confirmatory factor analysis

The discriminant validity of the four variables—GAI, MDC, NBMI, and EBMI—was evaluated using confirmatory factor analysis (CFA). We built models with one, two, three, and four factors. The confirmatory factor analysis findings are shown in Table 3. Significantly surpassing the other models, the four-factor model had the best fit ($\chi^2/df = 1.108$, RMSEA = 0.015, GFI = 0.971, CFI = 0.997, TLI = 0.997, SRMR = 0.022). As a result, the four-factor model fits our data better, demonstrating the excellent discriminant validity of the assessment tools utilized in this investigation.

Table 3
Results of confirmatory factor analyses.

Model	χ^2	df	χ^2/df	RMSEA	GFI	CFI	TLI	SRMR
One-factor model: GAI + MDC+NBMI+ERMI	2247.571	135	16.649	0.175	0.558	0.565	0.506	0.133
Two-factor model: GAI + MDC; NBMI+ERMI	1511.924	134	11.283	0.142	0.653	0.716	0.676	0.117
Three-factor model: GAI; MDC; NBMI+ERMI	1098.688	132	8.323	0.119	0.705	0.801	0.769	0.092
Four-factor model: GAI; MDC; NBMI; ERMI	142.926	129	1.108	0.015	0.971	0.997	0.997	0.022

4. Results

4.1 Descriptive statistics and correlation analysis

Table 4 presents the descriptive statistics, including mean values, standard deviations, variance inflation factors (VIF), and the correlation analysis of the primary variables. The mean values are as follows: NBMI = 3.366, EBMI = 3.330, GAI = 3.322, and MDC = 3.304. The correlation matrix reveals modest associations among the variables, and all VIF values remain well below commonly accepted thresholds, alleviating concerns regarding multicollinearity. Notably, the associations between GAI and NBMI ($r = 0.378$) and between GAI and EBMI ($r = 0.347$) are positive and statistically meaningful, offering initial empirical signals consistent with the proposed theoretical expectations.

Table 4
Descriptive statistics and correlation analysis.

Variable	1	2	3	4	5	6	7	8	9	10
1.NBMI	1									
2.EBMI	0.415***	1								
3.GAI	0.378***	0.347***	1							
4.MDC	0.421***	0.395***	0.440***	1						
5.Firm age	-0.095**	0.010	0.030	-0.017	1					
6.Firm size	0.096**	-0.019	-0.044	-0.068	-0.003	1				
7.Firm ownership	-0.040	-0.032	-0.055	-0.028	-0.004	-0.088**	1			
8.R&D	0.010	-0.002	0.053	0.041	0.067	-0.031	-0.051	1		
9.Sales Revenue	-0.026	0.016	-0.019	0.026	0.006	0.066	-0.005	0.060	1	
10.Environmental Dynamic	0.237***	0.318***	0.350***	0.332***	-0.001	-0.009	-0.018	0.058	0.014	1
Mean	3.366	3.330	3.322	3.304	2.630	1.827	1.683	2.965	3.597	3.397
Std	0.968	0.963	0.953	1.000	0.731	0.736	0.234	1.052	1.127	1.13
VIF	—	—	1.32	1.30	1.01	1.02	1.01	1.02	1.01	1.20

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Main effects

The results from the hierarchical regression analyses are reported in Table 5. The first two models incorporate only control variables to establish benchmark specifications, whereas subsequent models introduce the focal explanatory factors. Results from Model 3 demonstrate a statistically significant and positive linkage between GAI and NBMI ($\beta = 0.3441$, $p < 0.01$), lending empirical support to Hypothesis 1. Similarly, Model 4 shows that GAI exerts a positive and significant influence on EBMI ($\beta = 0.2691$, $p < 0.01$), thereby confirming Hypothesis 2. A comparison of coefficient magnitudes further suggests that the impact of GAI is more pronounced for NBMI than for EBMI.

Table A1
Measurement items.

Variables	Item	Source
Generative AI adoption (GAI)	Adopting generative AI in my position would significantly increase firm productivity	Singh et al., (2024)
	With the use of generative AI techniques, I could do difficult jobs more quickly	
	I could easily provide instructions to generative AI to carry out particular jobs	
	I could carry out my organizing duties more easily if we have generative AI	
	Learning to use generative AI effectively would be a simple and doable task	
Managerial digital concern (MDC)	Our firm fosters an environment that encourages experimenting with novel digital innovation methods to enhance our digital management strategy	Yao et al., (2023)
	Our firm regards digital technology innovation as a key component of digital management	
	Our firm believes that achieving high levels of digital performance does not require digital innovation as a component	
Novelty business model innovation (NBMI)	New ways can bring new partners to firms	Amit & Zott (2007)
	Firms create value for their partners with new trading methods	
	Firms are good at meeting customers' needs with partners in new ways	
	Firms increase transaction volume through continuous innovation in business models	
	New mode of cooperation enables firms to provide new products or services to customers	
Efficiency business model innovation (EBMI)	Firms are committed to improving the efficiency of the use of existing resources	Amit & Zott (2007)
	Firms are committed to information communication with partners to reduce various costs	
	Firms can keep abreast of information about products, services and partners	
	Firms have been reducing communication costs, reducing transaction processes and improving efficiency	
	Firms use their existing resources for multiple purposes as much as possible	

Title page

How generative AI drives business model innovation: evidence from Chinese manufacturing firms

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Table 5
Hierarchical multiple regression results.

Variable	NBMI	EBMI	NBMI	EBMI	NBMI	EBMI
	Model1	Model2	Model3	Model4	Model5	Model6
Firm age	-0.1298** (0.0585)	0.0158 (0.0577)	-0.1431*** (0.0553)	0.0054 (0.0557)	-0.1328** (0.0520)	0.0139 (0.0532)
Firm size	0.1327** (0.0584)	-0.0278 (0.0576)	0.1527*** (0.0552)	-0.0122 (0.0556)	0.1425*** (0.0525)	-0.0245 (0.0538)
Firm ownership	-0.3588 (0.5627)	-0.3868 (0.5546)	-0.1300 (0.5317)	-0.2079 (0.5361)	-0.1375 (0.4999)	-0.2187 (0.5121)
R&D	0.0063 (0.0409)	-0.0232 (0.0403)	-0.0031 (0.0386)	-0.0305 (0.0389)	-0.0016 (0.0363)	-0.0288 (0.0372)
Sales Revenue	-0.0321 (0.0380)	0.0127 (0.0375)	-0.0250 (0.0359)	0.0183 (0.0362)	-0.0274 (0.0338)	0.0170 (0.0346)
Environmental Dynamic	0.2100*** (0.0378)	0.2821*** (0.0373)	0.1041*** (0.0381)	0.1993*** (0.0384)	0.0254 (0.0370)	0.1298*** (0.0380)
GAI			0.3441*** (0.0431)	0.2691*** (0.0435)	0.2134*** (0.0437)	0.1562*** (0.0448)
MDC					0.2854*** (0.0436)	0.2397*** (0.0447)
GAI*MDC					0.1654*** (0.0395)	0.1592*** (0.0405)
Constants	0.1979 (1.1740)	-0.1547 (1.1570)	0.1022 (1.1077)	-0.2296 (1.1168)	0.3078 (1.0415)	-0.0421 (1.0671)
N	514	514	514	514	514	514
adj. R^2	0.0658	0.0926	0.1684	0.1547	0.2654	0.2289
F	7.0200	9.7251	15.8440	14.4149	21.5900	17.9233
Notes: Standard errors in parentheses						
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$						

4.3 Moderating effects

Models 5 and 6 include the moderating variable and the interaction term between GAI and MDC. The estimation results indicate that the interaction between GAI and MDC is positively and statistically associated with NBMI ($\beta = 0.1654$, $p < 0.01$), providing empirical evidence in favor of the moderation mechanism proposed in Hypothesis 3. A comparable pattern emerges for EBMI, where the interaction term also exhibits a positive and significant coefficient ($\beta = 0.1592$, $p < 0.01$), thereby lending support to Hypothesis 4. The nature of these interaction effects is visually depicted in Figs. 2 and 3.

5. Discussion and implications

As market competition intensifies, understanding the role of GAI in BMI becomes increasingly critical. This study integrates the RBV and ABV to examine the impact of GAI on BMI and to analyze potential mechanisms and moderating effects. Empirical results indicate that GAI has a positive impact on both NBMI and EBMI. NBMI emphasizes new ways of economic transactions among different participants, with GAI driving this innovation by enhancing the generation of new ideas, products, and services. EBMI, on the other hand, focuses on reducing transaction costs and improving information transparency. GAI facilitates this type of innovation by enhancing decision-making efficiency, market responsiveness, and optimizing resource management. Additionally, we find that MDC moderates the relationship between GAI and BMI. Firms with high levels of digital concern enable executives to better identify and leverage the potential of GAI, thereby amplifying its positive effects on BMI. This suggests that executives with high concern are more likely to view GAI as a vital tool for strategic transformation, implementing related strategies, allocating resources, and cultivating talent to drive BMI. In summary, this study extends the theoretical and empirical research on GAI and BMI, providing valuable insights into how firms can effectively apply GAI in their commercial activities.

5.1 Theoretical implications

First, this study enhances the understanding of the role of GAI in BMI, expanding the boundaries of GAI application research. Previous studies have predominantly focused on the application of GAI in specific domains such as marketing (Kshetri et al., 2023), finance (Zheng et al., 2024), innovation management (Cimino et al., 2024), healthcare (Varghese & Chapiro, 2023), and education (Michel-Villarreal et al., 2023; Lim et al., 2023). However, research on the potential impacts of GAI on BMI has been relatively sparse. This study, grounded in RBV theory, systematically explores for the first time how GAI facilitates BMI through empirical analysis and theoretical argumentation. This research not only fills a gap in the application of GAI in BMI but also provides valuable theoretical guidance and practical references for firms on effectively leveraging GAI during digital transformation.

Second, this study expands the antecedent research on BMI, offering a new perspective on understanding BMI driven by emerging technologies. In the rapidly evolving digital environment, the emergence of new technologies continually drives the transformation of business models. Although existing research acknowledges the importance of GAI in BMI, there has been insufficient exploration of its specific mechanisms and impact pathways. By integrating GAI with the critical issue of BMI, this study delves into how GAI promotes BMI through innovative service delivery methods, enhanced decision-making efficiency, and optimized resource allocation. These results contribute to our knowledge of the underlying mechanics of BMI and give firms a theoretical foundation for optimizing and modifying their business models in response to technological advancements.

Finally, this study extends the research on the moderating effects of MDC, broadening the perspective of attention theory. Existing research has mainly examined the direct impact of MDC on innovation performance (Wang et al., 2024), with limited investigation into its role as a boundary condition affecting the application of emerging technologies. Grounded in the ABV theory, this study conceptualizes MDC as a strategically important intangible asset and examines its contingent role in shaping the influence of GAI adoption on business model innovation. The results demonstrate that heightened managerial attention to digital technologies strengthens the innovation-enhancing effects of GAI. By doing so, this research clarifies an important boundary condition for the effectiveness of generative AI applications and advances the application of attention-based theory within the emerging digital transformation context.

5.2 Management implications

Firms should shift their strategic focus toward the development and application of cutting-edge technologies such as GAI, and increase their investment in GAI technologies. Tools like ChatGPT offer powerful content generation and processing capabilities, and firms should actively explore their potential applications in content marketing, customer service, and product development. By leveraging GAI for market trend analysis, consumer behavior prediction, and personalized service design, organizations can better meet market demands, enhance customer experience, and improve customer loyalty. Additionally, firms should invest in employee training and education to enhance their teams' understanding and application of GAI tools, ensuring effective utilization of the technology and fostering innovative thinking. The quick advancement of GAI technology offers many benefits, but it also poses problems including data security, privacy protection, and moral dilemmas. Firms should

establish robust data management and protection mechanisms to ensure legal and compliant use of AI applications. Enhancing the transparency and explainability of AI technologies will also increase public trust. Furthermore, firms should actively participate in the formulation and revision of industry standards to promote a healthy and orderly AI application ecosystem.

Executives should intensify their concern on digital trends and utilize GAI technology to identify new business opportunities and enhance decision-making efficiency. The digital vision and strategic decisions of executives are crucial for the effective utilization of GAI within organizations. It is essential that executive teams have a deep understanding of the importance of digital transformation and can drive the integration and application of GAI from a strategic perspective. Organizations are encouraged to institutionalize continuous capability-building initiatives, such as targeted learning programs and knowledge-sharing forums, to strengthen managerial awareness of digital developments and deepen competence in emerging technologies. Such efforts can help firms proactively adapt to technological change and more effectively exploit generative artificial intelligence and related tools to improve operational effectiveness and foster innovation. Additionally, organizations should foster an open innovation culture that encourages executives and employees to actively explore and experiment with new business models, using GAI technologies to uncover new growth opportunities.

5.3 Limitations and future research

First, the data for this study primarily originates from survey responses, which may introduce subjective biases and sample selection biases. The data collection and analysis were concentrated within a relatively short time frame, limiting the ability to reflect the long-term impacts of GAI applications on firms. Future research could address this limitation by incorporating case studies, simulation modeling, and longitudinal studies to validate and supplement the findings from different perspectives, thereby enhancing the comprehensiveness and accuracy of the research. Second, the empirical evidence presented in this study is derived exclusively from manufacturing enterprises located in the Yangtze River Delta, which may limit the extent to which the results can be extrapolated to other contexts. Subsequent research could broaden the analytical scope by incorporating firms operating across diverse geographic regions and industrial sectors, thereby assessing both the robustness and contextual variation of the relationship between GAI adoption and BMI. Finally, this study focuses primarily on the internal application of GAI and the role of managing digital concern in BMI, without adequately considering external environmental factors such as market competition, regulatory changes, and technological advancements that may affect BMI. Future research could broaden its scope to include these external factors and explore their combined effects with GAI on BMI.

Declarations

Competing interests

The authors declare no competing interests.

Ethical Approval

This study involved a non-interventional questionnaire survey with human participants. The study protocol was reviewed and approved by Nanjing University. No ethics approval number was assigned to this study.

Compliance with Ethical Guidelines

All procedures performed in this study were conducted in accordance with the relevant ethical requirements of Nanjing University for research involving human participants, as well as applicable guidelines and regulations. The study adhered to fundamental ethical principles, including voluntary participation, respect for participants' rights, protection of privacy, and confidentiality of research data. As this study involved a non-interventional social science questionnaire survey and did not involve any medical, clinical, or biomedical intervention, it was conducted in accordance with the ethical principles applicable to social science research involving human participants.

Informed Consent

All participants were adult corporate managers with full legal capacity to provide informed consent. Prior to participating in the questionnaire survey, all participants were informed of the purpose of the study, the content and procedures of the survey, the intended use of the collected data, confidentiality measures, the voluntary nature of participation, and their right to withdraw from the study. After receiving and understanding this information, all participants voluntarily agreed to participate in the study and provided informed consent. The collected data were used solely for academic research purposes, and the findings were reported only in aggregate form. No information that could directly identify individual participants or their organizations was disclosed.

Author Contribution

Author contributions X.H. conceived and designed the study, collected and analysed the data, and drafted the manuscript. X.C. critically reviewed and revised the manuscript. Both authors read and approved the final manuscript.

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Data availability

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

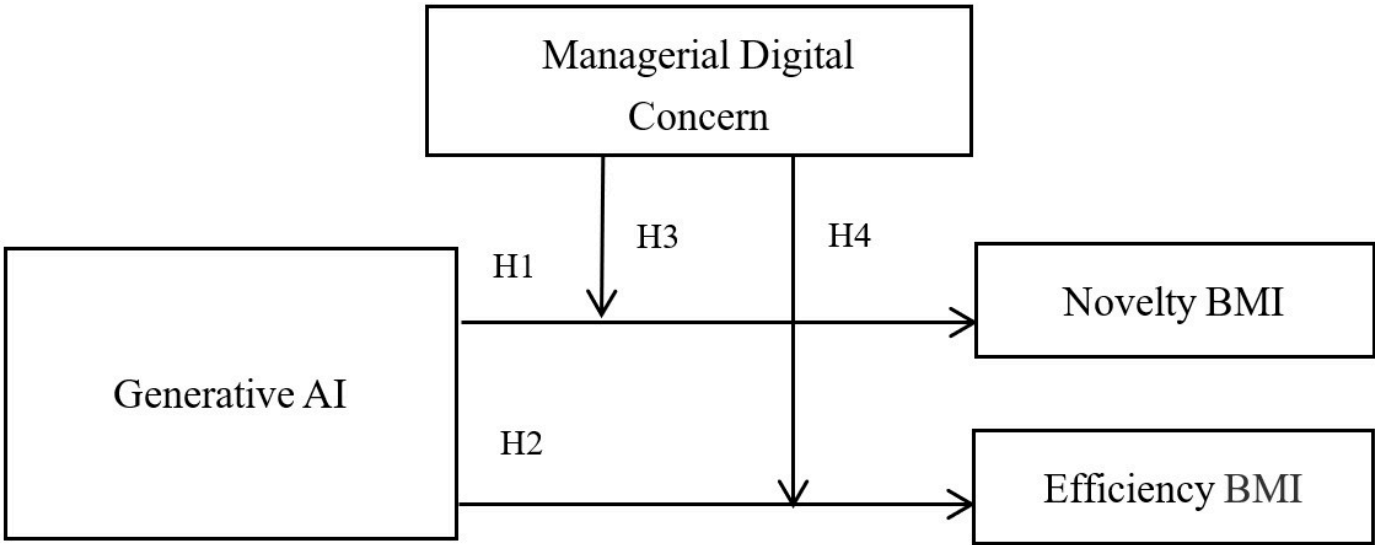


Figure 1

Theoretical model

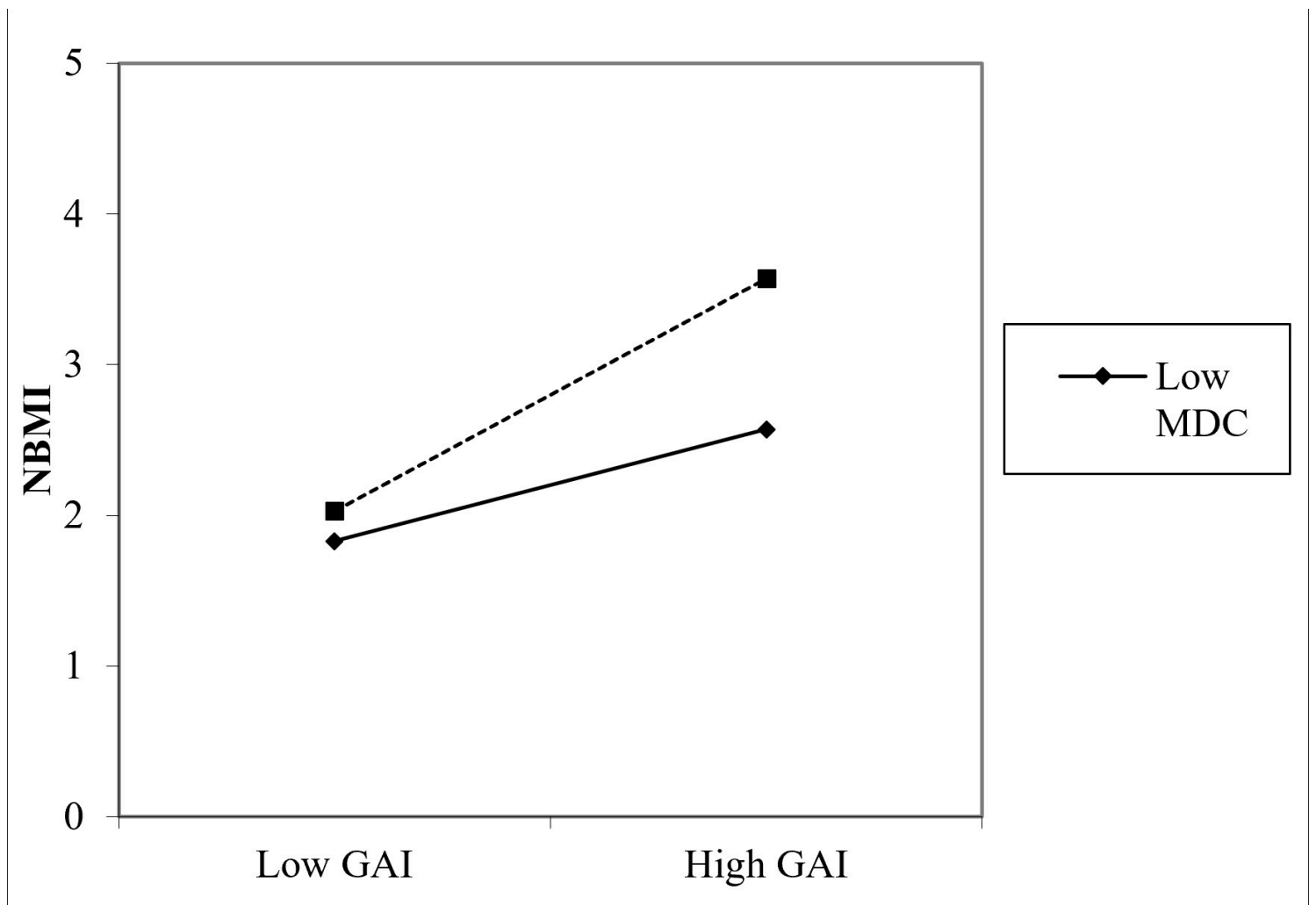


Figure 2

MDC moderating the GAI - NBMI relationship

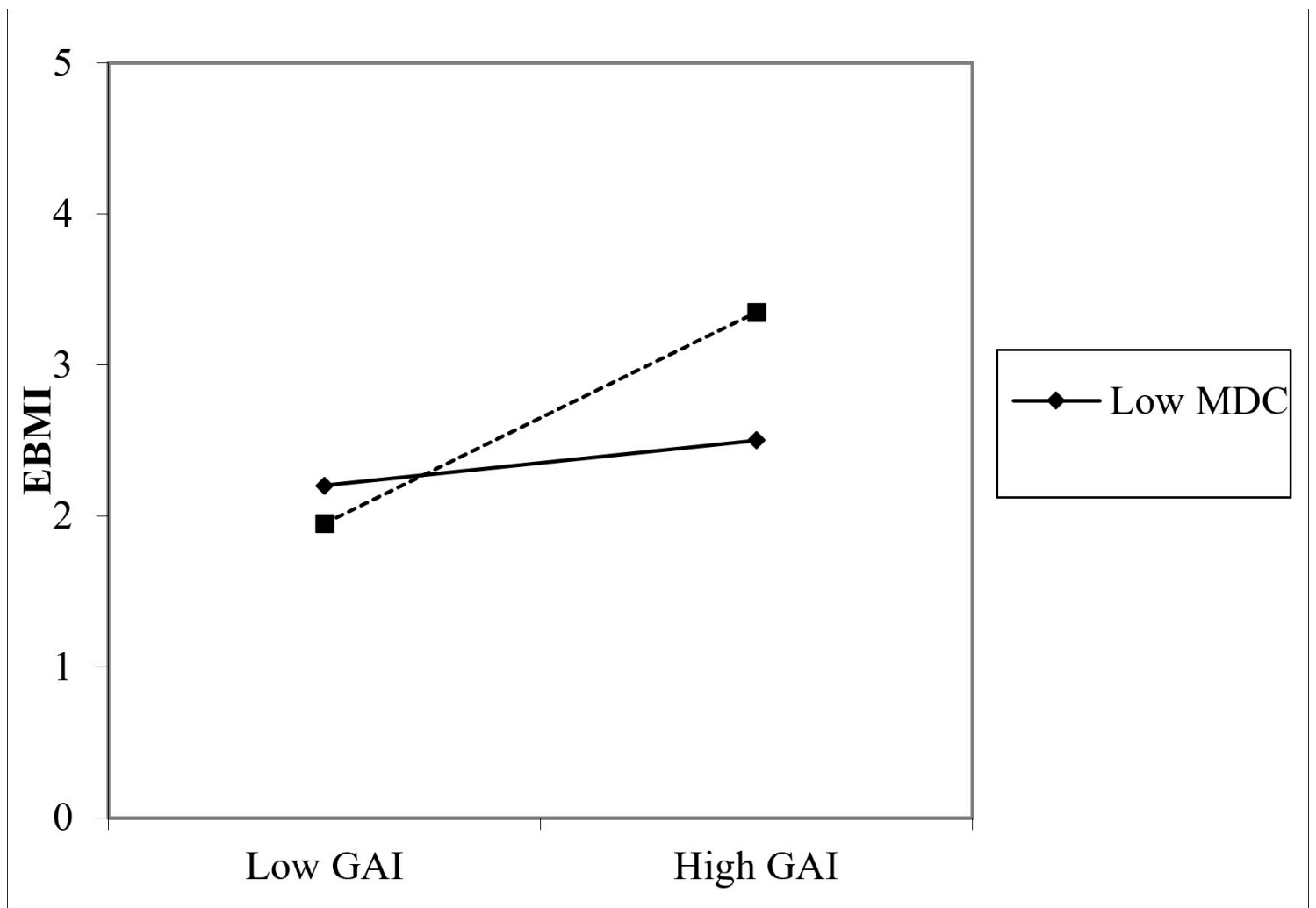


Figure 3

MDC moderating the GAI - EBMI relationship