RESEARCH-ARTICLE

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Generative AI-Driven Brand Equity Growth: Evidence from GBA Enterprises

Xiaoting Xiong*
Business School
Dongguan City University
Donguan, Guangdong Province, China
xenia.x@qq.com

Tao Jia*
School of Art and Design
Changzhou University
Changzhou, Jiangsu Province, China
00009207@cczu.edu.cn

Abstract

Based on the theoretical framework of generative AI enabling brand equity creation, this paper takes the enterprises that have continuously been listed in the 21st CHINA's 500 MOST VALUABLE BRANDS from 2020 to 2024 in the Guangdong-Hong Kong-Macao Greater Bay Area as samples to empirically test the mechanism of the application of generative AI technology on the brand equity of enterprises. The study finds that: Firstly, there is a significant positive correlation between the application level of generative AI and brand equity. Secondly, there is a partial mediating effect of enterprises' R&D investment between generative AI and brand equity, indicating that technology transformation needs to rely on the R&D system to achieve value precipitation. The heterogeneity analysis further reveals that the digital transformation of traditional industries has a latecomer advantage, while technology-driven enterprises show a significant scale multiplier effect. The study also finds that the maturity of digital infrastructure and the implementation intensity of local special AI policies regulate the depth of value conversion of generative AI through technical adaptability and institutional legitimacy respectively. The conclusions provide a decision-making basis for enterprises to optimize resource allocation relying on generative AI technology, and for the government to improve digital infrastructure and provide gradient policy support.

CCS Concepts

• **Applied computing**; • **Enterprise computing**; • **Business-IT alignment**;

Keywords

Generative AI, Brand Equity, Mechanism Analysis

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*Correspondence author

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1 Introduction

Generative Artificial Intelligence has emerged as a transformative force in the digital era, defined by Feuerriegel et al. (2024) as a class of AI systems capable of creating novel, contextually relevant content through learning patterns from training data [1] This paradigm shift is exemplified by multimodal models like GPT-4 and PathChat, which redefine value creation mechanisms across industries [2] In the marketing space, generative AI exceeds operational efficiencies by reshaping brand-consumer interactions, with core capabilities including hyper-personalized content generation, real-time cross-cultural adaptation, and predictive brand sentiment analysis.

The Guangdong-Hong Kong-Macao Greater Bay Area (GBA) is one of the most economically dynamic regions in China, with a GDP of more than US$2 trillion in 2023, and it is home to a large industrial cluster including the headquarters of more than 50 Fortune Global 500 companies and more than 300 unicorn startups [3] This region concentrates globally renowned brands such as Huawei and Tencent, and its unique market ecology provides a highly representative research scenario for exploring the dynamic association between generative AI and brand equity. Choosing GBA enterprises as the research object can not only reveal the core mechanism of brand equity enhancement by generative AI technology, but also its experience can be radiated to the digital transformation practice of other emerging economies, which has significant theoretical innovation and practical guidance value.

Although the established literature has partially revealed the correlation between digital transformation and brand equity, there is still a significant research gap in the mechanism of generative AI in reshaping brand equity and its application validation in GBA enterprise scenarios. Xu et al. (2024) showed that brand capital curbs earnings management, enhancing firm value, while Wang et al. (2024) highlighted brand trust and premiums as drivers of supply chain resilience, but these studies are based on the traditional digital technology framework and fail to touch on the technological paradigm change of generative AI [4, 5] Current research faces two limitations. Firstly, the theoretical perspective lags behind the technological development, existing results mostly focus on traditional AI technologies such as data analysis and automation, and lack the mechanistic exploration of core capabilities such as content generation and interaction creation of generative AI. A second limitation of existing research is the lack of region-specific studies. No systematic empirical conclusions have been drawn on how enterprises in innovation-intensive regions, represented by GBA, use generative AI to achieve a leap in brand equity. This paper makes a breakthrough by taking GBA enterprises as the empirical carrier, and through the combination of mechanism analysis and empirical test, it deeply explores the impact of the application of generative AI on the brand equity enhancement of GBA enterprises and its mechanism of action.

2 RESEARCH MECHANISM AND HYPOTHESE

2.1 The direct impact of Generative AI Intensity on Corporate Brand Equity

This paper argues that generative AI systematically empowers firms by optimizing brand equity creation pathways in three dimensions. According to the Resource-Based View proposed by the management expert Barney (1991), generative AI is a heterogeneous technological resource that can be used through different mechanisms to enhance brand equity, a company's competitive agility and global reach.[6] First, generative AI can generate dynamic content that enhances brand equity. Through the personalized advertising narratives and multimodal interaction design that generative AI has, it can enhance consumers' brand awareness. Meanwhile, generative AI also optimizes customer relationship management through real-time sentiment analysis, which further enables targeted marketing. Second, generative AI improves market competitiveness by shortening the strategic decision cycle. It accelerates the Observe–Orient–Decide–Act Loop by effectively modelling competitors' responses and reinforcing the logic inherent in learning, thus enabling rapid adaptation to dynamic market conditions [7] Third, generative AI significantly overcomes the limitations that traditional brand management faces when spreading its global reach. Its automatic multilingual and multicultural adaptability overcomes geographic and cultural barriers, while algorithmically optimized content distribution creates self-reinforcing distribution networks. These mechanisms are consistent with the Diffusion of Innovations theory, thus enabling a non-linear scaling effect of brand penetration beyond traditional human-centered approaches [8]

Based on the above background and theoretical framework, we propose the following hypotheses 1:

H1: The intensity of generative AI application has a significant positive impact on brand equity.

2.2 The mechanism of generative AI intensity on corporate brand equity

Some previous research has been conducted on the creation of enterprise value by AI, but it remains unexplored the mechanisms by which generative AI shapes brand equity [9] This paper argues that, on the one hand, generative AI can enhance brand equity through real-time interaction with consumers and signaling mechanisms. The ability of generative AI to create personalized content enhances the user experience. Of course, the adoption of generative AI also serves as a reliable market signal that communicates a firm's technological leadership to investors and stakeholders, thereby amplifying brand value in a competitive capital market [10] On the other hand, generative AI contributes to the upgrading of R&D intensity. The technology reduces design costs and accelerates development cycles, thereby increasing innovation output per unit of R&D expenditure [11] Such efficiency benefits incentivize firms to allocate more resources to R&D, while AI market analysis reduces innovation risk by improving the accuracy of demand forecasts, so that continued R&D investment translates into patent portfolios and product differentiation, which cumulatively increases long-term brand equity [12]

Based on the above background and theoretical framework, we propose the following hypotheses 2:

H2: R&D intensity partially mediates the generative AI-brand equity relationship, with generative AI adoption both directly elevating brand equity and indirectly promoting it through augmented R&D resource allocation.

3 MEASUREMENT OF VARIABLES AND MODEL DEVELOPMENT

3.1 Measurement of variables

3.1.1 Explained Variable: Brand equity. Brand equity is one of the most central elements of brand management. Since 2019, World Brand Lab has improved its valuation methodology by adopting an enhanced present value of earnings approach to brand valuation. The method uses a combination of consumer behavior analysis, competitive benchmarking and discounted cash flow projections to systematically capture operational efficiency and brand-driven revenue growth. This study focuses on GBA companies that have been listed in the 21st China's 500 Most Valuable Brands for five consecutive years, and the brand equity of the companies published in the list is log-transformed. The logarithmic transformation mitigates heteroskedasticity on the one hand, while preserving the ordinal relationships of the financial indicators.

3.1.2 Explanatory variable: Generative AI Intensity. The application intensity of generative AI is calculated as:

$$\text{GAI Intensity} = \frac{\sum \text{Keyword Frequencies}}{\text{Total Word Count}} \times 1000 \tag{1}$$

*3.1.3 **Mediating variable: R&D intensity ratio.*** The R&D intensity ratio is a core indicator of the extent to which a firm invests in R&D activities, expressed as a percentage of R&D expenditures to operating revenues. This study argues that R&D investment is a key intermediary in transforming generative AI technology into a competitive advantage for brands. The ratio is calculated as

$$\text{R\&D intensity ratio} = \frac{R\&D\ Expenditures}{Operating\ Revenue} \times 100\% \tag{2}$$

3.1.4 Control variables. The following control variables were included:

- Firm size: Natural logarithm of total assets.
- Financial leverage: Total liabilities divided by total assets.
- ROA: Net profit divided by total assets.
- Marketing expenditure: Selling expenses divided by operating revenue.

3.2 Model development

3.2.1 Baseline regression model. Drawing on the theoretical framework, the baseline regression model is specified as follows.

$$\begin{aligned}&\text{Brand Equity}_{\,it} = \propto_0 + \propto_1 \text{GAI Intensity}_{it}\\&+\propto_2 Controls_{it} + \delta_i + \lambda_t + \varepsilon_{it}\end{aligned} \tag{3}$$

Table 1: Baseline regression results

Variables	Coefficient	Std. Error	t	p	R^2	F
GAI Intensity	0.041	0.011	3.613	0.000***	Within=0.169 Between=0.601 Overall=0.582	F=21.427 P=0.000***
Log Firm Size	0.275	0.059	4.652	0.000***		
Financial Leverage	-0.017	0.007	-2.569	0.011**		
Marketing Expenditure	-1.606	0.407	-3.945	0.000***		
Constant	4.619	0.372	12.41	0.000***		

***,** and * indicate significance at the 1%, 5%, and 10% levels, respectively; this notation applies consistently to all subsequent tables.

3.2.2 Mediation effect models. To examine the mechanism underlying GAI's impact on brand equity, the following mediation models are established. Mediation path model is given by:

$$\begin{aligned} &R\&D\ Intensity\ Ratio_{it} = \beta_0 + \beta_1 \text{ GAI Intensity}_{it} \\ &+\beta_2 Controls_{it} + \delta_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{4}$$

Combined model is given by:

$$\begin{aligned} &\text{Brand Equity}_{it} = \gamma_0 + \gamma_1 \text{ GAI\_Intensity}_{it} \\ &+\gamma_2 R\&D\ Intensity\ Ratio_{it} + \gamma_3 Controls_{it} + \delta_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{5}$$

3.3 Data sources

This study analyses 49 Greater Bay Area firms that were consecutively selected for the 21st China's 500 Most Valuable Brands, yielding a total of 245 firm-year observations. The data used for the calculations in the paper combines valuation metrics from the World Brand Lab, audited financial disclosures, and artificial intelligence adoption metrics extracted from corporate communications through NLP techniques. In this paper, SPSSPRO was chosen to perform regression analyses and tests on the relevant data.

4 EMPIRICAL ANALYSIS

4.1 Baseline regression

In order to examine the impact of generative AI on corporate brand equity, the study used three forms of models for testing. Hierarchical testing show that time effects mainly reflect macroeconomic changes rather than firm-specific trends, which justifies the use of a mixed model with time fixed effects and firm random effects. Diagnostic tests confirmed model validity: F-test ($p < 0.01$) favored fixed effects over pooled OLS. Breusch-Pagan test ($p < 0.01$) supported random effects. Hausman test ($p = 0.97$) failed to reject random effects assumptions. Consequently, the random effects model was selected as the baseline specification. The baseline regression results are summarized in Table 1.

According to the results of the baseline regression operation, the coefficient is 0.041, which indicates that for every unit increase in GAI Intensity, brand equity increases by 0.041 units on average. This result is both statistically and economically significant, thus validating hypothesis H1 of this paper.

Further analyzing the control variable component, the baseline regression results show that firm size has a significant positive impact on brand equity, while marketing expenditure exhibits a significant negative association. This result reflects the role of economies of scale in promoting brand building, but excessive resource allocation or inefficient marketing investment poses potential risks. Financial leverage has a significant negative impact on brand equity, suggesting that higher debt ratios constrain brand value. ROA is not included in this report due to its lack of statistical significance. Overall, the model has strong explanatory power with a significant F-statistic and an R^2 of 0.582, indicating that about 58.2% of the variation in brand equity is explained by predictors.

Table 2: Comparative Analysis of FE vs. RE Coefficients

Variable	FE Model	RE Model	% Difference
GAI Intensity	0.04	0.041	2.5%
Log Firm Size	0.26	0.275	5.7%
Financial Leverage	-0.017	-0.017	0.0%

4.2 Robustness checks

4.2.1 Comparative analysis of FE vs. RE coefficients. In order to assess the sensitivity of the findings to model specification, Table 2 compares the regression estimates from the fixed and random effects models. A comparison of the results of the two models shows that the coefficients on the core explanatory variable, GAI Intensity, are 0.040 and 0.041, respectively, with a marginal difference of 2.5%, which is well below the 5% economic significance threshold. Although the coefficient on the logarithm of firm size differs somewhat, the direction of its positive effect and its statistical significance at the 1% level remain consistent across the two models. These results suggest that the effect of productive AI on brand equity enhancement is robust regardless of whether unobserved individual heterogeneity is modelled as a fixed or random effect.

4.2.2 Time fixed effects validation. In order to verify the potential impact of macroeconomic cycles on firms' generative AI and brand equity, the paper introduces time fixed effects in Table 3. The estimated coefficient for GAI Intensity is 0.043, which is very close to that of the baseline RE model of 0.041 and is statistically significant at the 1% level. Besides, the within-group R^2 of the time fixed effects model is lower than that of the individual fixed effects model, which means temporal trends contribute relatively limited explanatory power to brand equity variation. These dual

Table 3: Time Fixed Effects Validation

Variable	RE Model	Time Fixed Effects Model
GAI Intensity	0.041	0.043
P	0.000***	0.001***
R^2	0.169	0.116

validations confirm that the observed GAI Intensity effect is not primarily driven by time-specific factors.

4.2.3 Robustness checks with alternative control variables. To reduce possible selection bias from the control variables, Table 4 reports the regression results under different combinations of variables. Specifically, the paper attempts to conduct robustness tests by sequentially excluding ROA and marketing expenditures from the control set. It is found that although the coefficient estimates are slightly different, the direction of influence and statistical significance of all variables remain consistent. Above all, there is no qualitative change in the enhancement of brand equity by GAI intensity under the other modelling configurations. This also demonstrates the robustness of the findings of the thesis to the different choices of control variables.

4.3 Mechanism analysis

Based on the theoretical framework and empirical model established earlier, to investigate whether the proportion of corporate R&D investment mediates the relationship between GAI intensity and brand equity, we conducted further mediation analysis. Results are presented in Table 5. The study shows that GAI intensity indirectly enhances brand equity through the technological innovation pathway, i.e., the R&D share calculated in the paper. More specifically, the adoption of generative AI optimizes the allocation of R&D resources, accelerates the accumulation of technological innovation capability, and ultimately enhances the core competitiveness of the brand. At the same time, it was found that GAI displays significant direct effects, suggesting that complementary value can be created through non-R&D channels, such as the technology's ability to improve operational efficiency and agile market responsiveness.

4.4 Heterogeneity analysis

Given potential variations across industries and regions in the GAI-brand equity relationship, we conducted subgroup analyses stratified by sector and location. Given that there may be differences in the relationship between generative AI and brand equity across industries and regions, we examined subgroups by industry and region. Firstly, the industry analysis shows that the coefficient of influence of generative AI on brand value in traditional industries is 0.082*, which is significantly higher than that of technology-intensive industries, which is 0.068*. Although both industries show statistically significant positive effects, the marginal brand equity gain per digital unit is 20.6% higher in the traditional industry, which indicates that the traditional industry has a higher value conversion efficiency in the process of generative AI application. Meanwhile, the enterprise size elasticity coefficient of technology-intensive industries reaches 0.645*, which is 4.8 times higher than that of traditional industries. This result suggests that scale expansion has a significant multiplier effect on brand equity in technology-centric enterprises.

In terms of regional heterogeneity, the coefficient of the impact of generative AI on brand equity for Shenzhen firms is 0.111*, with a marginal effect that is 2.17 times higher than that of non-Shenzhen GBA firms. This difference may stem from Shenzhen's advanced digital infrastructure maturity and intensive policy support for AI applications.

5 DISCUSSION AND CONCLUSION

Based on the relevant data from 49 high-brand-equity enterprises in GBA spanning 2020–2024, this study employs benchmark regression and mechanism analyses to uncover the mechanisms through which generative AI influences corporate brand equity. Empirical results from the benchmark regression analysis demonstrate a statistically significant positive relationship between generative AI-driven digital transformation and brand equity, even after controlling for firm size, financial leverage, ROA and marketing expenditure. The Hausman test-supported random effects model, which accounts for unobserved heterogeneity across firms, exhibits robust explanatory power. Mechanistically, generative AI facilitates structural enhancement of brand equity by accelerating product innovation cycles, elevating consumer interaction touchpoints through

Table 4: Robustness Checks with Alternative Control Variables

Variable	Baseline Model	Excluding ROA	Excluding Marketing Expenditure
GAI Intensity	0.041	0.035	0.037
p	0.000***	0.001***	0.001***
R^2	0.169	0.254	0.218

Table 5: Mechanism Analysis

Test Type	Key Coefficients	p
Baseline (RE Model)	GAI: 0.035*	0.001***
Mediation (Pooled OLS)	GAI → R&D:0.005	0.000***
Combined (RE Model)	R&D Investment → Brand Equity: 3.944	0.000***

Table 6: Heterogeneity Analysis

Variable	Industry Classification		Regional Classification	
	Traditional Industries	Technology-Intensive	Shenzhen	Other GBA Sub-regionsa
GAI Intensity	0.082	0.068	0.111	0.051
p	0.000***	0.000***	0.000***	0.003***
Log Firm Size	0.134	0.645	0.2115	0.153

AI-driven personalization, and reinforcing technology centric brand narratives. The analysis of regional heterogeneity further reveals that, as a regional innovation center, Shenzhen has a marginal effect of digital transformation that is 2.2 times that of non-Shenzhen regions, highlighting the moderating role of the regional innovation ecosystem. Analysis demonstrates a total generative AI effect on brand equity, with 64.3% attributed to direct pathways mediated by operational efficiency optimization and agile market responsiveness. While the indirect effect accounts for 35.7%, which is realized through the mediating path where GAI drives the optimization of R&D resource allocation, and then enhances the technological innovation capability.

The conclusions of this study are limited by the coverage scope and time span of the data sample. Although the two-way fixed effects are adopted in the benchmark regression to mitigate the omitted variable bias, the instrumental variable method or exogenous shock test has not been systematically introduced to deal with the endogeneity problem. In the future, causal inference can be further strengthened through dynamic panel regression or quasi-natural experimental design. In addition, the analysis of industry heterogeneity only focuses on the binary division between traditional industries and technology-intensive industries, which may overlook the characteristics of specific sub-sectors, such as the division of labor in the industrial chain. The research on industry classification can be deepened by combining the dimensions of technology penetration rate or business model innovation.

This study reveals from an empirical perspective the promoting effect of generative AI on the brand equity of enterprises and the partial mediating path of R&D investment, providing a theoretical basis for enterprises to optimize the allocation of technological resources during the digital transformation. In the future, with the continuous iteration of generative AI technology and the continuous deepening of its industry applications, the dynamic impact mechanism of generative AI on the long-term brand value of enterprises is worthy of continuous exploration, so as to provide more accurate practical guidance for AI to empower the real economy.

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