Impact of Generative AI on Small and Medium Enterprises' Revenue Growth: The Moderating Role of Human, Technological, and Market Factors

Vishvesh Soni
Marketing specialist and market research analyst at Alliage Inc.

Abstract

Background: The generative artificial intelligence (AI) technologies have become strategic tools for small businesses seeking maintain competitive advantage. The usefulness of of these technologies are well-recognized in SMEs, yet it is becoming important to explore how other factors might affect the degree to which these benefits are realized. The present study emerges from this necessity, aiming to provide a quantitative assessment of how generative AI adoption affects SME revenue growth and to what degree this effect relies on human capital, technological infrastructure, and market competition.

Objectives: The aim of this research is to empirically examine not only the direct effects generative AI on revenue growth but also how this relationship is shaped by several moderating factors such as human, technological, and market factors. These factors can either amplify or diminish the potential gains from generative AI adoption.

Data and Methods: To understand the relationships, data from 331 SMEs were analyzed using 3 Regularization regression methods, namely, Ridge, Lesso, and Elastic Net Regression methods.

Findings: The results indicates that companies benefit from adopting generative AI technologies. The moderating effects of human capital indicates that businesses not only benefit from adopting generative AI but do so especially when they have highly educated employees. This implies that human capital can enhance or is complementary to the advantages provided by the generative AI, possibly through more effective utilization. The moderating effects of existing firm's infrastructure also has a positive effect, suggesting that the benefits of generative AI are amplified when a business has good existing technological infrastructure. This means that businesses with modern or advanced tech facilities can leverage AI technology more effectively than those with outdated or less capable infrastructure. The moderating effects of market competition showed a negative result indicating that the advantage gained from generative AI adoption may decrease as market competition intensifies. This suggests that in highly competitive markets, the edge provided by AI is less distinct, perhaps because competitors are also likely to adopt similar technologies, negating the competitive advantage.

Conclusion:

The findings suggest that simply deploying generative AI will not suffice; instead, it should be part of a broader strategy that considers market dynamics, skilled human capital to operate, and improving existing technological infrastructure.

Keywords:

1. *Artificial Intelligence Adoption*
2. *Competitive Markets*
3. *Generative AI*
4. *Revenue Growth*
5. *Small and Medium Enterprises (SMEs)*
6. *Technological Infrastructure*

Introduction

The surge in artificial intelligence (AI) tools has significantly impacted how business organizations operate, marking a transition from traditional processes to more technology-driven approaches. These AI-driven systems are primarily defined by their capacity to automate routine tasks, enabling organizations to allocate human resources to more strategic initiatives [1]–[3]. The automation spectrum ranges from simple tasks like data entry to more complex processes like supply chain management, where predictive algorithms can anticipate disruptions and suggest mitigations. AI's role in knowledge extraction from large datasets has been particularly transformative, allowing businesses to gain actionable insights that were previously obscured by the volume of information. AI-powered analytics have transcended human analytical capabilities, offering a level of precision and efficiency that can drastically enhance decision-making processes. The integration of AI into business systems has, therefore, not just been a matter of adopting new technologies, but has fundamentally altered how organizations conceive and execute their operations. The consequences of AI's integration into business models are extensive, leading to the emergence of novel business models and consumer offerings. The incorporation of AI tools has enabled businesses to reimagine their products and services, resulting in innovative solutions that were once thought impossible.

Table 1. An Overview of Generative Modeling Frameworks in AI

Generative Model	**Key Components**	**Training Process**	**Output Quality**	**Speed of Generation**	**Best Use Cases**
GAN (Generative Adversarial Network)	Generator Network, Discriminator Network	Adversarial training until the discriminator cannot distinguish synthetic content [4]	High	Fast	High-fidelity images, domain-specific data generation
Diffusion Models (DDPMs)	Forward Diffusion, Reverse Diffusion	Add noise to data, then reverse to reconstruct original data [5]	Very High	Slow due to complex training	High-quality image and audio generation, foundation models
VAE (Variational Autoencoder)	Encoder, Decoder	Encode input into latent space and decode to reconstruct [6]	Moderate	Fast	Quick data generation with less detail required
GPT (Generative Pre-trained Transformer)	Transformer Architecture	Pre-training on large datasets, followed by fine-tuning [7]	High (for text)	Varies with application scale	Natural language generation, text-based AI applications

Generative artificial intelligence (AI) encompasses a range of technologies that can create new content, such as text, images, or various forms of media, through the use of advanced algorithms known as generative models. The inception of this technology dates back to the 1960s with the creation of early chatbots, which represented the primitive stages of AI's ability to produce human-like text. However, it was not until the development of Generative Adversarial Networks (GANs) in 2014 that generative AI truly began to demonstrate a remarkable capacity to synthesize highly realistic images, videos, and audio recordings [8]. These GANs employ a unique machine learning approach, involving dueling neural networks, to improve the quality of artificial creations to the point where they are often indistinguishable from authentic human-generated content.

Generative modeling artificial intelligence (GAI) represents a transformative subset of machine learning that diverges from traditional supervised learning. These models, operating either with minimal human supervision or without any at all, leverage statistical methods and probabilistic frameworks to create new, artificial artifacts. By analyzing vast amounts of digital content—from text and images to audio and video—GAI identifies patterns, assimilates the distribution of the input data, and then generates novel outputs that reflect the learned data characteristics. These outputs are not just mimicries but often indistinguishable from their real-world counterparts, blurring the lines between what is generated and what is organic. The development of deep learning (DL) techniques has been pivotal to the evolution of GAI, allowing the creation of complex and nuanced artificial content. The field has made significant strides, particularly in the areas of content generation and enhancement, enabling applications that span from artistic image synthesis to the augmentation of virtual realities.

Two architectures within GAI are the Generative Adversarial Network (GAN) and the Generative Pre-trained Transformer (GPT), each with unique mechanisms and applications [9]. GANs function through a dynamic training system involving two competing neural networks: the generator, which creates synthetic data, and the discriminator, which evaluates the authenticity of this data. This interplay progresses iteratively; the generator learns to produce increasingly convincing artifacts, while the discriminator becomes more adept at detecting nuances that differentiate the artificial from the real. The training continues until the discriminator can no longer reliably identify synthetic content, effectively accepting it as real. This adversarial process has been instrumental in generating highly realistic images, videos, and voices, making GANs the prevailing technique.

Diffusion models, especially denoising diffusion probabilistic models (DDPMs), add another aspect to the GAI. Through a sophisticated two-phase training methodology—forward diffusion that corrupts the training data with noise, and reverse diffusion that seeks to recover the data by removing the noise—these models learn to generate new samples from pure noise [10]. This iterative noise addition and subtraction process endows diffusion models with the potential to train numerous layers, conferring upon them the capacity to produce outputs of remarkable quality. Although their training is more time-consuming compared to other models like variational autoencoders (VAEs), the fidelity of the outputs often justifies the investment in computational resources and time.

Diffusion models have also gained prominence as foundation models because they are scalable, versatile, and produce high-fidelity results that are applicable to a variety of generalized use cases. The significant computational demands of these models, stemming from their reverse sampling process, mean they are not the quickest. The quality of the end product is frequently superior to that of other generative models.

VAEs introduce another approach to generative modeling by focusing on encoding input data into a compressed latent space before reconstructing it back to its original form through a decoder. This encoder-decoder architecture ensures that only the most relevant features of the data are captured and preserved, enabling the model to generate new data that mirrors the original input. While VAEs excel in the rapid generation of new data instances, their output often lacks the detailed precision found in diffusion models. Nonetheless, their efficiency in generating content quickly and their relative simplicity make them a valuable tool for tasks that require faster output generation without the necessity for minute detail.

Table 2. Use cases of Generative AI in SMEs	
Use case	Use Case Description
Content Creation	- Marketing Content: Generate text for ads, social media, and campaigns.
	- Blogging and SEO: Create draft articles that are SEO-friendly.
Personalized Customer Communications	- Generate personalized emails and messages based on customer data.
Product Design and Development	- Create new product designs or modify existing ones based on feedback and trends.
Graphic Design	- Design logos, marketing materials, and other elements without a full-time designer.
Prototyping and 3D Modeling	- Assist in creating prototypes for rapid iteration and testing.
Automation of Paperwork and Reports	- Draft reports, generate invoices, and handle routine paperwork tasks.
Customer Support	- Provide first-level support through AI chatbots.
Language Translation	- Translate content into multiple languages to aid operation in different regions without language barriers.

Generative AI offers substantial utility in enhancing the operational efficiencies and marketing endeavors of Small and Medium-sized Enterprises (SMEs). AI-facilitated text generation for advertising, social media, and campaigns enables these enterprises to produce a consistent and engaging digital presence with minimal human capital investment. Moreover, the capability of generative AI to compose search engine optimization (SEO)-friendly blog posts augments an SME's visibility and searchability online, which is critical for capturing and maintaining digital market share. Such technological leverage in content creation allows SMEs to reallocate financial and human resources to strategic growth areas, fostering an environment conducive to revenue enhancement by broadening their digital footprint and consumer base.

Generative AI is instrumental crafts individualized emails and messages by intelligently analyzing customer data, facilitating a level of bespoke engagement that often surpasses that of larger corporations. This heightened personalization can translate into customer loyalty and increased transaction frequency, both pivotal for an SME's revenue.

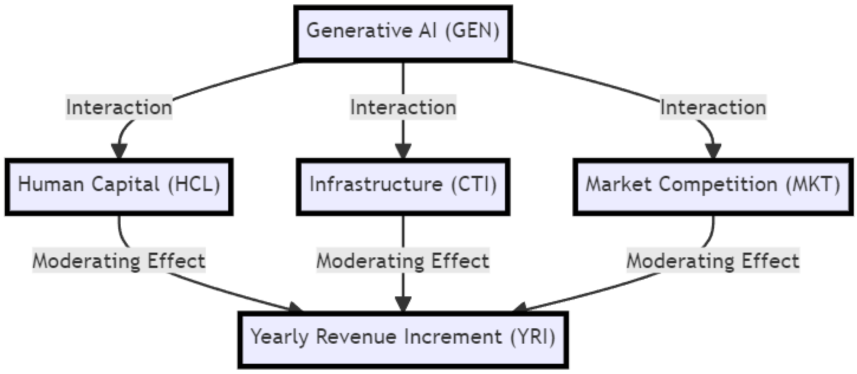
Concurrently, generative AI expedites the product design and development process. It autonomously generates innovative product designs or iteratively refines existing ones, informed by consumer feedback and emergent trends. This accelerates the product life cycle, empowering SMEs to more swiftly adapt to market demands and expedite time-to-market for new offerings, enhancing competitive advantage and revenue potential. Furthermore, generative AI's application in graphic design and prototyping presents cost-effective solutions for SMEs. By facilitating the creation of marketing materials and logos, adopter SMEs avoids the substantial expenditures associated with professional design services. In prototyping and 3D modeling, generative AI aids in the rapid production and modification of prototypes, substantially reducing the costs and time associated with traditional prototyping methods. The automation of routine documentation and report generation similarly mitigates administrative burdens, allowing SMEs to economize on operational costs and minimize human error. These efficiencies not only optimize resource allocation but also maximizes the capacity for business growth and profit maximization.

Conceptual framework

This study argues that the successful implementation and utilization of Generative AI is heavily moderated by the human capital within these organizations. Human capital, defined as the stock of expertise, knowledge, skills, and social attributes, is critical in leveraging AI tools effectively. The proficiency of employees in understanding and interfacing with advanced AI systems can significantly dictate the extent to which these technologies enhance productivity and creative capacity. For SMEs, where resource constraints are common, the quality of human capital assumes an even greater significance, as it becomes a pivotal factor in ensuring that AI adoption leads to actual economic and strategic benefits rather than merely adding to the technological overhead.

The agility offered by a skilled workforce is crucial in adapting to the disruptive nature of Generative AI. Such a workforce can pivot and align the organization's operational strategies with the capabilities of AI, ensuring that technology acts as a complement to human effort rather than a replacement [11]. This synergetic relationship is essential as it can lead to the creation of new products, services, and business models that are informed by AI-driven insights yet curated by human expertise and understanding of market nuances. Furthermore, employees who are adept in utilizing AI can perform higher-level tasks, delegate routine processes to AI systems, and focus on complex decision-making and strategic planning. This not only enhances efficiency but also fosters an environment of continuous learning and innovation, which is vital for SMEs to maintain a competitive edge in their respective sectors. The capacity of human capital to adapt to and integrate generative AI tools can also enhance customer experiences and open up new revenue channels for SMEs. Service-oriented SMEs, in particular, can benefit from the personalized and efficient customer interactions that AI enables. Employees who can skillfully manage AI tools can offer swift and accurate responses to customer inquiries, leading to higher satisfaction rates and repeat business, thereby increasing customer lifetime value. Sales and customer service representatives equipped with AI-generated insights can provide customized recommendations, improving conversion rates and boosting sales figures. The emotional intelligence and ethical decision-making capabilities of humans are irreplaceable assets in interpreting AI-generated data and results, making strategic decisions that align with the core values and mission of the SME, and maintaining the trust of customers and stakeholders in an increasingly technology-driven business environment.

Figure 1. Conceptual framework



The existing technological infrastructure within small and medium-sized enterprises (SMEs) plays a significant role in moderating the impact of generative AI adoption on these organizations. Infrastructure readiness can either accelerate the benefits or become a bottleneck in the effective deployment of AI technologies. On one hand, SMEs with robust and scalable IT systems can seamlessly integrate generative AI into their operations, allowing them to rapidly leverage the technology for enhanced data processing, product development, and customer service. This seamless integration can lead to immediate improvements in efficiency and productivity, which can translate into cost savings and potentially increased revenue. Conversely, SMEs with outdated or limited IT capabilities may struggle to support the advanced computational and data storage needs of generative AI, potentially leading to disruptions and increased costs.

Furthermore, the current technological setup determines an SME's agility in adopting new tools and solutions. A modular and interoperable IT architecture allows for plug-and-play integration of AI systems, reducing the time and resources needed for implementation [12]. This agility is critical for maintaining competitiveness, as it enables SMEs to rapidly adapt to market changes and technological advancements. For example, if an SME's infrastructure is already cloud-enabled, it can easily scale up its use of AI services offered by cloud providers, benefiting from the latest developments without the need for substantial upfront investment. In contrast, SMEs with rigid systems may find themselves facing significant overhauls or custom development, both of which can be costly and time-consuming, potentially delaying the realization of AI benefits.

In markets where competition is intense, the rapid deployment of generative AI by SMEs can quickly transform from a unique strategic asset to a universal requirement. The initial competitive advantage offered by AI's adoption fades as more competitors harness similar technologies. This rapid leveling of the playing field means that SMEs must adopt AI not to lead the market but merely to keep pace with it. As such, the technology's adoption becomes less about seeking a competitive edge and more about not falling behind. Consequently, SMEs are pressured to continuously evolve their AI capabilities to find new avenues for differentiation as the technology itself becomes a common commodity in the industry.

With generative AI becoming a standard tool across competitors, the marginal benefits for each enterprise begin to decrease. When all players in the market deploy AI to optimize their operations and enhance product offerings, the unique value that AI could provide when less widespread is significantly reduced. For SMEs, this saturation leads to smaller gains from AI, as operational efficiencies and innovations become uniform across the board. In this environment, the focus shifts from the adoption of generative AI to maximizing its efficiency and finding innovative ways to apply its outputs to create value that can distinguish an SME from its rivals.

Moreover, the financial strain of operating in a highly competitive market impacts SMEs' ability to invest in generative AI. With a relentless focus on reducing prices to stay competitive, SMEs often operate on slim margins, which can restrict their capacity for significant investments in new technologies. As a result, SMEs might opt for more affordable, less advanced AI solutions that do not fully exploit the technology's potential due to budgetary limitations. This cost-sensitive approach to AI investment means that while SMEs may implement generative AI to some extent, their ability to benefit from its full suite of capabilities is limited, potentially curbing the more profound transformational effects that AI could have on revenue and growth.

Method

Building upon the discussion presented in the conceptual framework, three moderating variables have been incorporated to represent proxies for human capital, technological capacity, and market factors. Tables 3 and 4 display a comprehensive list of the independent variables and the corresponding interaction terms, respectively. Detailed descriptions of each variable are also provided within these tables. The following equation present the basic model formulation of the study:

$$\begin{aligned} YRI = \beta_0 + \beta_{\mathrm{TIL}} \cdot \mathrm{TIL} + \beta_{\mathrm{ED}} \cdot \mathrm{ED} + \beta_{\mathrm{IA}} \cdot \mathrm{IA} + \beta_{\mathrm{ITS}} \cdot \mathrm{ITS} + \\ \beta_{\mathrm{CO}} \cdot \mathrm{CO} + \beta_{\mathrm{GBI}} \cdot \mathrm{GBI} + \beta_{\mathrm{HCL}} \cdot \mathrm{HCL} + \beta_{\mathrm{PET}} \cdot \mathrm{PET} + \\ \beta_{\mathrm{CTI}} \cdot \mathrm{CTI} + \beta_{MKT} \cdot MKT + \epsilon \end{aligned}$$

Where, β_{TIL} is the coefficient for the Generative AI Integration Level (TIL).

β_{ED} is the coefficient for the Establishment Duration (ED).

β_{IA} is the coefficient for Infrastructure Adjacency (IA).

β_{ITS} is the coefficient for International Trade Status (ITS).

β_{CO} is the coefficient for Capital Origination (CO).

β_{GBI} is the coefficient for Generational Business Indicator (GBI).

β_{HCL} is the coefficient for Human Capital Level (HCL).

β_{PET} is the coefficient for Proprietor Expertise Tenure (PET).

β_{CTI} is the coefficient for Current Technological Infrastructure (CTI).

B_{MKT} is the coefficient for the Market Competitor Density (MKT).

With the interactions terms (moderating variables),

$$YRI = \beta_0 + \beta_{\text{Gen*HCL}} \cdot \text{Gen*HCL} + \beta_{\text{Gen*CTI}} \cdot \text{Gen*CTI} + \beta_{\text{Gen*MKT}} \cdot \text{Gen*MKT} + \sum_{i=1}^{k} \beta_{Z_i} \cdot Z_i + \epsilon$$

Where, $\beta_{\text{Gen*HCL}}$, $\beta_{\text{Gen*CTI}}$, $\beta_{\text{Gen*MKT}}$ are the coefficients for the interaction terms.

$\sum_{i=1}^{k} \beta_{Z_i} \cdot Z$ represents the sum of the products of the coefficients and the other independent variables (denoted as Z) in the model. ϵ is the error term.

Table 3. the dependent and independent variables

SL	Variable Name	Symbol	Type	Description
1	Yearly Revenue Increment	***YRI***	Continuous, Dependent	This represents the percentage increase or decrease in the revenue of a business on an annual basis.
2	Generative AI Integration Level	***TIL***	Categorical, Independent	Indicates whether the business has implemented Generative Artificial Intelligence technology, where a value of 0 signifies no adoption, and a value of 1, and 2 signify moderate and high adoption.
3	Establishment Duration	***ED***	Continuous, Independent	Denotes the number of years the business has been operational.
4	Infrastructure Adjacency	***IA***	Dummy, Independent	Assess the business's location in relation to major roadways, with 0 indicating no proximity to main roads and 1 indicating close proximity.
5	International Trade Status	***ITS***	Dummy, Independent	Designates whether the business is engaged in international trade of its products or services. The value is 0 if it does not export, and 1 if it does.
6	Capital Origination	***CO***	Dummy, Independent	Describes the origin of the business's capital. A value of 0 means the capital is sourced internally, and a 1 means it is sourced from external credit institutions.
7	Generational Business Indicator	***GBI***	Dummy, Independent	Identifies whether a business is family-owned with 0 for non-family-owned and 1 for family-owned enterprises.
8	Human Capital Level	***HCL***	Continuous, Independent	The average academic achievement level of the employees, measured by the highest educational qualification obtained.
9	Current Technological Infrastructure	***CTI***	Continuous, Independent	The existing technological assets and systems within the business, quantitatively measured by age, capability, and capacity.

Table 4. interaction terms (moderating variables)				
SL	Variable Name	Notation	Type	Description
10	Generative AI and Human Capital Interaction	***Gen*HCL***	Continuous, Independent	This captures the combined effect of Generative AI Adoption and the level of employee education or expertise, hypothesizing that skilled employees may utilize AI technologies more proficiently.
11	Generative AI and Infrastructure Interaction	***Gen*CTI***	Continuous, Independent	Represents the interaction between Generative AI Adoption and the Current Technological Infrastructure, investigating whether entities with established technological resources benefit more from Generative AI.
12	Generative AI and Market Competition Interaction	***Gen*MKT***	Continuous, Independent	Explores the potential differential impact of Generative AI Adoption in relation to the intensity of Market Competition, distinguishing effects in various competitive environments.

Regularized regressions

Ridge Regression, also known as L2 Regularization, stabilizes the regression estimates in such a way that it reduces the standard errors by imposing a penalty on the size of coefficients. The Ridge Regression function to be minimized is [13]:

$$\mathrm{Ridge}(Y, X; \lambda) = \sum_{i=1}^{n} (y_i - x_i^T \beta)^2 + \lambda \sum_{j=1}^{p} \beta_j^2$$

where Y is the response variable, X the matrix of predictors, β the vector of coefficients, and λ the regularization parameter. The regularization term $\lambda \sum_{j=1}^{p} \beta_j^2$ penalizes the magnitude of the coefficients and effectively shrinks them towards zero. However, unlike Lasso Regression, the Ridge penalty tends to shrink the coefficients evenly and does not set them to zero, thus, all variables are kept in the model. This technique is particularly useful when there is a need to retain all features in the model but still mitigate the problem of multicollinearity.

Lasso Regression, known as L1 Regularization, is another linear regression technique that includes a penalty term to the loss function, but with a different approach to constraint coefficient estimates. The Lasso's objective function can be written as [14]:

$$\mathrm{Lasso}(Y, X; \lambda) = \sum_{i=1}^{n} (y_i - x_i^T \beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

In the equation, Y represents the vector of observations, X is the predictor matrix, β stands for the coefficient vector, and λ is the regularization parameter. The Lasso technique differs from Ridge Regression by the type of penalty it applies; the L1 penalty, $\lambda \sum_{j=1}^{p} |\beta_j|$, encourages sparsity in the model by allowing some of the coefficient estimates to be exactly zero.

Elastic Net Regression combines the strengths of Lasso and Ridge regression methods into a single type of regularized linear regression. It is highly effective when dealing with a scenario where there are more predictors than observations or when there is a high degree of correlation among the predictors. The goal of the Elastic Net is to minimize the total of the squared differences between observed and predicted values, which is akin to what is done in ordinary least squares (OLS). However, it distinguishes itself by adding two extra terms to the function it seeks to minimize, which are specifically for the purpose of regularization. [15]. The objective function in Elastic Net Regression is:

$$J(\theta) = \frac{1}{2n}\sum_{i=1}^{n}(y_i - \theta^T x_i)^2 + \alpha\rho\sum_{j=1}^{m}\left|\theta_j\right| + \frac{\alpha(1-\rho)}{2}\sum_{j=1}^{m}\theta_j^{\,2}$$

where $\boldsymbol{\alpha}$ represents the regularization parameter, while ρ determines the equilibrium between the Lasso and Ridge regularization methods. These parameters are crucial in adjusting the model to achieve the desired level of regularization, with α controlling the overall strength and $\boldsymbol{\rho}$ setting the proportion of the mix between the two techniques

The regularization component within the objective function of Elastic Net is composed of an L1 penalty term ***(|θj|)*** and an L2 penalty term ***(θj²).*** The L1 penalty promotes sparsity within the model, potentially shrinking some coefficients to zero, effectively omitting those predictors. This is particularly advantageous in datasets with a large number of dimensions, aiding in feature selection. Conversely, the L2 penalty shrinks coefficients towards zero but usually not to zero, which is useful for dealing with predictor variables that are highly correlated. The mixing parameter ρ provides the means to find a middle ground between Lasso and Ridge regularization methods. At ***ρ=1***, the Elastic Net is equivalent to Lasso regression, and at ***ρ=0***, it corresponds to Ridge regression [16], [17]. Thus, Elastic Net allows for more nuanced model adjustment.

In Elastic Net Regression, estimating parameters is commonly done using optimization techniques like gradient descent or coordinate descent. The convexity of the objective function guarantees that global minimization is attainable. Selecting the appropriate values for the regularization parameter α and the mixing parameter ***ρ*** typically involves methods such as cross-validation. A grid search may be conducted over a spectrum of ***α*** and ***ρ*** values to find the pair that minimizes cross-validation error. This process enables Elastic Net to be versatile and effective for different data sets and modeling problems.

Results

The results from Ridge Regression are provided in Table 5 and 6. The R-squared value of 0.81 shows that the model accounts for 81% of the variance in the dependent variable. The Adjusted R-squared remains at 0.76, reaffirming that after adjusting for the number of predictors, the model still retains a strong explanatory power. The Mean Squared Error (MSE) slightly improved to 8.94, along with a minimal decrease in the Root Mean Squared Error (RMSE) to 2.99 and a steady Mean Absolute Error (MAE) at 2.31, suggesting a consistent average deviation of the predictions from the actual values. The Cross-Validation Score is unchanged at 0.77, which aligns with the adjusted R-squared value, indicating the model's performance is robust across different subsets of the dataset. However, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) have increased significantly to 292.87 and 323.74, respectively. This increase could indicate a model with higher complexity or a different model structure altogether when compared to the previous ones.

Table 5. Model performance of Ridge Regression

Metric	Value
R-squared	0.81
Adjusted R-squared	0.76
Mean Squared Error (MSE)	8.94
Root Mean Squared Error (RMSE)	2.99
Mean Absolute Error (MAE)	2.31
Cross-Validation Scores	0.77
Akaike Information Criterion (AIC)	292.87
Bayesian Information Criterion (BIC)	323.74

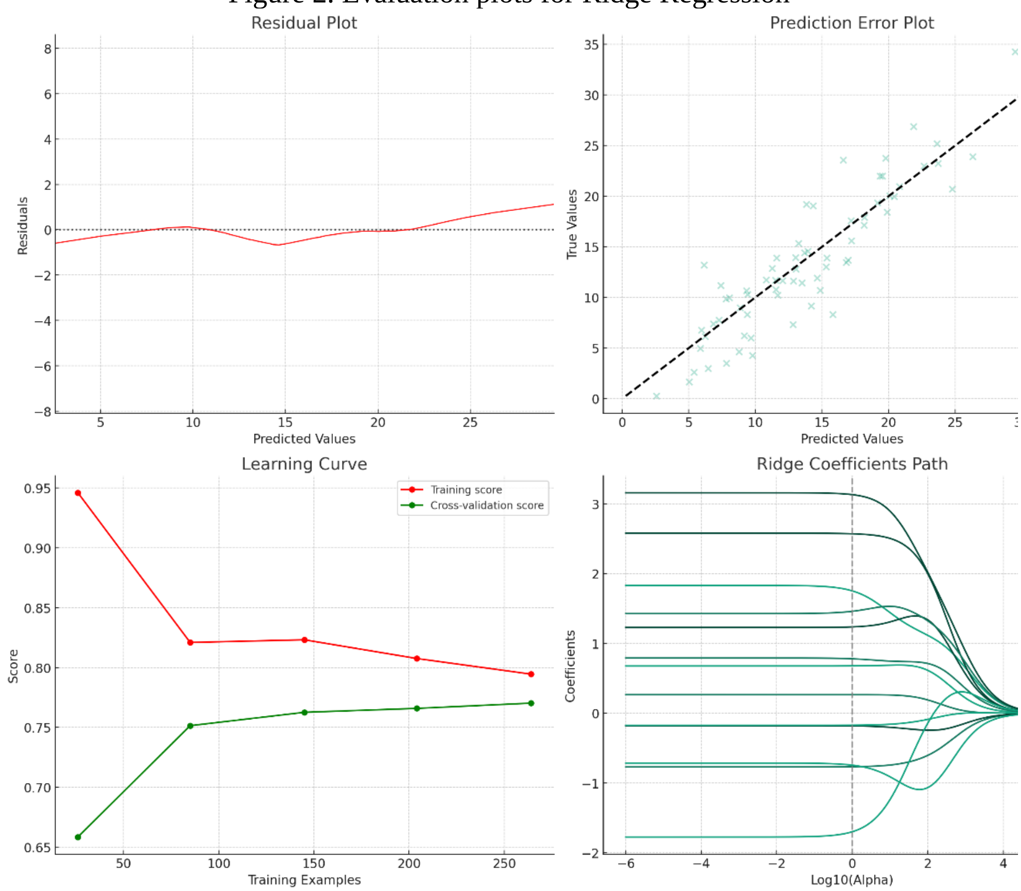
Table 6. Feature importance in Ridge regression

Feature	Importance Score
Gen*CTI	3.13
ED	2.57
Gen	1.75
Gen*HCL	1.46
CTI	1.24
HCL	0.78
IA	0.68
ITS	0.27
GBI	-0.17
CO	-0.18
MKT	-0.74
IC	-0.77
Gen*MKT	-1.70

Gen*CTI still holds the highest positive importance score but has decreased slightly to 3.13. ED's importance has increased, suggesting a greater relevance in this model iteration. Gen remains an important feature with a small decrement in its score, while Gen*HCL has seen an increase, indicating a stronger impact on the model's output. CTI continues to be a positive predictor but with a slightly increased score, while HCL and IA both have positive importance, although IA's score has decreased. ITS shows a minor positive importance. GBI and CO have small negative scores, reflecting a minimal but negative relationship with the dependent variable. MKT, IC, and Gen*MKT hold negative importance values, with Gen*MKT having the largest negative importance, which has increased from the previous model. This suggests that these features are inversely related to the target variable and that their role may be more significant in this iteration of the model.

Interaction terms like Gen*CTI and Gen*HCL remain significant, emphasizing the importance of these combined features in the model's predictive capability. The negative importance of Gen*MKT has grown, which could imply a stronger inverse relationship between this interaction term and the dependent variable in this model.

Figure 2. Evaluation plots for Ridge Regression



The Residual Plot in the top left quadrant in figure 2 demonstrates the relationship between the predicted values of the dependent variable (YRI) and the residuals, which are the differences between the observed and predicted values. The relatively random dispersion of points around the horizontal axis suggests that the model's errors are distributed fairly evenly for different levels of predicted values, without any obvious pattern. This lack of systematic structure is indicative of a well-fitting model. However, there's a slight trend in the data as indicated by the red line, suggesting that the model may systematically over or underestimate the YRI across the range of predictions.

The Prediction Error Plot in the top right quadrant is used to compare the actual and predicted values. Ideally, the points should fall along the dashed line, where the predicted values are equal to the actual values. The plot shows that the model predicts YRI reasonably well, as most points are clustered around the line, but there are deviations, particularly for higher values. The Learning Curve in the bottom left quadrant shows the model's performance on the training and validation sets as the training size increases. The convergence of the training and cross-validation scores suggests that adding more data might not significantly improve the model's performance. The Ridge Coefficients Path in the bottom right quadrant illustrates how the model's coefficients change with different regularization strengths (alpha). As alpha increases, the coefficients of certain features are driven towards zero, which is characteristic of Ridge Regression's ability to reduce overfitting by penalizing large coefficients. The vertical line indicates the alpha value chosen for the final model, balancing the need to penalize large coefficients while retaining predictive power.

Table 7. Model performance of Lasso Regression

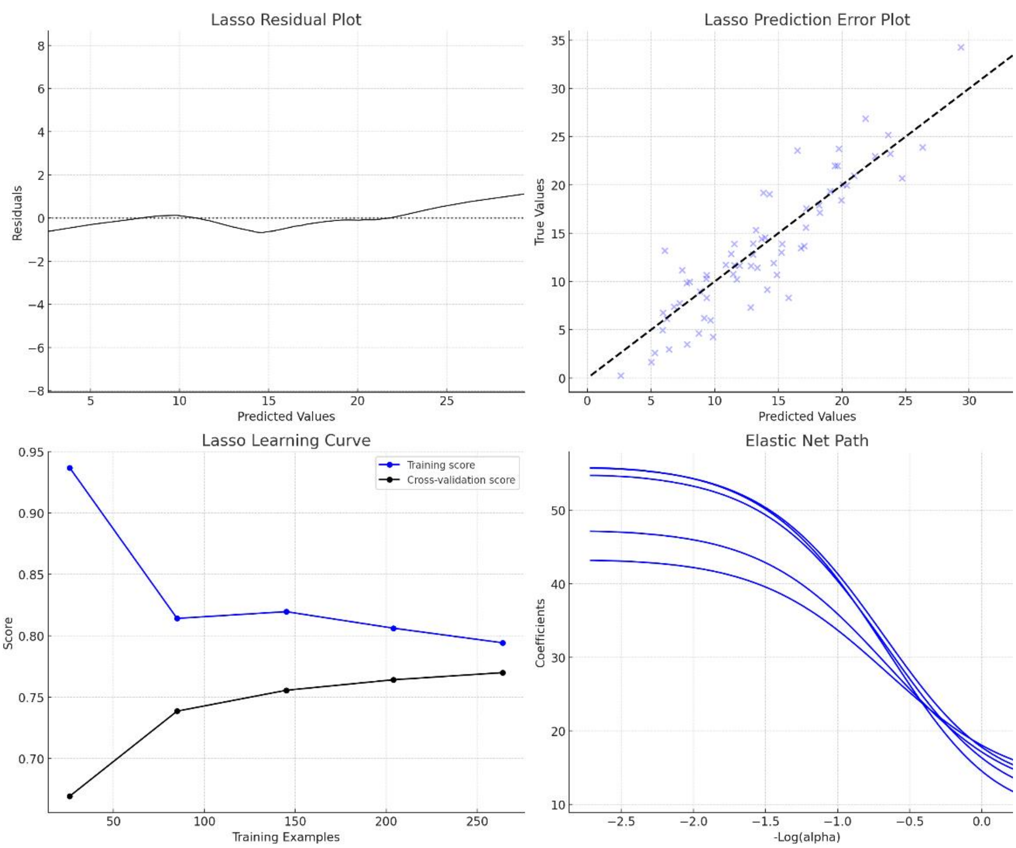
Metric	**Value**
Adjusted R-squared	0.76
Mean Squared Error (MSE)	8.98
Root Mean Squared Error (RMSE)	3.00
Mean Absolute Error (MAE)	2.31
Cross-Validation Scores	0.77
Akaike Information Criterion (AIC)	175.08
Bayesian Information Criterion (BIC)	205.94

Table 8. Feature importance in Lasso Regression

Feature	**Importance**
Gen*CTI	3.27
ED	2.49
Gen	1.79
CTI	1.10
Gen*HCL	1.01
HCL	0.84
IA	0.83
ITS	0.18
CO	-0.16
GBI	-0.25
IC	-0.70
MKT	-0.84
Gen*MKT	-1.39

The results from Lasso Regression are presented in tables 7 and 8. The model's adjusted R-squared value stands at 0.76, indicating a strong explanatory power for the variance of the dependent variable. The Mean Squared Error (MSE) is calculated to be 8.98, with a Root Mean Squared Error (RMSE) of 3.00 and a Mean Absolute Error (MAE) of 2.31, which all point to the model's predictions being relatively close to the actual values. The Cross-Validation Score is similar to the adjusted R-squared at 0.77, suggesting the model's predictive stability. The feature importance scores reveal that Gen*CTI is the most positively influential feature in the model. Following this, ED, Gen, and CTI also show substantial positive importance, indicating they are significant predictors within the model. Features such as Gen*HCL, HCL, IA, and ITS are also positively valued but have a smaller impact. In contrast, CO, GBI, IC, MKT, and Gen*MKT have negative importance values, suggesting a decrease in the dependent variable as these increase or a complex relationship where their presence may enhance the predictive quality of the model due to interactions with other variables. The interaction terms such as Gen*CTI, Gen*HCL, and Gen*MKT imply that the combined effect of these variables significantly influences the model's output and their relationships with the dependent variable are not simply additive but interactive.

Figure 3. Evaluation plots for Lasso Regression



The Residual Plot in the top left reveals the distribution of the residuals, which are the differences between the observed and predicted values. The residuals are scattered around the zero line without any clear pattern, suggesting that the Lasso Regression model does not suffer from systematic errors or bias across the range of predictions. The concentration of residuals around the zero line also indicates that there are no extreme errors in prediction, which is desirable. Nevertheless, some

structure in the residuals could indicate potential improvements in model fit, such as non-linearity in the data that the model does not currently capture.
The Prediction Error Plot in the top right quadrant is a visual representation of the accuracy of the Lasso Regression model's predictions. The fact that most points are clustered around the identity line (where actual values equal predicted values) suggests that the model has a good level of accuracy. However, there are deviations from the line, especially at the higher end of the scale, which implies that the model is less accurate at predicting higher values of the dependent variable. The Learning Curve on the bottom left indicates that the training and cross-validation scores are converging, suggesting that the model is stabilizing and that additional training data is unlikely to improve the model's performance significantly. The Elastic Net Path on the bottom right shows the trajectory of the model's coefficients as the regularization strength is varied. The blue lines represent individual feature coefficients, and their convergence towards zero indicates the model's increasing preference for simplicity and feature selection as regularization becomes more stringent. This path helps in understanding the impact of regularization on the model complexity and feature selection.

Table 9. Model performance of Elastic Net Regression

Metric	Value
Adjusted R-squared	0.76
Mean Squared Error (MSE)	9.1
Root Mean Squared Error (RMSE)	3.02
Mean Absolute Error (MAE)	2.32
Cross-Validation Scores	0.77
Akaike Information Criterion (AIC)	175.95
Bayesian Information Criterion (BIC)	206.82

Table 10. Feature importance in Elastic Net regression

Feature	Importance
Gen*CTI	3.00
ED	2.42
Gen	1.38
Gen*HCL	1.24
CTI	1.18
IA	0.84
HCL	0.77
ITS	0.18
CO	-0.18
GBI	-0.24
IC	-0.68
Gen*MKT	-0.95
MKT	-1.00

The adjusted R-squared value of 0.76 shows that the model explains a significant proportion of the variance in the dependent variable. The Mean Squared Error (MSE) has increased slightly to 9.1 from the previous set of results, as has the Root Mean

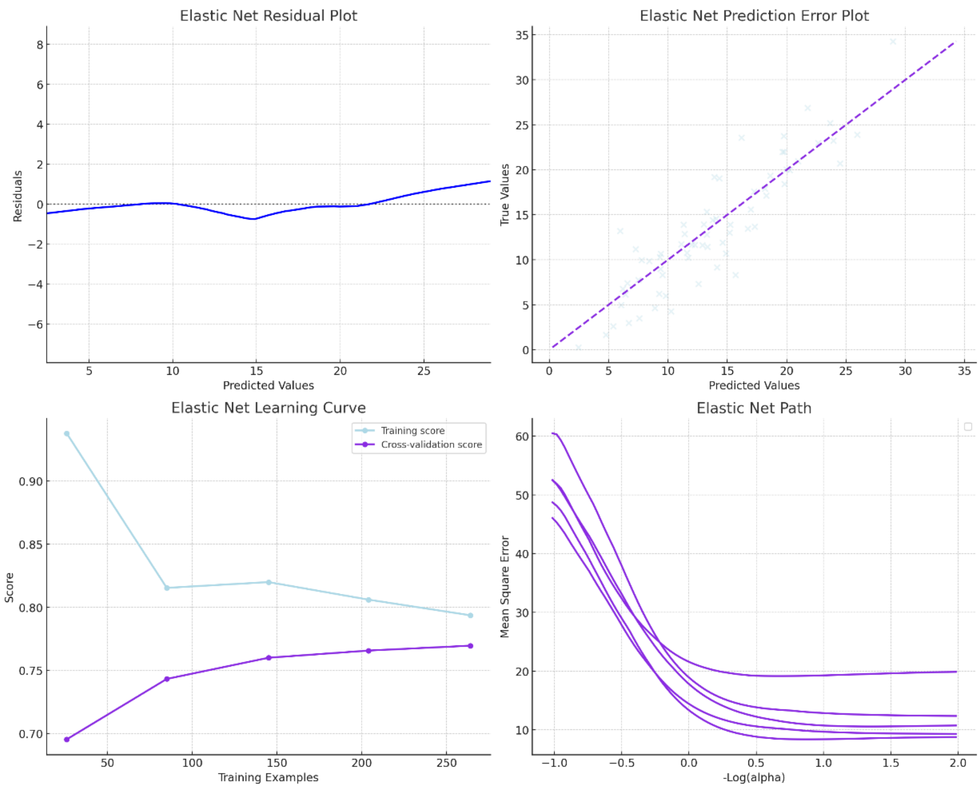
Squared Error (RMSE), now at 3.02, and the Mean Absolute Error (MAE) at 2.32, indicating a marginal increase in the average errors of the model's predictions. However, the Cross-Validation Score remains consistent at 0.77, suggesting that the model's performance is stable across different data subsets. The small increments in the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to 175.95 and 206.82, respectively, might be inconsequential without a direct comparison to other models, but they suggest a slight decrease in the model's relative quality.

Gen*CTI remains the most positively influential feature, albeit with a slightly reduced score from the previous result. ED, Gen, and CTI are also key positive contributors to the model's predictions, with Gen having a noticeably lower score than in the previous set. Gen*HCL and CTI show a small increase in importance, indicating their more significant role in the model. IA and HCL have positive impacts as well, although to a lesser extent. On the other hand, CO, GBI, IC, Gen*MKT, and MKT are negatively associated with the dependent variable. The feature MKT shows a larger negative importance than before, while Gen*MKT's negative influence has decreased. This could imply that the decrease in the target variable with respect to these features is more pronounced in the current model iteration. The interaction terms continue to indicate that the combined effect of certain features (Gen*CTI and Gen*HCL) is substantial, reflecting the importance of considering how features interact with each other rather than just their individual effects. These interactions can sometimes elucidate hidden relationships in the predictive modeling process.

The Residual Plot for the Elastic Net regression, presented in the top left quadrant, shows the distribution of residuals across different predicted values. The light blue points are evenly scattered around the zero line, with the blue trend line remaining close to zero across the range of predictions, indicating a uniform variance of residuals. This uniformity suggests that the Elastic Net model is consistent in its predictive errors across the range of values, without showing signs of heteroscedasticity (a condition where the variance of the residuals is not constant across all levels of the explanatory variables). The slight spread of residuals at higher predicted values may point to potential model improvements, such as accounting for non-linear relationships that the current model might not fully capture.

The Prediction Error Plot illustrates the relationship between the Elastic Net model's predicted values and the actual values. The light blue points, which denote individual predictions, are mostly clustered around the blue violet dashed line that represents perfect prediction. This close clustering indicates a strong predictive accuracy of the model, especially around the lower to mid-range of values, while deviations at the higher end suggest less accuracy for larger values of the dependent variable. The Learning Curve in the bottom left shows a good balance between training and validation scores, with both lines plateauing as more data is used for training. This indicates that the model is generalizing well and is neither underfitting nor overfitting. Finally, the Elastic Net Path in the bottom right reveals the impact of regularization on model complexity: as the regularization parameter increases, the model simplifies by reducing the magnitude of coefficients, which can be seen in the transition of lines towards the baseline. This illustrates the trade-off between model complexity and regularization strength, where the Elastic Net model balances the inclusion of features and the prevention of overfitting through its penalty terms

Figure 4. Evaluation plots for Elastic Net Regression



All three models present an adjusted R-squared of 0.76, signifying that, despite differences in their constraining mechanisms, they equally account for a substantial proportion of the variance in the dependent variable after adjustment for the number of predictors. In terms of predictive accuracy, Ridge Regression shows a marginally better performance with the lowest MSE and RMSE values, implying that it has the smallest average prediction errors. The Cross-Validation Scores are consistent across all models at 0.77, indicating similar robustness in predictive performance when generalized to unseen data.

Gen*CTI consistently appears as the most positively influential feature across all models, although its importance score varies slightly. The Lasso Regression appears to assign more pronounced importance to the features, both positive and negative, which aligns with its characteristic of possibly reducing the coefficients of less important features to zero. In contrast, Elastic Net, which blends L1 and L2 regularization, distributes feature importance more evenly, neither exaggerating nor minimizing them to the extent seen in Lasso.The negative importance scores of features like CO, GBI, IC, MKT, and Gen*MKT vary across the models, with the most substantial negative weights seen in Ridge Regression, particularly for Gen*MKT. This could indicate a stronger penalization for these features, which Lasso and Elastic Net may not emphasize as much due to their propensity to eliminate certain predictors altogether. The use of interaction terms such as Gen*CTI and Gen*HCL is validated in all models, although the magnitude of their importance fluctuates. This underscores the relevance of considering not only the individual contribution of each feature but also the synergistic effects that occur when combining them.

Conclusion

The findings of this study indicate that when Generative AI adoption and Current Technological Infrastructure interact, their combined effect on revenue growth in SMEs seems to be considerably stronger than their individual impacts. This robust interaction indicates that a well-established technological environment within a business significantly enhances the utility and effectiveness of Generative AI. It is likely that existing technological frameworks provide a fertile ground for AI applications to be deployed and integrated into the business processes more seamlessly. For SMEs, this can result in more effective data processing, automation of complex tasks, and an overall more adaptive use of AI capabilities to meet business objectives. Consequently, SMEs that already have modern technology infrastructure are in a better position to extract more value from Generative AI, leading to potentially larger increments in revenue.

For SMEs, the prominent role of technology infrastructure in maximizing the benefits of Generative AI cannot be overstated. This means that prior investments in technology can significantly dictate the scale and pace at which AI can be adopted and used to drive revenue growth. If an SME’s existing infrastructure is dated, integrating AI may require additional resources and could lead to less-than-optimal results. For these businesses, it may be necessary to upgrade their technological framework to create a conducive environment for AI. This does not necessarily mean that all legacy systems need to be replaced; however, it does emphasize the importance of ensuring that the technology in place can support and amplify the advantages that AI is expected to bring.

The substantial impact of the interaction between Generative AI and technological infrastructure on business outcomes suggests that decision-making around AI should not be isolated from the consideration of the business’s technological status quo. SMEs might need to conduct an in-depth analysis of their existing systems to identify compatibility and scalability in the context of AI integration. For those with modern infrastructures, adopting AI could represent a strategic enhancement, driving innovation and creating opportunities to outperform competitors. This dual focus on technology and AI can become a critical aspect of strategic planning for SMEs aiming to achieve significant revenue growth in the dynamic market landscape.

The moderate importance scores for the interaction between Generative AI adoption and Human Capital Level suggest that while there is a clear relationship, it's not as strong as the interaction with technological infrastructure. This finding can be interpreted to mean that the education level and expertise of employees do enhance the implementation and utilization of Generative AI, but these human factors may not be as critical to revenue growth as having the right technological assets in place. SMEs should take note of this as it indicates that simply having a well-educated workforce is not enough to fully capitalize on the advantages of Generative AI. There might be other elements at play that determine the success of AI integration, such as the nature of the business, the specific industry sector, or the type of AI applications being adopted.

For SMEs, this could mean that while investing in employee education is important, expecting it to be the sole driver of significant growth through Generative AI could be unrealistic. Instead, the skills and knowledge of the workforce should be seen as complementary to the technological infrastructure. Employees with higher academic achievements may be better equipped to interact with advanced AI systems and could contribute to more innovative approaches in AI application. However, the potential of these contributions to translate into revenue growth is likely tempered by how well the AI systems are integrated with the existing technology and how they're applied to the business's operations and strategy.

This distinction is vital for SMEs in allocating resources and shaping strategies for AI adoption. It suggests that companies may benefit more from a balanced investment in both technological infrastructure and human capital development. By recognizing that the impact of human capital on leveraging AI is significant but not paramount, SMEs can aim to create a more harmonious interaction between their workforce's capabilities and their technological advancements. This balance is likely to be a key factor in achieving optimal outcomes from AI investments, especially in terms of revenue growth and business performance.

The negative importance scores associated with the interaction between Generative AI adoption and Market Competition in all datasets are intriguing, as they suggest a consistent adverse influence on the revenue growth of SMEs. It appears that the presence of Generative AI in a highly competitive market does not necessarily translate to better financial performance, as one might intuitively expect. This could imply that the pressures and dynamics of a competitive market may diminish the effectiveness of Generative AI technologies, or perhaps that the saturation of AI within an industry makes it harder for any single SME to gain a distinct advantage. The introduction of AI might lead to a race where all competitors rapidly adopt similar technologies, thus nullifying the competitive edge that such a technology could otherwise provide.

This finding serves as a cautionary for SMEs that operate in very competitive markets, suggesting that the deployment of Generative AI alone is not a panacea for revenue growth. It could be that in such markets, the rapid diffusion of AI technologies levels the playing field, making it more difficult for any individual firm to leverage AI for a significant competitive advantage. Alternatively, it could reflect a misalignment between the AI applications and the actual needs or strategic goals of SMEs within these markets. It seems that in competitive sectors, the ability to harness AI effectively requires a nuanced approach, considering factors such as the timing of adoption, the uniqueness of the application, and the ability to integrate AI deeply into the value proposition of the business.

SMEs may need to reconsider how they view the role of Generative AI within their competitive strategy. Rather than expecting AI to be a straightforward driver of growth, it may be more prudent to think of AI as a tool that needs to be carefully integrated into a broader strategy that includes other competitive factors. For SMEs, this could mean a greater focus on innovation in the application of generative AI, or perhaps a tailored approach that focuses on niche market segments where generative AI can be used to meet specific customer needs in ways that competitors have not yet exploited. It indicates the importance of a strategic, rather than purely technological, approach to generative AI adoption — one that is aware of the market dynamics and is designed to create a competitive advantage rather than just keeping pace with competitors.

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