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Implications of Generative AI on Small to Medium Size E-commerce Businesses

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Implications of Generative AI on Small to Medium Sized E-commerce Businesses

This study investigates the implications of generative AI on small to medium-sized e-commerce businesses. While digital technologies have rapidly reshaped the e-commerce landscape, the integration of generative AI remains in its early stages for many SMEs.

The study addresses the question: “What are the implications of generative AI on marketing strategies, product development, and the competitive landscape for small to medium-sized e-commerce businesses?” It aims to identify key opportunities and challenges, offering insights on how SMEs can effectively leverage generative AI to improve operations and stay competitive.

The study employs survey methodology, gathering data from 49 small to medium-sized e-commerce organizations. The survey explores aspects associated with generative AI such as the adoption rates, perceived benefits, encountered challenges and future trends.

The findings indicate that generative AI is mainly used in marketing for marketing content creation. While the impact on personalized customer experience creation and improved customer experience remains moderate. In product development, it supports early-stage design and prototyping, accelerating time-to-market but contributes less to breakthrough innovation. Competitively, generative AI is seen as lowering barriers to entry, however its broader impact on the market and competition with larger firms remains modest.

Keywords: Generative AI, E-commerce, Marketing, Product Development, Competitive Landscape, SMEs

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List of abbreviations (or) symbols

AI	Artificial Intelligence
B2B	Business to business
B2C	Business to consumer
C2C	Consumer to consumer
C2B	Consumer to business
CRM	Customer relationship management
EU	European Union
GDP	Gross domestic product
GDPR	General data protection regulation
GAN	Generative adversarial network
HR	Human resources
LLM	Large language model
OECD	Organisation for Economic Co-operation and Development
RAG	Retrieval augmented generation
SEO	Search engine optimization
SME	Small to medium enterprise
USA	United States of America
VADER	Valence aware dictionary and sentiment reasoner
VAE	Variational autoencoder

1 Introduction

1.1 Background and Motivation

The rapid advancement of digitalization and digital technologies has transformed how businesses operate, with e-commerce becoming a central part for businesses of all sizes (Chevalier, 2024b; Demiroglu, 2021). Among these technologies, generative artificial intelligence (AI) has recently gained significant attention as it provides novel opportunities as well as challenges for online businesses (AXA Investment Managers, 2024; Feuerriegel et al., 2024). These AI models are capable of producing novel content such as text, images and even videos. Their increasing accessibility, driven by improvements in computational power and model architectures, has significantly lowered barriers for adoption (Dani, 2025; Slattery et al., 2025). For small and medium-sized enterprises (SMEs), the integration of generative AI into e-commerce activities holds the potential to enhance efficiency and competitiveness. However, it also introduces new challenges such as content reliability and novel security risks (Maynez et al., 2020; Peng et al., 2024). Therefore, understanding the implications of integrating generative AI into business activities is important for SMEs operating in a continuously evolving digital marketplace.

Definition of SMEs typically vary depending on the region. In European Union (EU) SMEs are defined as businesses with fewer than 250 employees (European Comission, 2024). On the other hand, according to United States International Trade Commission (2010), in United States of America (USA) a company is considered an SME if it has less than 500 employees. In China, the definition is more complex, incorporating factors such as the number of employees, total assets, business revenue and industry sector (Xiangfeng, 2008). Based on this definition, the number of employees in SMEs vary between 100 to 3000 for different industries in China. In this work, an SME is defined as a company with fewer than 500 employees as the focus is on global businesses. Companies are further categorized by size: those with fewer than

20 employees are classified as Micro, those with up to 100 employees as Small, and those with up to 500 employees as Medium.

In terms of global economic development, SMEs play a vital role, acting as a driving force for job creation, innovation and localized economic growth (Stel et al., 2005). Representing a significant proportion of businesses worldwide, SMEs make substantial contributions to gross domestic product (GDP) and employment rates, often forming the economic backbone of both developed and emerging economies. In EU-27, SMEs make up 99% of all enterprises across every industry sector (European Comission, 2024). Globally, SMEs make up approximately 90% of businesses, providing over 50% of employment in emerging markets and developing economies and contributing around 40% to global GDP (Carvajal & Didier, 2024).

E-commerce has become an essential arena for SMEs, offering great opportunities for reaching a global customer base and expanding their market presence beyond physical limitations (Demiroglu, 2021; Nejadirani et al., 2011; Savrul et al., 2014). E-commerce has been experiencing rapid growth, driven by increased digital connectivity, consumer demand for convenience and advancements in technology, making it one of the fastest-growing sectors in today’s economy (Chevalier, 2024b). In 2024, the revenue in the e-commerce market estimated to be $4,117 billion and reach $6,478 billion by 2029 (Statista, 2024).

As generative AI continues to evolve rapidly, its impact on SMEs remains both promising and uncertain. While these technologies can enable innovation and operational growth, they also introduce new complexities that SMEs must carefully consider.

1.2 Aim and Research Questions

There is a need to study the implications of generative AI on the e-commerce sector, particularly for SMEs since SMEs can benefit significantly from generative AI, while being also more susceptible to the challenges it presents compared to larger enterprises. This thesis aims to investigate the implications of generative AI on small to medium e-commerce businesses, examining how these tools influence marketing, product innovation and competitive dynamics. The analysis provides insights into both the opportunities generative AI presents and the potential drawbacks for SMEs, contributing to clear understanding of AI's implications on the evolving landscape of e-commerce. By addressing the implications of these technologies, this research also provides insights into the strategic decisions and adaptations necessary for SMEs to become successful in an increasingly AI-driven market.

The research questions of this study are:

1. How does the integration of generative AI tools impact the marketing strategies of small to medium e-commerce businesses?
2. In what ways do generative AI tools influence the product development and innovation processes in small to medium e-commerce businesses?
3. How has generative AI affected the competitive landscape for small to medium e-commerce businesses, particularly in terms of barriers to entry and market saturation?

1.3 Research Method

The research was conducted through a survey that combines both closed-ended and open-ended questions to address the complexity of the research questions. The survey was designed to collect both quantitative and qualitative data to ensure a comprehensive exploration of the topic. Quantitative data, derived from structured questions like Likert scales, allows for statistical analysis of trends and patterns, such as the extent to which SMEs perceive AI impacts their marketing strategies. Qualitative data from open-ended questions, on the other hand, provides deeper insights into the underlying reasons and contextual nuances behind these perceptions (Creswell & Clark, 2007). By combining these methods, the study ensures both breadth and depth, capturing measurable trends while also exploring the diverse experiences and perspectives of SMEs.

The survey was distributed to 112 SME representatives from organizations of various sizes, sectors and countries using LinkedIn platform. Total number of responses were 49. The quantitative results were analysed using descriptive statistics such as mean, median, percentage and standard deviation and results were presented using various visualizations. On the other hand, qualitative results were analysed by content and text analysis to provide numerical summary of qualitative insights.

2 E-Commerce and Generative AI

2.1 Definition of E-commerce and Its Development

There are various definitions of e-commerce in the literature. For instance, Turban et al. (2017) defines the e-commerce as the process of conducting transactions, including buying and selling goods, services and information, over electronic networks, primarily the Internet. According to Laudon and Traver, (2016), e-commerce refers to conducting business through the Internet, the web and mobile applications or browsers on mobile devices. OECD (2011) provides a broader definition of an e-commerce transaction as the sale or purchase of goods or services conducted via computer networks using methods specifically designed for placing or receiving orders. According to OECD (2011) although the order is made online, payment and delivery do not have to occur through digital channels and such transactions can take place between businesses, individuals, households, government entities and other public or private organizations.

The birth and evolution of e-commerce was facilitated by various technologies. The first uses of e-commerce can be attributed to the development and use of electronic fund transfer system in early 1970s, which was mainly used by the business to business transactions (Nogoev et al., 2011). Another milestone in the evolution of e-commerce was the standardization of electronic data interchange, which ensures reliable transactions between two parties (Nogoev et al., 2011). The technological advancements of the 1990s led to rapid development of world wide web and this created a surge in e-commerce technologies across various industries, which contributed to the rise of internet startup companies. Two of these companies are Amazon and eBay which was founded in 1994 and 1995, respectively. Thanks to this technology boom, in 2000, the total e-commerce retail sale volume in United States surpassed $25 billion (Coppola, 2024).

One of the key milestones in the history of e-commerce especially for SMEs is the launch of Amazon Marketplace and Shopify in 2000 and 2004, respectively. Amazon Marketplace is an e-commerce platform that is owned and managed by Amazon and it enables third party sellers to sell products (Amazon, 2001). By utilizing Amazon Marketplace businesses can access to customer base of Amazon which is huge. For instance, according to a report by Chevalier, (2024a), in 2023 Amazon accounted for 37.6% of the e-commerce market in the United States. This access to large customer base creates huge convenience especially for small businesses. Today many businesses utilize Amazon Marketplace. As reported by Toogood, (2024), in 2023 more than 60% of the sales in Amazon came from third party sellers and most of these businesses were SMEs.

On the other hand, Shopify is a platform that provides unified ready-made tools to design an e-commerce website, implement payment checkout system, automate shipping and more to entrepreneurs and businesses who want to start their own e-commerce shopping site with ease (Hitchcock, 2024). According to a report by Singh, (2024), as of 2024, there are 5.23 million active stores in Shopify with 2.1 million active daily users globally. Another platform called Etsy has been started on 2005 and the target audience is mainly the small businesses. It is a managed platform for marketplaces for selling and buying designed, crafted or collected goods (Gebel, 2020). Similar to Amazon Marketplace, the businesses can open a store on Etsy and start selling goods immediately. Mohammad (2024) reported that there are 7.5 million active sellers and 95.1 million active customers on Etsy as of 2024.

Today there are various other platforms similar to Amazon Marketplace, Shopify and Etsy which are not covered here. However, the key point is that all these platforms create a perfect environment to for small businesses to start with e-commerce, establish a brand online and gain a customer base. Although these services lower the barrier to entry to e-commerce market significantly, it is worth mentioning that the services are provided with a monthly fee and commission on successful sales.

An important cornerstone in the history of e-commerce is the Covid-19 pandemic. During the peak of the pandemic through 2020, many countries enforced restrictions such as quarantines, stay-at-home orders and similar societal restrictions. This caused people to turn to e-commerce shopping for necessary goods from the comfort of their home. In return, this had a significant impact on the digital economy, affecting many businesses worldwide. A report published by International Trade Administration (2021) indicates that, in 2020 the share of e-commerce in total global retail sales jumped to 18% with an increase of 4.4%. This is significant considering between 2015 to 2019 the average growth of e-commerce share in global retail sales was only 1.6%. According to another report by International Trade Administration (2023), the global e-commerce revenue increased 24% during 2020, compared to average 8.5% increase in 2018 and 2019. With the use of e-commerce more often, the customer sentiment towards e-commerce has also been generally positive during this time in various countries (Ecommerce Europe, 2021). The pandemic also impacted the businesses heavily. The companies that did not adopt e-commerce during pandemic experienced significant losses compared to e-commerce adopters. Lestari et al. (2021) found that, this disparity in return pushed the companies to adopt e-commerce to meet the customer demands and stay competitive. O’Toole et al. (2020) found that this shift also prompted businesses to fast-track their digital transformation efforts, often accelerating these initiatives by several years. That said, the speed of increase did not continue after the pandemic and it is estimated the growth will slow down, albeit higher than pre-pandemic levels, as can be seen in Figure 1.

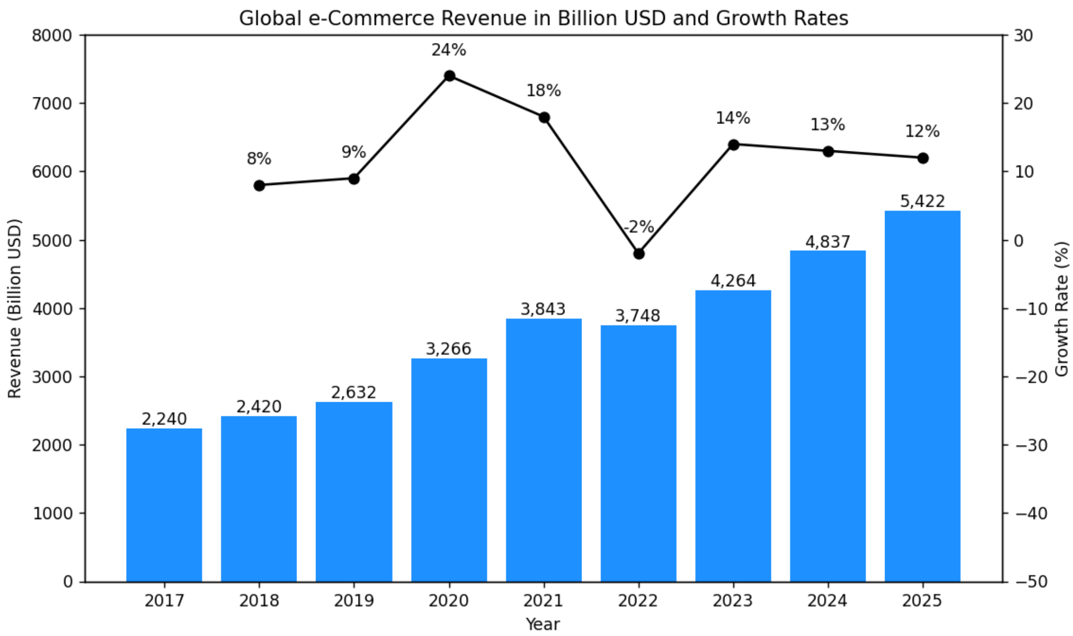

Figure 1. Global e-commerce revenue in billion USD and growth rates (International Trade Administration, 2023).

In the longer run, the estimation on the revenue growth in e-commerce is positive as reported by Statista (2024). Revenue is projected to grow at an annual rate of 9.49% in terms of compound annual growth rate from 2024 to 2029, reaching an estimated market volume of $6,478 billion by 2029. According to the same report, the main drivers for the revenue growth in 2024 are enhanced online shopping experience, social commerce trend and increasing number of internet users. On the other hand, negative consumer sentiment, geopolitical uncertainty and supply chain pressures are the main factors to affect the growth negatively as shown in Figure 2.

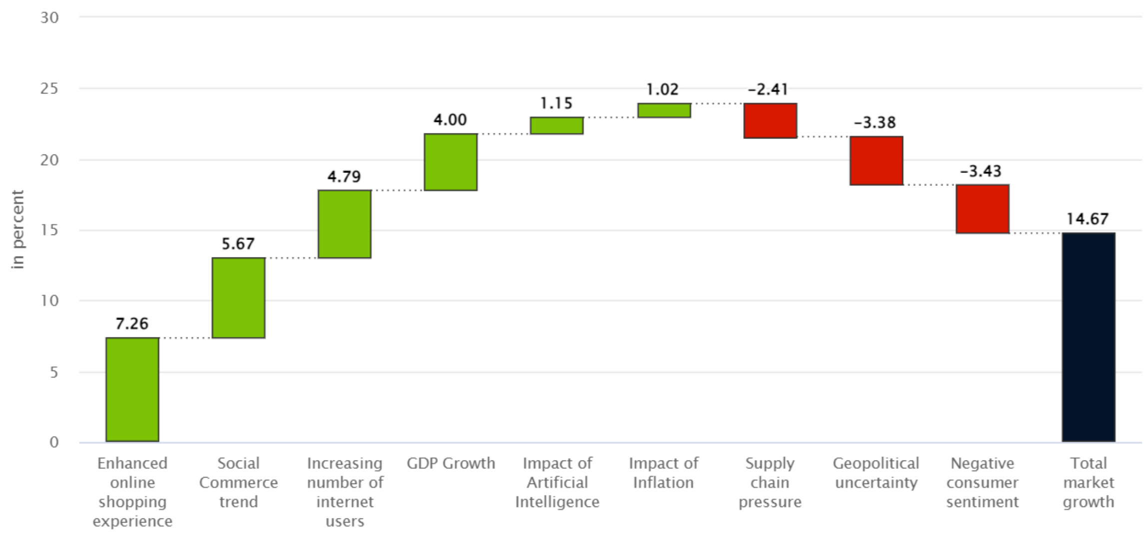

Figure 2. Global e-commerce market drivers for 2024 (Statista, 2024).

Considering the SMEs, many of them are increasingly utilizing e-commerce. For instance, Mehta (2023) stated that in 2022, over 60% of sales in Amazon's store come from independent sellers, with nearly all of them being small and medium-sized businesses. According to another survey by Chevalier, (2024b) in United States at least six out of ten SMEs prioritizing going digital. In Australia and New Zealand, around 40% and 50% of SMEs got online orders in 2022, respectively (van Gelder, 2024b). In EU, the figures are lower with 20.8% of small size businesses (10-49 employees) and 30.2% of medium size businesses (50-249 employees) made e-commerce sales in 2023, respectively (van Gelder, 2024a). These figures indicate that e-commerce is an important part of many SMEs.

Types of E-commerce

As agreed by Jain et al. (2021) and Joshi and Dumber (2017), e-commerce types can commonly be classified based on the participating parties in the transaction. Based on this, the main types of e-commerce are business to business (B2B), business to consumer (B2C), consumer to consumer (C2C) and consumer to business (C2B).

In B2B e-commerce, transactions occur between two businesses, often involving high transaction volumes and values. For instance, a restaurant chain ordering bulk kitchen supplies from an online wholesaler is an example of B2B e-commerce.

B2C e-commerce allows businesses to sell directly to consumers, with well-known examples being platforms that offer online retail shopping. For instance, a clothing brand selling products directly to consumers through its website can be classified as B2C e-commerce, which eliminates the need for physical stores. However, managing logistics costs and delivery can be challenging in this model.

C2B e-commerce occurs when consumers create requests that businesses fulfil. A common example is a freelancer posting their skills and services on a platform where companies can bid on their projects or a consumer listing their preferences for a custom product, which various businesses compete to provide.

C2C e-commerce enables consumers to sell directly to each other, with a platform acting as an intermediary. For example, a marketplace where people sell second-hand items directly to other consumers, like a used electronics site, is a form of C2C e-commerce.

Advantages of E-commerce for SMEs

There are various advantages and disadvantages of adopting e-commerce for SMEs as discussed by Savrul et al. (2014), Demiroglu (2021) and Nejadirani et al. (2011). Savrul et al. (2014) highlight how e-commerce enables small and medium-sized enterprises (SMEs) to innovate by developing value-added services, exploring new business models and implementing strategies for expanding into new markets, including international ones. Through these efforts, SMEs can enhance their operational effectiveness and establish electronic partnerships with larger firms or industry-wide associations, which are often key players in their supply chain. Similarly, Demiroglu (2021) emphasizes that e-commerce reduces the need for a physical location, providing buyers with access to products and services 24/7 and lowering the operational costs associated with maintaining a physical store. Additionally, an online presence enhances brand image and allows SMEs to sell digital goods without geographic restrictions. Nejadirani et al. (2011) further note that e-commerce can reduce transactional and advertising costs, create effective communication between buyers and sellers, minimize transportation challenges and reduce delivery expenses. Together, these benefits make e-commerce an attractive avenue for SMEs, allowing them to optimize costs and expand their market reach more efficiently. Considering these advantages, it is clear that e-commerce serves mainly as a barrier remover for many companies to start and scale their businesses.

Disadvantages of E-commerce for SMEs

Despite the advantages e-commerce can offer, there are significant technical and non-technical challenges that SMEs face. For instance, according to Savrul et al. (2014), many SMEs in the EU report that their products or services are not well-suited for online marketing, which limits their ability to effectively engage in e-commerce. Additionally, SMEs encounter logistical and payment-related difficulties, which vary depending on firm size but are common across different types of enterprises. Security concerns and a complex legal framework further obstruct SMEs' e-commerce adoption, alongside a lack of awareness, knowledge gaps and infrastructure limitations. These factors, along with high costs, often require more systemic changes beyond what SMEs can achieve independently. Demiroglu (2021) adds that offline trading remains prevalent and that SMEs relying on e-commerce must contend with intense competition, the need for stable software and the challenge of building buyer trust. Similarly, Nejadirani et al. (2011) highlight that many SMEs lack knowledge in information and communication technology and often resort to a trial-and-error approach in developing their e-commerce strategies. This lack of planning can cause challenges for SMEs to fully leverage e-commerce opportunities, as they struggle to identify suitable applications and strategies. Together, these factors reveal how e-commerce, while advantageous, presents various challenges that can complicate its integration for smaller businesses. As the technology evolves, some of the explained disadvantages become less of a challenge. Especially the developments in AI front, can help for tackling some of these challenges as will be discussed in the next sections of this thesis.

Advantages of E-commerce for Consumers

E-commerce offers various advantages for customers, providing them with flexibility, savings, and convenience. Khan (2016) notes that online shopping reduces transaction costs and allows customers to make purchases at any time of day, providing a level of comfort and accessibility that is not dependent on physical interaction with a store. Customers can save time by quickly comparing products and prices on different websites, as well as by making purchases from the comfort of home or any location. E-commerce also offers customers a broad selection of products, enabling them to access items that may not be available locally or nationally. Additionally, the ease of switching providers if service quality is unsatisfactory gives customers greater control over their purchasing experience. Sammer and Malkova (2016) add that e-commerce platforms often offer more economical pricing compared to traditional stores, as they typically incur lower operational costs. Online stores also tend to run frequent sales and discounts, benefiting cost-conscious shoppers. Furthermore, customers can thoroughly research product details and reviews before making a purchase, allowing for more informed decisions. E-commerce provides a high level of psychological comfort by eliminating the need to wait in lines or rush through crowded stores, especially during holiday seasons. Payment methods are convenient, and delivery options add to the ease of online shopping, making e-commerce an attractive option for customers.

Disadvantages of E-commerce for Consumers

While e-commerce offers convenience, it also presents certain challenges for consumers. According to Khan (2016), one of the primary concerns is a lack of robust system security and reliability, which increases the risk of financial losses if an e-commerce site is hacked. Additionally, consumers may face uncertainties regarding the legality and authenticity of online transactions, particularly in regions where electronic transaction laws and security measures are not well-developed. Trust is essential for electronic transactions, but the absence of clear legal definitions, such as for electronic signatures, can damage consumer confidence. Taher (2021) adds that online shopping limits customers’ ability to inspect items firsthand, which can lead to dissatisfaction if products do not meet expectations upon arrival. Delivery delays and potential damage during transit are also common concerns, as consumers may have to wait for their purchases and risk receiving damaged items. Furthermore, customer service options on e-commerce sites are often limited compared to physical stores, where assistance is readily available. Many sites only offer customer support during specific hours, and long hold times can deter customers from seeking help. Security risks, such as cyber fraud, also persist, requiring customers to remain vigilant. Sammer and Malkova (2016) note additional inconveniences like the need to register with online stores, which may lead to excessive promotional emails. These challenges highlight how, despite its many benefits, e-commerce can sometimes leave consumers facing issues they wouldn’t typically encounter in traditional shopping experiences.

Considering advantages and disadvantages of e-commerce and current consumer statistics, it is undeniable that e-commerce has become an essential part of modern consumer life (Statista, 2024). The technology evolution will potentially help remove some of the challenges discussed here in the future.

2.2 Generative AI

There are various definitions of generative AI in the literature. Feuerriegel et al. (2024) defines generative AI as “computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data.”. Foster (2019) attributes the term generative AI to models that can generate human-like content that can be understood easily rather than models that generate numerical values such as probabilities of observations. In order to find a universal definition for generative AI García-Peñalvo and Vázquez-Ingelmo (2023) performed an extensive literature review and they concluded that the term generative AI can be defined as “the production of previously unseen synthetic content, in any form and to support any task, through generative modelling.” (p. 14).

The types of generative AI can be classified based on several criteria, including output modality, model architecture, application domain, and system level types (Feuerriegel et al., 2024). Each classification provides a different perspective on how these models function and where they can be applied. However, in this work, we will focus on classifying generative AI by their modality, specifically, the type of synthetic data they are designed to accept and generate.

Based on modality, generative AI can be broadly categorized into two main types: unimodal and multimodal generative AI. Unimodal generative AI is characterized by its use of a single, consistent type of input and output data. For example, a unimodal generative AI might be designed exclusively for text, generating new text from text-based inputs. This specialization allows unimodal models to perform well in their specific domain, achieving high levels of accuracy and quality in tasks such as text generation, image synthesis or audio creation.

On the other hand, multimodal generative AI is designed to handle multiple types of input and output data. These models can process and generate a variety of data types, including text, images, video, and audio. For instance, a multimodal generative AI might take a textual description and generate a corresponding image or video, or it might combine visual and auditory inputs to create a synchronized audio-visual output. This capability is particularly valuable in complex tasks that require the synthesis of information across different modalities (Cao et al., 2023; Feuerriegel et al., 2024). This classification of generative AI by modality is illustrated in Figure 3.

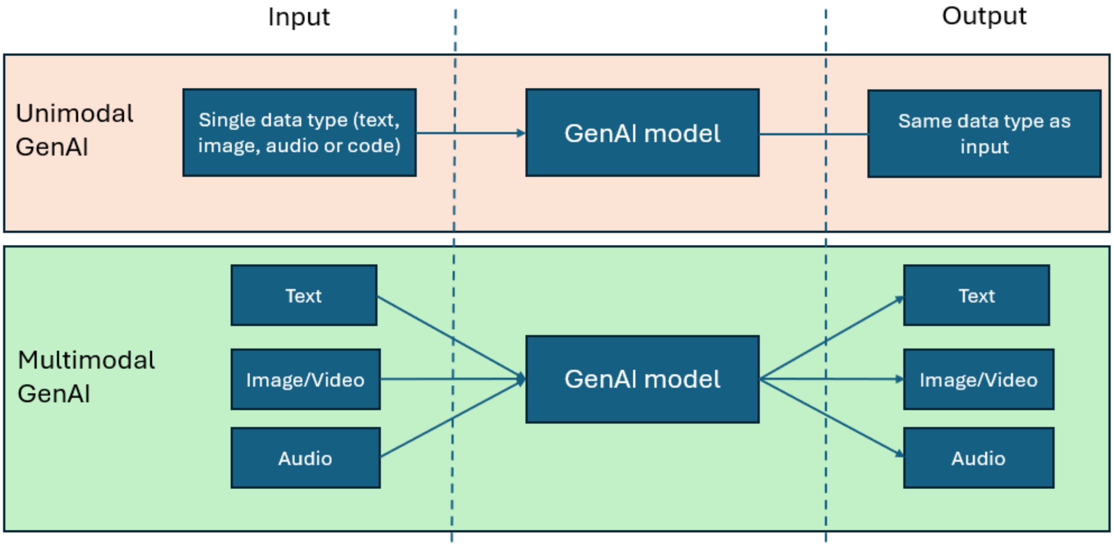

Figure 3. Illustration of the classification of generative AI by modality, adapted from Cao et al. (2023).

2.2.1 Unimodal Generative AI

Text Generation

The early examples of text generation models in the form of chatbots for natural language processing to enable computers to communicate with humans, were developed in 1960s and 1970s (Carbonell, 1970; Shortliffe et al., 1975; Weizenbaum, 1983). The underlying models of these chatbots are utilizing rule-based algorithms which makes them unable to generate novel content or understand the context of the conversations (Gupta et al., 2024). Various models and applications for providing human-machine communication have been developed in the past, however the main advancements have been seen in the past decade (Adamopoulou & Moussiades, 2020; Cao et al., 2023; García-Peñalvo & Vázquez-Ingelmo, 2023; Zemcik, 2019).

In the early 2010s recurrent neural networks (RNNs) and long short-term memory models (LSTMs) were utilized for natural language processing (NLP) tasks (Graves, 2012; Mikolov et al., 2010). As explained by Tarwani and Edem, (2017) RNNs predict the next sequence of words by taking into account the previous sequences. RNNs however encounter various problems when trying to handle long sequences such as vanishing gradient (Khan et al., 2023). LSTMs provide improvement over RNNs as they introduce the concept of memory cells to consider longer sequences. Another type of model architecture so-called gated recurrent unit (GRU) provides further improvement over LSTMs as it allows models to handle longer sequences with lower computational complexity (Khan et al., 2023). Despite the advancements they provide, the context length that these models can consider remains a challenge (Khan et al., 2023; Khandelwal et al., 2018).

A key advancement in the generative AI domain happened in 2017 with the release of transformer architecture by Vaswani et al. (2017). The transformer architecture allows models to process longer sequences efficiently solving many of the issues that previous model architectures had. Advanced language models have been developed using this architecture. For example, Radford et al. (2018) developed Generative Pre-trained Transformer (GPT), while Devlin et al. (2019) created the Bidirectional Encoder Representations from Transformers (BERT). These models require large amounts of data to be trained and they have billions of parameters to be determined during training (Khan et al., 2023). Thanks to the advancements in the technology, more computational power became available and this allowed lots of improvements to be made and new larger models to be trained (García-Peñalvo & Vázquez-Ingelmo, 2023; Gozalo-Brizuela & Garrido-Merchan, 2023). Due to the requirements of computational power, it is impractical to train these models often. Therefore, most of the state-of-the-art large language models (LLMs) are pretrained before their release to public such as GPT-4 by OpenAI et al. (2024), Gemini by Google Gemini Team et al. (2024), Claude by Anthropic (2024) and Llama by Touvron et al. (2023). Based on these models, many applications such as ChatGPT, Bing Chat, Microsoft Copilot have been built and released to public (Mehdi, 2023a, 2023b; OpenAI, 2022). Some LLMs also have ability to generate code which may assist in software development. An example tool is GitHub Copilot as a software development assistant (Friedman, 2022).

Image and Video Generation

Meanwhile, considering the role of generative AI in computer vision, significant advancements in this field were relatively limited until the introduction of the Generative Adversarial Network (GAN) architecture by Goodfellow et al. (2014). The release of GANs marked a turning point, as they demonstrated a novel approach to image generation that surpassed previous methods in both quality and realism. GANs employ a unique adversarial process, where two neural networks, so called a generator and a discriminator, compete against each other, leading to the creation of increasingly refined images. The success of GANs in generating high-quality images quickly led to their adaptation and enhancement for other media forms, including video generation. An example of such a model is VideoGAN, developed by Vondrick et al. (2016), which extended the GAN framework to create coherent video sequences from static images.

In addition to GANs, other architectures have also played a crucial role in advancing generative AI for image and video synthesis. Variational Autoencoders (VAEs) emerged as a powerful alternative, offering a probabilistic approach to image generation that allows for more controlled and interpretable outputs. As explained Vahdat and Kautz, (2020), VAEs work by learning latent representations of the training data, enabling the generation of new images by sampling from these latent spaces during the inference. Similarly, diffusion models have gained prominence for their ability to generate images through a gradual process of noise reduction, starting from a noisy version of the image and refining it over successive steps to produce a clear and high-quality output (Ho et al., 2022; Rombach et al., 2022).

The impact of the transformer architecture on generative AI in computer vision has also been significant. Originally designed for natural language processing tasks, transformers have been adapted for vision tasks, where their self-attention mechanisms enable the capture of complex dependencies within image data. This adaptation has led to breakthroughs in image generation with greater detail and coherence as shown by Parmar et al. (2018), Esser et al. (2021) and Han et al. (2023).

Audio Generation

Beyond the image and video generation domains, VAE, GAN, diffusion, and transformers architectures have also been successfully applied to audio generation tasks, including speech and music synthesis. For example, GANs and VAEs have been used typically to generate speech with varying intonations and accents, while diffusion models have been adapted to generate high-fidelity music by gradually refining synthesized audio waveforms. On the other hand, as shown by Božić and Horvat (2024) transformer-based models have been used to capture long-range dependencies in audio data, enabling the generation of complex audio such as musical compositions.

2.2.2 Multimodal Generative AI

Multimodal model development advanced following the successful unimodal architectures which was discussed in the previous chapter. Particularly in recent years, the further development of transformer and diffusion architectures, combined with advances in hardware, has enabled the creation and training of sophisticated multimodal models capable of generating multi modal content such as text-to-image, text-to-audio, and text-to-video (Božić & Horvat, 2024; Cao et al., 2023; C. Zhang et al., 2023; Zhou et al., 2024). Some examples of recent multimodal generative AI models are CLIP by Radford et al. (2021), DALL-E by Ramesh et al. (2021), GPT-4o by OpenAI (2024), Claude by Anthropic (2024), Gemini by Google Gemini Team et al. (2024) and Sora by Brooks et al. (2024).

These multimodal models show a remarkable ability to process and synthesize information across different forms of data, allowing them to generate high-quality output in various modalities. For instance, models like DALL-E are capable of generating detailed and contextually appropriate images from textual descriptions, demonstrating an advanced understanding of both language and visual representation (Ramesh et al., 2021). On the other hand, one of the recent and powerful model GPT-4o, is capable of responding audio inputs in an average of 320 milliseconds which allows a natural human and machine conversation (Pichai et al., 2024). Recently, with reinforcement learning training, generative AI models gained much better capabilities at reasoning to solve challenging problems. Some examples of such models are OpenAI o-series and Gemini Thinking series models (OpenAI, 2024; Pichai et al., 2024).

The multimodal synthesis allows for effective transition between different types of data inputs and outputs, making these models versatile tools for a wide range of creative and technical tasks. Overall, the high-quality output generated by these models, as evidenced by their strong performance in various benchmarks, demonstrates their potential in several tasks (Pichai et al., 2024).

2.3 Generative AI Use Cases and Adoption in E-Commerce

Generative AI can be applied in several areas in e-commerce such as marketing, product development, customer experience, supply chain and logistics optimization to provide improvements in various aspects (AXA Investment Managers, 2024). The adoption of generative AI has already been happening in e-commerce considering these use cases. A report from Salesforce, (2023a) shows that overall, 48% of the surveyed 2700 e-commerce organizations are working on developing generative AI solutions and 29% of the respondents fully implemented them. Considering the implementations, the report shows that the prevalent use cases are related to marketing, sales and customer service. Some of the applications of generative AI will be discussed in the following subsections.

2.3.1 Generative AI Applications in Marketing and Recommendations

Generative AI can be utilized in many marketing related use cases in e-commerce domain. One of these cases is writing product descriptions. Product descriptions in an e-commerce setting can have a significant impact on product cognitive involvement, product affective involvement, platform enduring involvement and platform situational involvement as reported by Mou et al. (2020). In addition, as found by Belém et al. (2020), the product description has impact on the ability of customers to find the desired products. By providing an LLM-based generative AI product details, brand profile together with a prompt, where the task of generating the product description is defined, appealing and grammatically correct product descriptions can be generated (Opuszko et al., 2024). Reisenbichler et al. (2022) suggest that while generating the product descriptions, the LLM-based generative AI can also be used for search engine optimization (SEO) by providing relevant keywords and product details. Also, Chagoury (2023) adds that nowadays LLMs can even be utilized to automatize the SEO by analysing the trends and user queries to update the product descriptions with minimal effort.

In addition to text-based product descriptions, generative AI can also be used to generate product images and visual marketing content. A recent extensive study by Hartmann et al. (2024) prompted seven leading text-to-image models to generate 10,320 synthetic marketing images using 2,400 real-world images as input. Through 254,400 human evaluations, the AI-generated images were found to surpass human-made ones in quality, realism and aesthetics. Furthermore, a field study with 173,000 impressions demonstrated that AI-generated banner ads achieved up to 50% higher click-through rates compared to human-made images. In another study, Jansen et al. (2024) trained stable diffusion generative AI model on marketing objectives. They demonstrated that the resulting visual content could match or even surpass conventionally produced advertising content in mindset performance metrics and click-through rates. The study also showed that generative AI can be fine-tuned for multiple communication objectives simultaneously and tailored to specific audiences.

The generative AI can also be utilized for personalized marketing and recommendations extensively (Kshetri et al., 2024; Lee et al., 2024). E-commerce customers generally react positively towards the company and the product when they receive personalized advertisements as reported by De Keyzer et al. (2015) and Garde (2024). A survey done by Epsilon Marketing, (2018) with 1000 participants shows that, 80% of the participants are more likely to make a purchase if they are offered a personalized experience. In addition, a report by Arora et al. (2021) shows that 71% of consumers expect personalized interactions and 67% of them get frustrated when this doesn’t happen. These reports indicate the importance of personalized marketing in today’s e-commerce era. Thanks to the recent advancements in the generative AI, the personalized marketing can even be automated. For instance Lee et al. (2024), developed a service called Personalized Message Intelligence by using LLMs to create personalized marketing messages. They utilized prompt engineering based on theory of persuasion and used customer data which included purchase history and basic personal information. Another example from Smolinski et al. (2023) demonstrated that Stable Diffusion together with GPT-4 can be used to generate personalized marketing visuals and texts. As customer data, they used personality of customers as introvert or extrovert. As a result, they showed with a survey that around 83% of the participants preferred personalized marketing content over non-personalized one. Based on LLMs autonomous agents that are designed to be good at particular tasks can be created (Martineau, 2024). A. Zhang et al. (2024) developed a user simulation agent using pretrained LLMs to capture user characteristics, tastes and behaviours, which can be used by downstream recommender systems to generate personalized recommendations. Similarly, Wang et al. (2024) developed an autonomous LLM-based agent to generate personalized recommendations. The tool is equipped with a self-inspiring algorithm that improves the model’s ability to consider historical data while generating recommendations. With this, they obtained superior performance compared to baseline models that were based on LLMs.

Another area where generative AI can be used is to generate visual advertisements such as images or videos. Using seven state-of-the-art text to image generation models Hartmann et al. (2024) performed an extensive research to study the effectiveness of generative AI synthesized visual advertisements. They found that human evaluations (254,400 total) indicate that AI-generated images can surpass human-made ones in quality, realism and aesthetics. Additionally, a comparison of AI and human-generated images based on the same creative brief shows AI's superior performance in creativity, ad attitudes and prompt accuracy. Finally, their field study with over 173,000 impressions reveals that AI-generated banner ads achieved up to a 50% higher click-through rate than human-made images. Similarly, Kumar and Kapoor, (2024) performed a study the effectiveness of synthesized personalized video advertisements with generative AI. Although they did not disclose the model used to generate videos, it was mentioned that the personalization happened utilizing the customer’s purchase histories. The study compared the engagement rate of generated personalized video advertisements to personalized image and non-personalized video advertisements. It was found that generative AI synthesized personalized video advertisements increased the engagement by 6% and 9% compared to personalized image and non-personalized video advertisements.

Considering the computer vision domain, generative AI can also be used is the virtual dressing and virtual try-ons (Attallah et al., 2024; Cecere Palazzo, 2024; Islam et al., 2024; Xu et al., 2024; Zhu et al., 2023). Virtual dressing is the process of using generative AI to digitally change or apply clothing to a model or avatar in real-time, whereas virtual try-on refers to the use of generative AI or augmented reality technologies to allow customers to try products on virtually, without physically wearing or interacting with them as explained by Cecere

Palazzo (2024). These can be achieved by different generative AI approaches such as GANs or diffusion models. For instance, Attallah et al. (2024) developed a cost efficient model for virtual try-on using GANs that takes two inputs, i.e., the garment and person, to generate a single output image that shows the person wearing the garment. Zhu et al. (2023) developed TryOnDiffusion model that is based on diffusion architecture. It works by taking two input images: one of a target person and another of a garment being worn by someone else. It then generates an output image showing the target person wearing the garment while preserving garment detail and considering significant pose change of the target person. On the other hand, Xu et al. (2024) developed an outfit recommendation application using diffusion models and historical user interaction data with successful results.

Typically, fine tuning or training models from scratch using the specific data and mannequins is needed to obtain good results (Attallah et al., 2024; Islam et al., 2024; Zhu et al., 2023). Considering this for instance, photos of the customer would be needed in order to fine tune the models for customer virtual try-on. Similar models can also be used for personalized outfit generation and recommendation.

While these examples demonstrate the effectiveness of generative AI in personalized marketing domain, achieving successful outcomes requires access to customer data. Although some studies indicate that customers are becoming more protective of their data and increasingly expect transparency from companies, other reports suggest that the majority of customers are still willing to share their data in exchange for more personalized experiences or lower prices as found by Accenture Interactive (2018), Curtis (2023) and Salesforce (2023b). Therefore, if the company data usage policies are transparent and reasonable, it is likely that customers will agree to share their data in exchange for more personalized marketing.

2.3.2 Generative AI Applications in Sales

Generative AI can boost the sales efficiency in various areas such as sales communications, sales forecasting and reporting as shown by Salesforce (2023a). For instance, Sinha et al. (2023) suggest that the LLMs can be integrated to customer relationship management (CRM) tools to assist the sales activities. With access to detailed customer data, LLMs can generate more personalized communications, such as emails and presentations, enable the development of better sales strategies, and produce more accurate forecasts. Examples of LLM integration to a CRM tools is Salesforce’s Einstein GPT and Microsoft’s Copilot for Sales (Sinha et al., 2023).

Apart from these integrations, more research is being conducted to improve the capabilities of generative AI in the sales activities. Singh et al. (2024) have designed a system to retrieve relevant information from a large information based in seconds using LLM embeddings to be shared with customers during a sales call. Reeder et al. (2024) developed a system to forecast sales utilizing LLMs and unstructured data from CRM software logs successfully. Liu et al. (2023) combined conversational recommender systems and LLMs to generate pre-sales dialogues in e-commerce.

LLM-based agents can also be used for sale negotiations by proper engineered prompts where the agent is assigned a buyer or a seller role as described by Deng et al. (2024). It was shown by Deng et al. (2024) that LLMs can be reasonable, efficient and effective negotiators with a negotiation game where one agent was assigned the buyer role and the another one was assigned a seller role with opposing objectives. Furthermore, Fu et al. (2023) showed that the performance of the negotiation agents can be improved further by different strategies such as utilizing an additional agent as critic to criticize the action of the agent and provide feedback to it.

2.3.3 Generative AI Applications in Customer Service

One of the most promising areas where generative AI can be utilized is the customer service domain. Ashfaq et al. (2020) states that customer service assistants and chatbots are already widely used across various industries for tasks such as resolving complaints, identifying items for purchase and providing post-sales support. The use of chatbots in customer service accounts for 39.5% of the global chatbot use cases according to a research by Grand View Research (2023). With the recent technological advancements in generative AI, many chatbots started utilizing generative AI and particularly LLMs as their backbone and following this the quality of the chatbots increased as well (Lin et al., 2023). As the quality of chatbots started increasing thanks to the advancements in generative AI, their popularity also increased in various business areas. According to a report by Boston Consulting Group, 95% of global customer service leaders anticipate that AI chatbots will play a role in customer service interactions within the next three years (Bamberger et al., 2023). The estimates by this report suggest that once implemented at scale, the generative AI chatbots could boost productivity by 30% to 50% or more. The e-commerce industry is no exception to this. In the e-commerce domain as well the generative AI driven chatbots are widely used (Babu & Akshara, 2024; Chang et al., 2024; Landim et al., 2022; Luo et al., 2024).

However, when it comes to customer facing chatbots, the reliability of these applications is extremely important. It is known that LLM-based chatbots produce hallucinations which can be defined as content produced by LLMs that are not based on the real world facts (Huang et al., 2023). In case customer service chatbot produces a fictious replies to customers, the consequences might be significant for the company that owns the chatbot. In order to avoid such a situation, the chatbots must be evaluated properly. Although this is a challenging task, there are various ways to do that such as automated, human and LLM-based approaches for evaluation as suggested by Abeysinghe and Circi (2024).

In addition, research is going on to make the chatbot-human interactions of higher quality. A framework so called retrieval augmented generation (RAG) to improve the chatbot performance on specific domain while reducing hallucinations was developed by Lewis et al. (2021). Utilizing RAG framework, the LLM model can be connected to a data source such as documentation on a specific domain to generate answers based on the facts. Thanks to this approach LLMs became better at domain specific question answering as shown by Lewis et al. (2021) and Gao et al. (2024). On the other hand, the LLMs can also be fined tuned to answer questions on specific domain better. Although there are various ways to fine-tune an LLM on specific data, they are typically expensive compared to RAG-based applications (J et al., 2024; Meyer et al., 2024). In addition, there is controversy on the effectiveness of fine-tuning compared to RAG-based solutions according to Barnett et al. (2024). Based on this information, the fine-tuning may not be needed for most of the cases for developing LLM-based chatbots for domain specific use cases. As today there are many tools that allow easy development of RAG-based chatbots, for small e-commerce businesses implementing these applications may not be a significant burden (Lehto, 2024).

Another area where generative AI can be used in customer service domain for e-commerce businesses is virtual assistants as stated by Bamberger et al. (2023). Although the speech generative models are not as advanced as text generative models, various text-to-voice approaches can be used together with LLM-based chatbot applications, to develop voice-based assistants as shown by Le et al. (2023). That said, the natively multimodal large generative models such as Gemini by Google Gemini Team et al. (2024) or GPT-4o by OpenAI (2024) can also be used to develop voice-based customer service assistants.

2.3.4 Generative AI Applications in Product Design and Development

Booth et al. (2024) suggest that generative AI can provide value by increasing the creativity and productivity of designers during a typical product design process steps such as market and user research, concept development, concept testing and refinement. Generative AI is especially strong when it is used as a brainstorming partner to create new ideas during the creative processes. For instance, Bouschery et al. (2024) demonstrated with an experiment that humans assisted with generative AI outperforms the humans alone on brainstorming productivity and creativity. Another study by Moreau et al. (2023) demonstrated with an experiment that when t-shirts were designed with generative AI assistance, they were preferred more by the customers, but only when the customers were unaware of the design's source. Additionally, tracking actual sales data over 20 weeks revealed a 127% sales increase for the t-shirts designed with AI assistance, highlighting the potential of AI in this area.

In addition to creativity, generative AI can boost the efficiency of the product design process. Creative Dock, a Czech company, leverages generative AI to enhance the efficiency of its design and development processes. By programming AI agents to generate market simulations and fine-tuning large language models for specific use cases, the company created a process for ideation, market needs identification and rapid concept testing. This approach has led to a 30% increase in technical development efficiency, a 40% gain in graphic design efficiency and a tripling of content creation speed. As a result, Creative Dock has achieved 50% year-over-year growth without expanding its full-time workforce as found by Marion et al. (2024). Considering this, the use of generative AI especially could be beneficial especially for the small to medium e-commerce companies that do not have a lot of resources to design new and original products.

2.4 Risks and Shortcomings of Generative AI

Although generative AI is a revolutionary technology that comes with many benefits, it also comes with various risks and shortcomings. Some of these factors will be discussed in this section.

One of the main shortcomings of generative AI is hallucinations. Maynez et al. (2020) state that hallucinations in generative AI, such as LLMs, occur when the system produces illogical or factually incorrect outputs. While hallucinations can help with creativity, they also pose challenges for generating accurate and reliable content. According to Ji et al. (2023) hallucinations particularly occur in novel or edge cases, as generative AI responds to prompts without a true "understanding" of the information and these errors may arise from insufficient, incomplete, biased training data or due to model architectures. For instance, in applications where generative AI is used to directly communicate with customers, such as customer service chatbots, the hallucinations could lead to significant misunderstandings, misinformation or customer dissatisfaction, potentially damaging the company's reputation and trust. For such applications, proper methods and guardrails must be implemented to mitigate the hallucinations as much as possible. Some of these methods were described by Tonmoy et al. (2024). In addition, Rahman et al. (2024) suggest that the human-in-the-loop approach where the human oversees and reviews the output of the application is advisable especially for critical cases.

Another risk considering the generative AI is the intellectual property risk. As explained previously, generative AI models require large amount of data to be trained. The large closed-source models such as GPT, Gemini or Claude may use the user data to improve their models. This in turn creates risk for the sensitive information inputted to the model to be shown to other users according to Colombo et al. (2023). For instance, there has been a major leak in March 2023 in ChatGPT that caused some users to see other users’ conversations with the tool as described by Derico (2023). Considering this, companies must be careful when using of generative AI with sensitive information. If possible, closed systems such as should be chosen for confidential data applications such as Azure OpenAI Service by Microsoft (2024). On the other hand, Lucchi (2023) warns that generative AI output may also contain intellectual property of another organization and the use of this information may lead to potential plagiarism and risk of copyright infringement.

The text-based generative AI models are also prone to jailbreaking meaning that their guard rails can be bypassed. By doing so, hackers can use the applications outside of their intendent functionality. One of such cyberattacks is called prompt injection attacks. Kosinski and Forrest (2024) defines the prompt injections as a way of manipulating the generative AI systems with prompts to remove their guard rails. For instance, with prompt injection, a customer chatbot application to give information about products of the company can be used to leak other information related to company. This information may also be false information however, company may still be held responsible. An example of such a case was when a customer convinced a chatbot to sell a Chevrolet 76000$ truck for 1$ using prompt-injection attack (Perry, 2024). Although some mitigation methods against jailbreaking exist, there is no silver bullet for all types of cyberattacks on generative AI yet and this creates a significant risk for the companies that use generative AI applications (Peng et al., 2024).

Last but not least is the risk of lack of expertise on developing and maintaining generative AI applications for small and medium-sized companies. Indeed, such applications can be purchased from other vendors however, the cost of doing so may be too large for small businesses. Also, even if vendors are used, some level of understanding how these systems work is required not to expose the company to aforementioned risks which could be serious.

3 Research Methodology

3.1 Research Approach of the Study

In order to answer the research questions concerning the implications of generative AI on marketing strategies, product development, innovation processes and the competitive landscape for SMEs in the e-commerce sector, this study utilizes a mixed-methods research design. The primary data collection tool was a structured survey, which was distributed to various companies. By incorporating both multiple-choice questions and open-ended questions, the survey facilitates a dual approach. The quantitative section provides data to enable statistical analysis to reveal trends and patterns while qualitative section enables respondents to express detailed perspectives and experiences regarding the impact of generative AI.

The mixed-methods approach is particularly suitable for exploring complex and fast changing phenomena like generative AI, as it leverages the strengths of both quantitative and qualitative methodologies (Creswell & Clark, 2007). Specifically, quantitative data offer statistically analysable hard data, while qualitative data provide context and insight into the underlying reasons behind the observed trends (Braun & Clarke, 2006).

As the main data collection strategy, a comprehensive survey to capture both broad trends and in-depth insights regarding the adoption and implications of generative AI within SMEs was prepared as given in Appendix 1. Employing survey methodology is a well-established method for gathering data from a relatively large sample to identify patterns and relationships within the target population (Fowler, 2013). The use of a survey was considered appropriate in this study as it allowed efficient data collection from a range of businesses and provided a structured format for respondents to share their experiences and perspectives. The survey was designed to include closed and open-ended questions as this combination allows for an in-depth understanding of the research topic than would be possible with a purely quantitative or qualitative approach (Teddlie & Tashakkori, 2009).

The quantitative component of the survey mainly obtained from the multiple-choice and scaled questions aims to provide statistical overview of generative AI adoption and its perceived implications across SMEs. The questions were designed to measure the impact and to potentially establish correlations between different variables, such as company size or industry sector and the adoption and effects of generative AI.

Complementing the quantitative data, qualitative component of the survey is established via open-ended questions. These questions seek to provide deeper understanding and richer insights into the experiences of SMEs with generative AI. This type of qualitative data is important for exploring “how” and “why” behind the quantitative trends, potentially providing a deeper understanding of the complex implications of generative AI (Creswell & Clark, 2007).

3.2 Data Collection

The survey consisted of 4 sections, where first section focused on obtaining data about the business demographics and adoption of generative AI in general. The remaining sections were designed to collect data relevant to each research question. The survey included in total 27 questions incorporating both open-ended and closed-ended questions such as multiple-choice questions and Likert-scale formats.

The survey was implemented utilizing Google Forms, and it was distributed to representatives of 112 SMEs via LinkedIn platform, resulting in 49 usable responses. The data collection via the survey was done between dates 2025/01/05 to 2025/02/16. The survey was conducted anonymously, ensuring that no personal information was collected. Respondents' identities were not recorded at any stage of the research. The data was collected using Google Forms and was accessible only to the author. It will be deleted permanently from the platform and any other media after the publication of this thesis. This approach aligns with GDPR regulations, ensuring the confidentiality and security of all collected data (Google Cloud, 2021; Office of the Data Protection Ombudsman, n.d.).

The distribution of the responses per company size is given in Table 1. Most of the responses were from small sized companies (42.9%), while the response rates of micro and medium sized companies were similar with rates 26.5% and 30.6%, respectively.

Table 1. Distribution of responses per company size.

Size	Number of responses	Percentage	Cumulative percentage
Micro (1-19 employees)	13	26.5%	26.5%
Small (20-99 employees)	21	42.9%	69.4%
Medium (100-499 employees)	15	30.6%	100.0%
Total	*49*		

In Table 2, the distribution of the responses per sector is shown. Most of the responses were collected from retail, fashion and technology sectors summing up to 73.5% of the responses.

Table 2. Distribution of responses per sector.

Sector	Number of responses	Percentage	Cumulative percentage
Retail	16	32.7%	32.7%
Fashion	11	22.4%	55.1%
Technology	9	18.4%	73.5%
Art	5	10.2%	83.7%
Food & beverage	5	10.2%	93.9%
Home goods	3	6.1%	100%
Total	*49*		

In Table 3, number of years that the responding companies are in operation are given. Majority (59.2%) of the responding companies, were in operation more than 5 years, whereas only 2% of the respondents were in operation less than 1 year.

Table 3. Distribution of responding companies' years of operation.

Sector	Number of responses	Percentage	Cumulative percentage
Less than 1 year	1	2.0%	2.0%
1-3 years	10	20.4%	22.4%
3-5 years	9	18.4%	40.8%
5-10 years	17	34.7%	75.5%
More than 10 years	12	24.5%	100%
Total	*49*		

On the other hand, in Table 4, annual revenue distribution of the respondents is shown. Majority (55.1%) of the responding companies had annual revenue between $100,000 and $1 million. Responses from companies with revenues less than $100,000 and between $1 million to $5 million were the least which made 14.3% of responses each.

Table 4. Distribution of responding companies' annual revenue.

Annual revenue	Number of responses	Percentage	Cumulative percentage
Less than $100,000	7	14.3%	14.3%
$100,000 - $500,000	15	30.6%	44.9%
$500,000 - $1 million	12	24.5%	69.4%
$1 million - $5 million	7	14.3%	83.7%
More than $5 million	8	16.3%	100%
Total	*49*		

Additionally, in Table 5, the distribution of responding person's role within the company is shown. Majority of the roles of the responders were Owner/Founder and within Operations, with 26.5% and 20.4%, respectively. There was only one responder with Director role and two persons did not want to disclose their role.

Table 5. Distribution of responding person's role within the company.

Role	Number of responses	Percentage	Cumulative percentage
Owner/Founder	13	26.5%	26.5%
Operations	10	20.4%	46.9%
Technology/IT	9	18.4%	65.3%
Sales	6	12.2%	77.6%
Marketing/Advertising	5	10.2%	87.8%
Product Development	3	6.1%	93.9%
Director	1	2.0%	95.9%
Prefer not to say	2	4.1%	100.0%
Total	*49*		

3.3 Data Analysis

The collected survey data was analysed using a mixed-methods approach utilizing both quantitative and qualitative techniques to ensure comprehensive coverage of the implications of generative AI on SMEs within the e-commerce domain.

Quantitative data obtained from closes-ended questions were first analysed using descriptive statistics and visualizations. Frequency distributions and summary measures such as means and medians were used to identify central tendencies and variations in AI adaption, perceived impacts and integration levels across different business use cases and functions. In the cases where multiple responses were permitted such as in the case of areas of application or planned adoption of generative AI, the data were compiled using individual selections to capture the extent of the use cases. These results were visualized using bar charts to show the trends in usage across the responding companies.

In order to explore the associations between the level of AI integration in different areas and its perceived impact on different business outcomes, selected survey responses were numerically coded. Positive responses were assigned positive values such as 1 or 2. Neutral responses were assigned value of 0 and negative responses were assigned negative values such as -1 or -2. Correlation analysis was then conducted using Pearson's correlation coefficient and statistical significance was assessed using p-values. Linear regression plots were also shown to give visual representations of these relationships.

Qualitative component of the analysis was based on responses to open-ended survey questions. A thematic analysis was performed through manual coding of the textual data into some determined themes. Commonly occurring patterns were identified and grouped into distinct themes that reflected common benefits, challenges and perceptions related to generative AI.

In addition to thematic coding, a sentiment analysis was conducted to asses the overall tone of the open-ended responses. The Valence Aware Dictionary and Sentiment Reasoner (VADER) model from Hutto & Gilbert (2014) was used to compute sentiment polarity scores ranging from -1 (negative sentiment) to +1 (positive sentiment). Based on these scores, responses were classified into positive, neutral and negative categories. This analysis added further quantitative insight to the opinions of the responders toward generative AI in their business.

For the open-ended question cases where sentiment analysis was not appropriate, word cloud analysis was used as a visual method to capture the most frequent terms. By representing word frequency through relative font sizes, word cloud offered an overview of dominant topics and recurring expressions.

As a result, the described comprehensive analysis using descriptive statistics, correlation analysis, thematic exploration, sentiment analysis and word frequency visualization provided in-depth understanding of how SMEs in the e-commerce domain perceive and utilize generative AI.

4 Results

4.1 Use of AI in Responding Organizations

There are two aspects to consider for understanding the use of AI in the organizations. First of all, some respondents might be using various tools with AI integration such as Microsoft Copilot integration with Microsoft Office products. On the other hand, some respondents might use AI models to develop custom AI tools to serve their internal purposes. The questions about the use of AI in the survey was formed to capture both of these aspects.

The response distribution is shown in Figure 4. About half of the respondents (23 respondents) uses tools with integrated generative AI in them, whereas only 9 respondents use custom-developed tools in daily operations. All the users that use custom-developed tools also use tools with integrated generative AI in them.

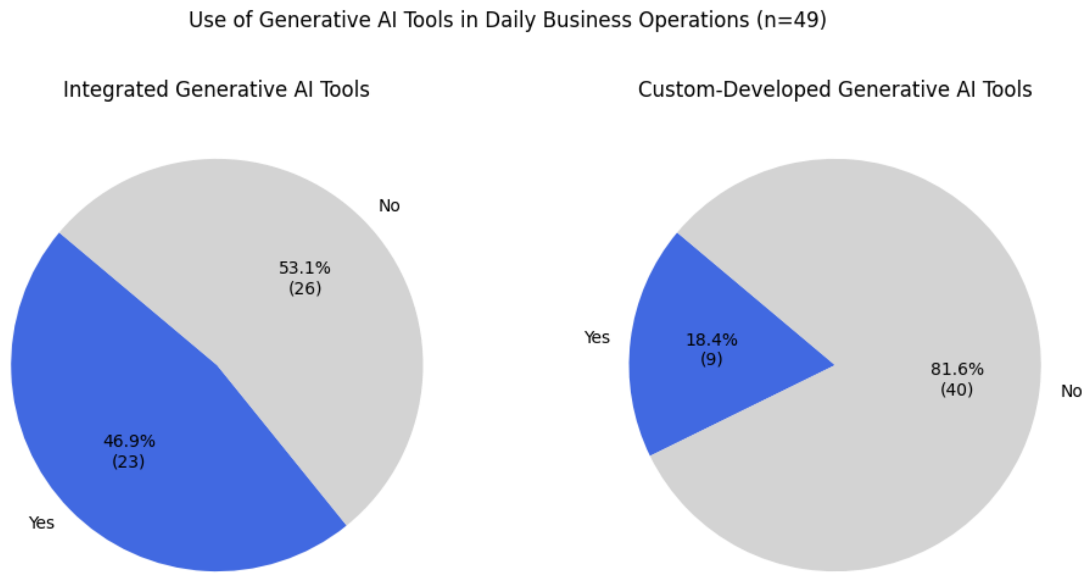

Figure 4. Generative AI usage among the responders.

In total 26 respondents do not use generative AI in daily operations. Out of these respondents, 14 of them has short term plans of using generative AI whereas 11 of them do not have any plans. One of the survey respondents did not provide answer to this question. These results are summarized in Figure 5. The respondents who replied to have plans for using generative AI in the near future were also asked about in what areas generative AI would be used. These responses are shown in Figure 6. The possible areas where selected to reflect the topics in the research questions. For this question the respondents could choose multiple areas therefore, the sum of numbers in Figure 6 is higher than population (n=14) who replied to this question.

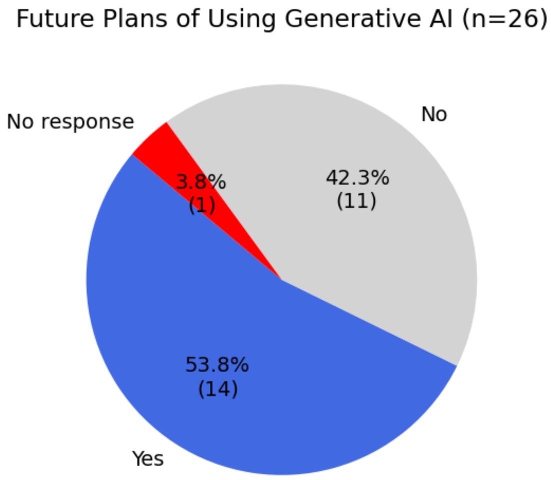

Figure 5. Future plans of using generative AI among the responders.

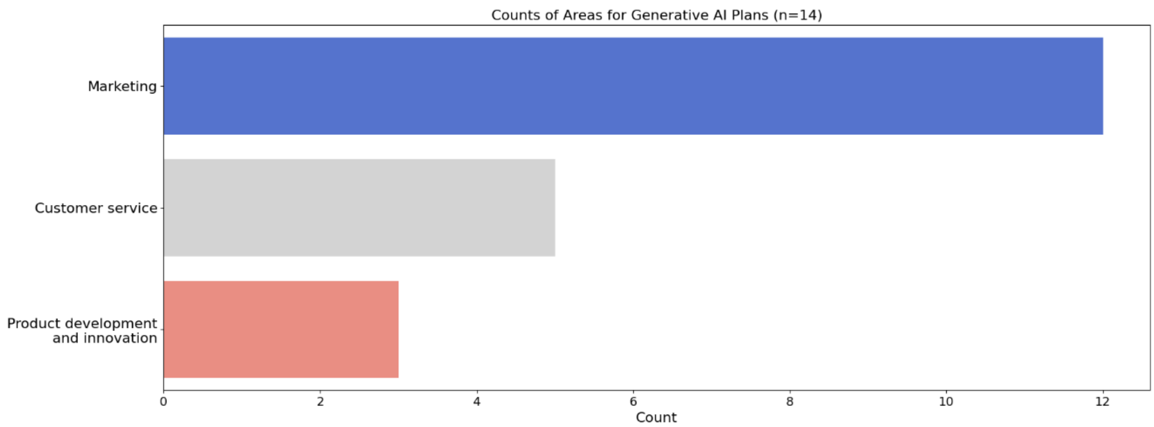

Figure 6. Responses for in what areas use of generative AI is planned.

4.2 Impact of Generative AI in Marketing Strategies

In Figure 7, the integration level of generative AI in marketing for responding companies is shown. Most of the companies do not have high level of integration of AI tools in their marketing strategies. The mean and median level of integration is 2.35 and 2, respectively with level 1 being no integration at all and level 5 being full integration. There are only 3 companies in the population which accounts to 13% of the population who responded that they have significant integration of generative AI in their marketing strategies with level 4. There were no respondents who responded with level 5. The data indicates that generative AI integration in marketing strategies is generally at a low to moderate level among responding companies. While a small portion shows significant integration, the majority are still in the early stages or have not yet fully adopted AI tools in their marketing practices.

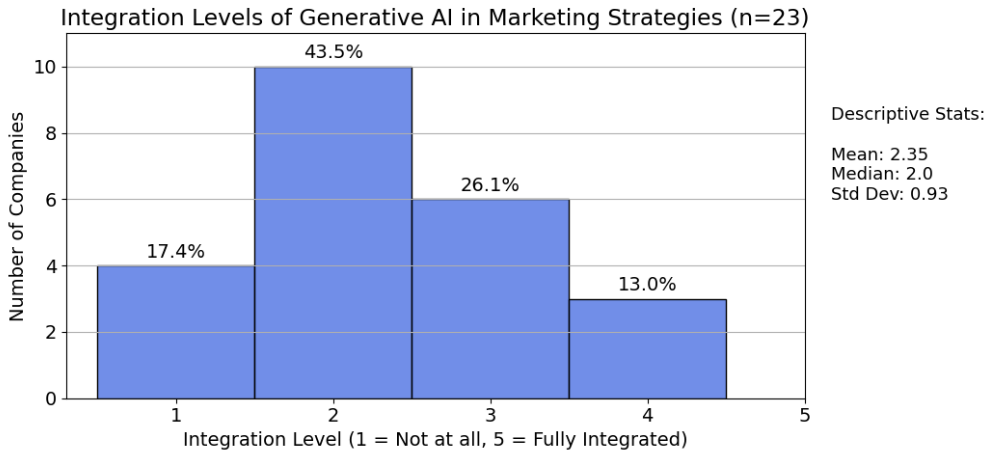

Figure 7. Integration levels of generative AI in marketing strategies among the responding companies.

In Figure 8, responses related to usage area of generative AI in marketing activities are shown. There were 20 valid responses for the question. Since this question was a multi-response type, there are more replies than the population count. Generative AI is used mostly in the content creation activity (95% of the population). A responder added an activity internal code generation using free text field of the question which related to software development which accounts for 5% of the population. The data reveals that content creation is the dominant application of generative AI in marketing among responding companies. While other applications exist, content creation is overwhelmingly the most utilized. Additionally, a small number of respondents are exploring applications of generative AI within the marketing area, such as internal code generation, indicating some cross-functional use of generative AI.

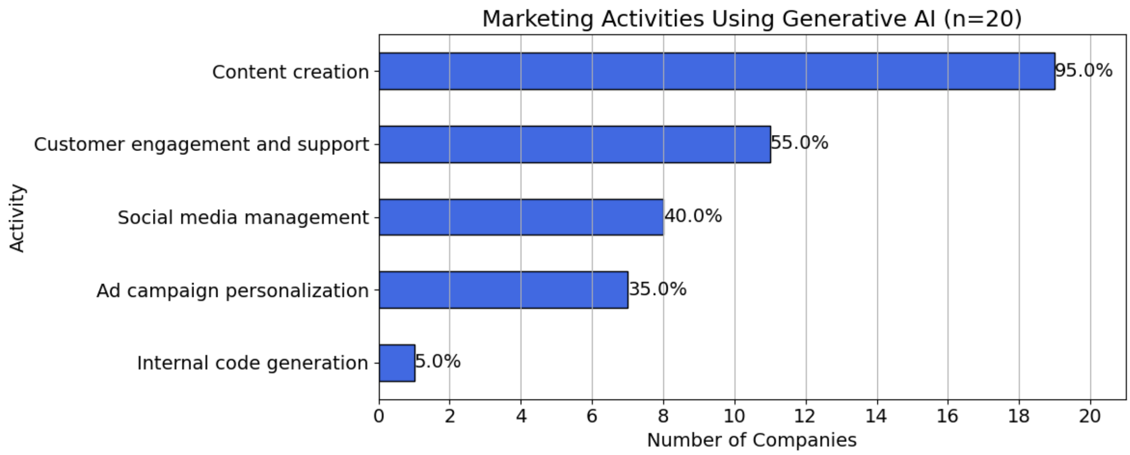

Figure 8. Marketing activities using generative AI within the responding companies.

In Figure 9, the impact of generative AI on the content creation efficiency is shown. Most of the respondents (13) responded that generative AI somewhat improved the efficiency of content creation process, while according 5 of the respondents generative AI improved their efficiency greatly. On the other hand, only 1 respondent saw no noticeable difference with the generative AI on the content creation efficiency. There were no responses for decreasing efficiency due to the use of generative AI.

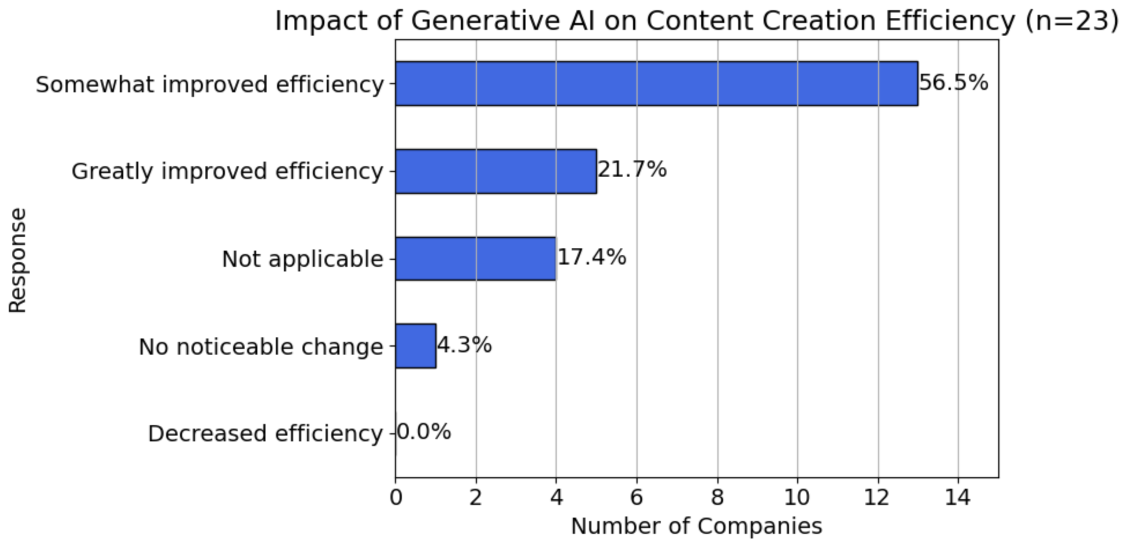

Figure 9. Perceived impact of generative AI on content creation efficiency.

In Figure 10, the impact of generative AI in customer interaction personalization is shown. The mean and median level of integration is 2.17 and 2, respectively with level 1 being no change and level 5 being significant improvement in the customer interaction personalization. 69.6% of the companies responded with minimal improvement (level 2) and no improvement at all (level 1). This group sums up to 16 responses. There are only 3 companies (17.4% of the population) who responded that they had significant improvement (level 4). There were no respondents who responded with level 5. The data indicates that the perceived impact of generative AI on customer interaction personalization is generally low to moderate. A significant majority of respondents reported minimal or no improvement, while a small minority perceived significant gains.

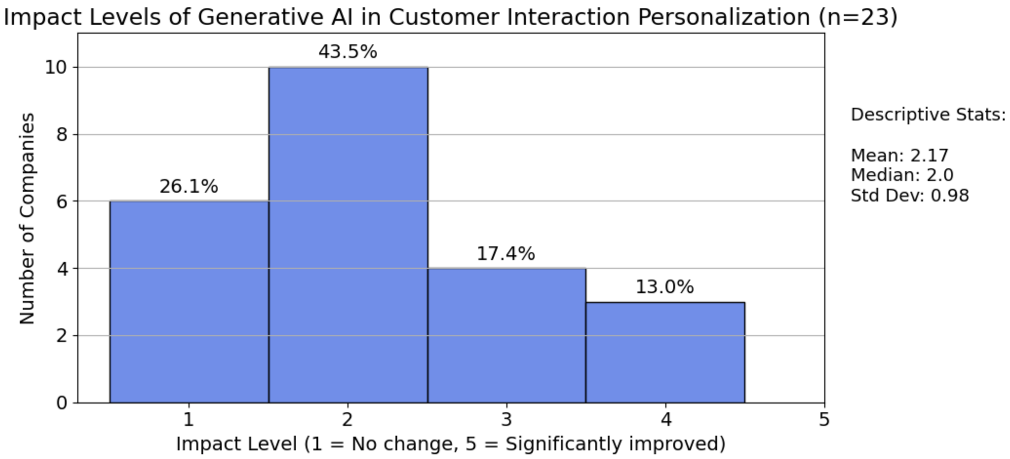

Figure 10. Perceived impact levels of generative AI in customer interaction personalization.

In Figure 11, the impact of generative AI on the marketing costs are shown. According to 47.8% of respondents, the marketing costs are not affected by generative AI. On the other hand, 39.1% of respondents replied that generative AI reduced the marketing costs. Only a single of respondent (4.3% of the population) replied that generative AI increased their marketing costs. The data suggests a mixed perception of generative AI's impact on marketing costs. While a significant portion of respondents reported no effect, a substantial minority observed cost reductions. A very small number perceived increased cost.

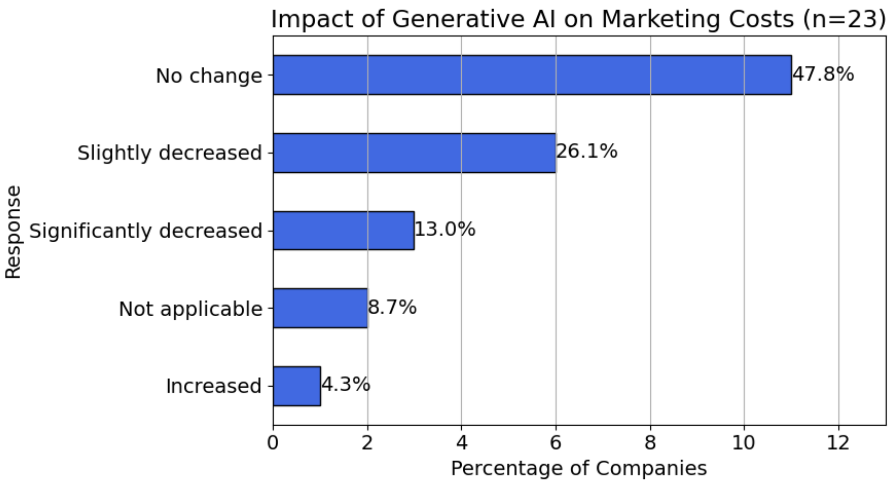

Figure 11. Impact of generative AI on respondents' marketing costs.

In Figure 12 responses for the impact of generative AI on marketing performance is shown. There were 22 valid responses for the relevant question. 50% of the respondents said that the generative AI increased the marketing performance slightly while according to 13.6% of respondents the performance increase was significant. On the other hand, 36.4% of respondents did not see any noticeable improvement on the marketing performance with the use of generative AI. The data reveals a generally positive, however moderate, impact of generative AI on marketing performance. On the one hand, a majority of respondents reported at least a slight increase in performance, on the other hand a significant portion saw no noticeable improvement.

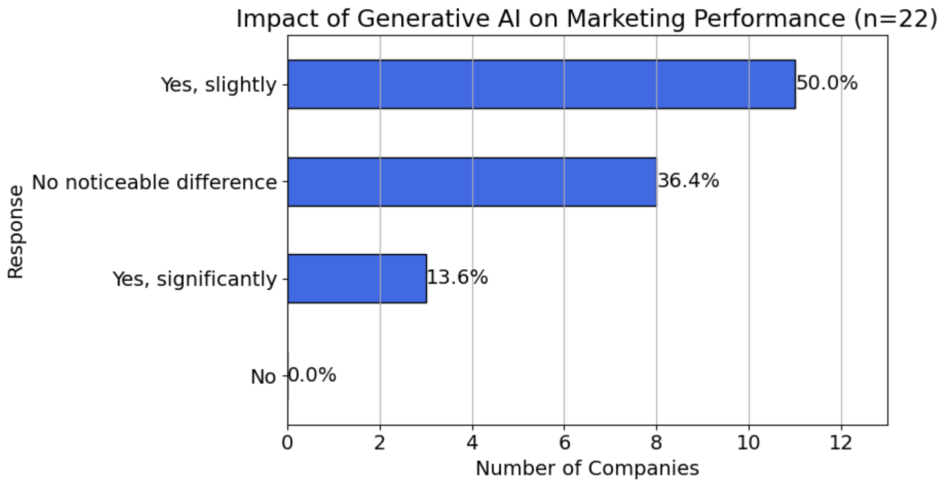

Figure 12. Impact of generative AI on respondents' marketing performance.

In Figure 13 the impact of generative AI on customer engagement is shown. According to 50% of the respondents, generative AI plays a minor role in customer engagement activities whereas 13.6% of respondents said that the role of generative AI is major. On the other hand, 36.4% of respondents replies that generative AI plays no role in the customer engagement activities. The data suggests that generative AI's impact on customer engagement is perceived as relatively limited. A majority of respondents see a minor role for AI in these activities and a smaller portion see a major role. However, a significant number report no impact at all.

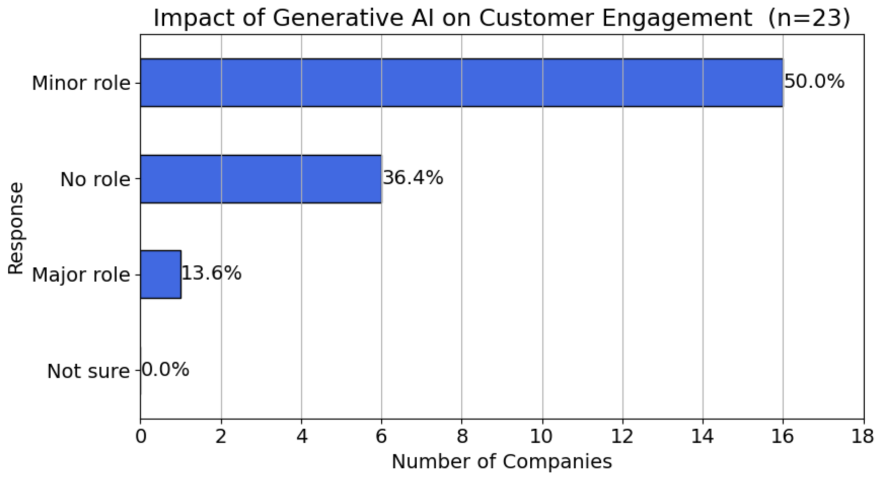

Figure 13. Perceived impact of generative AI on customer engagement.

In order to analyse the correlation between the generative AI integration level with content creation effectiveness, content personalization, cost impact and marketing effectiveness some of the responses were mapped to numerical values as shown in Table 6 for relevant questions. In these questions there were mainly two positive, one neutral and one negative response possibilities. Positive responses were assigned to scores 1 and 2 whereas neutral responses were assigned as score 0. In order to balance the scores, the negative replies were assigned score -2.

Based on this mapping, a regression plot is drawn and shown in Figure 14. In Figure 14 the respondent population sizes (*n*) for corresponding questions, Pearson correlation coefficient (*r*) and p-values are also shown where the higher Pearson correlation coefficient indicates the higher level of correlation and p-value indicates statistical significance. In this work, it is assumed that when $p < 0.05$ results are statistically significant, $0.1 < p < 0.05$, results are marginally significant and $p > 0.1$ results are not significant.

Generative AI integration has clear positive correlations between content personalization, content creation effectiveness and marketing effectiveness. On the other hand, there is very weak positive correlation between AI integration and cost savings.

Table 6. Mapping marketing responses for correlation analysis.

Q: How has the use of generative AI impacted your marketing content creation process?	
Actual Response	**Numerical mapping**
Greatly improved efficiency	2
Somewhat improved efficiency	1
No noticeable change	0
Decreased efficiency	-2
Q: Since implementing generative AI, how has your marketing cost been affected?	
Actual Response	**Numerical mapping**
Significantly decreased	2
Slightly decreased	1
No change	0
Increased	-2
Not applicable	NA
Q: Has generative AI improved your marketing performance in terms of reach, engagement or conversions?	
Actual Response	**Numerical mapping**
Yes, significantly	2
Yes, slightly	1
No noticeable difference	0
No	-2

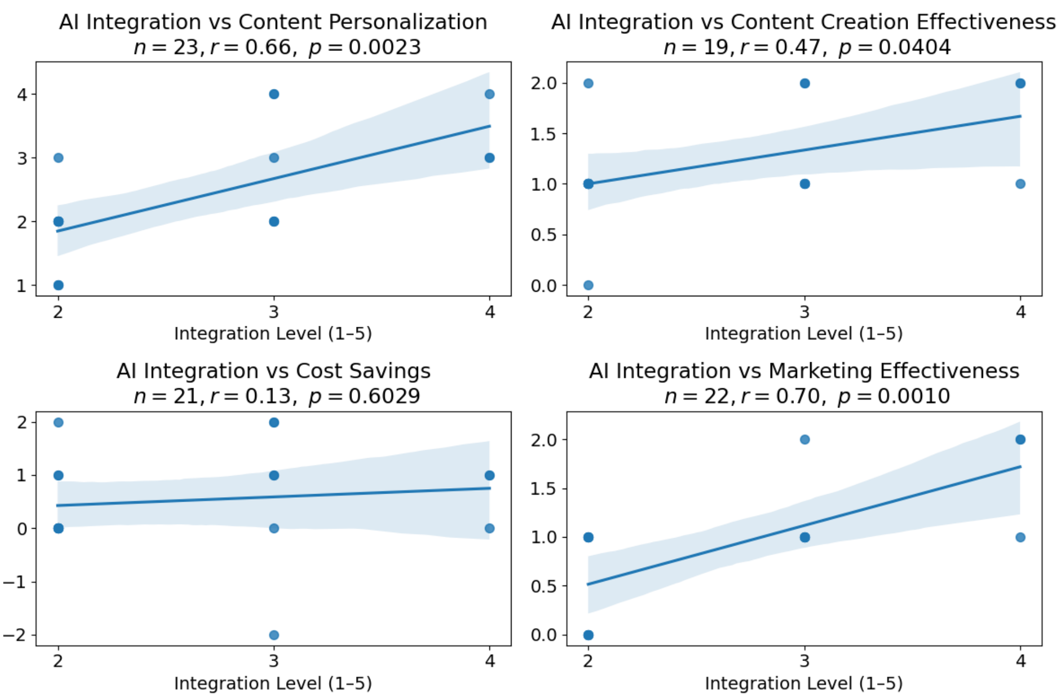

Figure 14. Linear correlation analysis between AI integration level with content creation effectiveness, content personalization, cost impact and marketing effectiveness.

There were 16 responders who replied to open-ended questions about generative AI usage in marketing. The open-ended question about the impact of generative AI on marketing has been analysed by using thematic grouping of the replies. Based on the manual analysis of the responses in total 10 themes were chosen then the frequency of appearance of these themes in the responses were counted. In Figure 15, the result of this analysis is shown. ‘Efficiency Gains’ appeared as the most frequent theme, indicating a strong understanding that AI significantly accelerates marketing activities. Following this, ‘AI Tool Adoption’ was also significant which indicates variety of specific AI applications are being utilized, such as ChatGPT and image generation tools. ‘Marketing Strategy Improvement’ and ‘Content Quality’ had also high frequency themes that appeared in the responses, which signals the benefits in improving overall marketing efforts and customizing content. On the other hand, ‘Learning Curve’ theme which indicates time and effort for learning the generative AI tools was also prominent. In addition, ‘HR Impact’ (job displacement), ‘Exploration/Pilot Projects’, ‘Cost Reduction’, ‘Too Early to Tell’ and ‘Not Using Yet’ were also present, though less frequent.

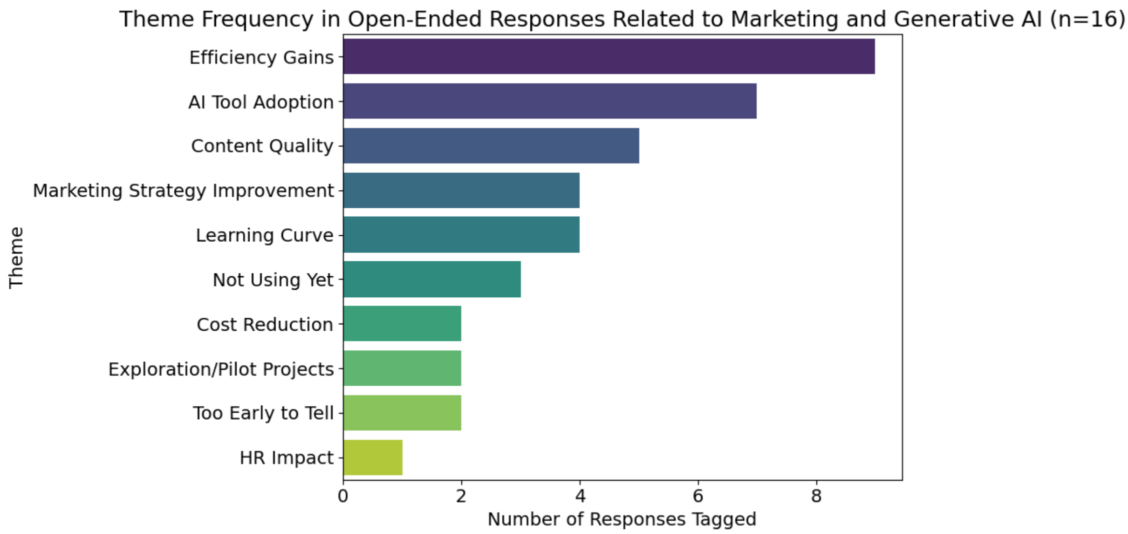

Figure 15. Theme frequency analysis for adoption of generative AI in marketing.

In addition to thematic analysis, open-ended responses were also analysed using sentiment analysis. This analysis was conducted using the VADER model. Each response was analysed and assigned a sentiment score ranging from -1 to +1. Based on these scores, the responses were categorized into positive, neutral and negative groups. The sentiment analysis results are shown in Figure 16. The analysis revealed that the most of responses were classified as positive, indicating a generally favourable perception of generative AI tools in marketing. Smaller portion of responses were neutral. Only a few responses were negative aligning with the results of thematic analysis.

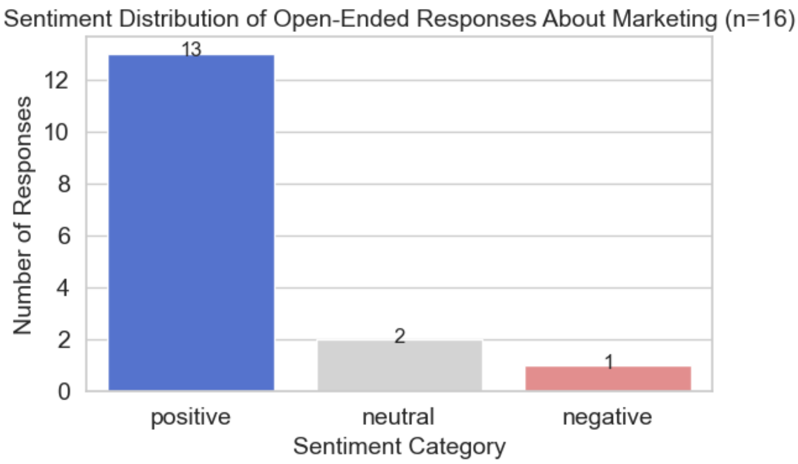

Figure 16. Sentiment analysis for open-ended responses about use of generative AI in marketing strategies.

4.3 Impact of Generative AI in Product Development and Innovation Process

Figure 17 shows the integration levels of generative AI within the product development based on responses from 23 companies. Similar to the marketing strategies, the data shows a tendency towards lower integration levels. The mean integration level is 2.39 and the median is 2.0 which indicates most companies are still in the early stages of adopting generative AI in their product development process. Notably, 34.8% of the respondents reported an integration level of 3 which indicates a moderate level of adoption. Only 13% of the companies responded with a level 4 integration, reflecting a significant integration. However, no respondents reported a full integration level of 5. The distribution in general indicates that while there is some adoption of generative AI in product development, full integration is not yet prevalent among the surveyed companies.

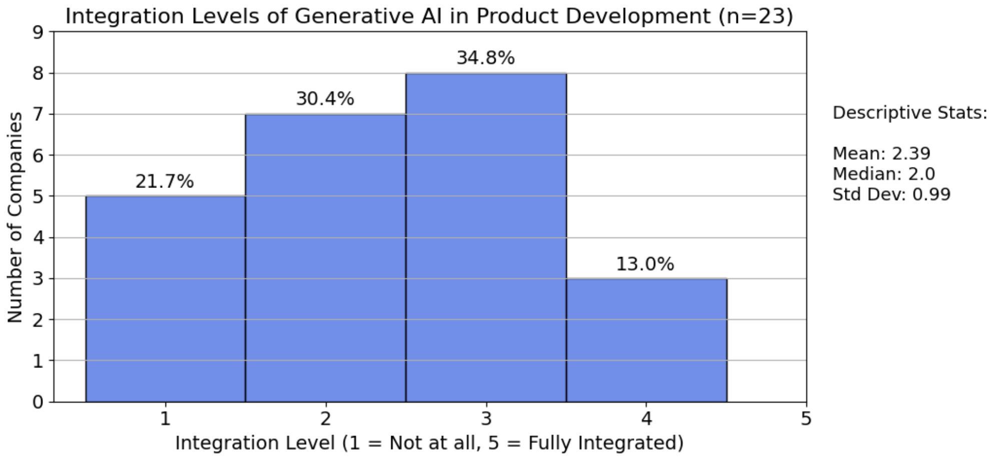

Figure 17. Integration levels of generative AI in product development for responding companies.

Figure 18 shows the responses for generative AI use areas within the product development activities. As this question allowed multiple responses, the total percentage exceeds 100%. The most frequently selected application was ‘Design or prototyping’ with 72.2% of respondents indicating use of generative AI in this area. This was followed by “Idea generation” and “Product testing and optimization” with 50% and 44.4% of responding companies are utilizing generative AI for these purposes, respectively. It is worth mentioning that ‘Software development’ was added by 27.8% of companies to the free text field, which indicates some overlap with ‘Design or prototyping’ area. ‘Customer feedback analysis’ and ‘Assisting in day-to-day tasks’ represent lower adoption rates with 11.1% and 5.6%, respectively. The data suggests a strong focus on using generative AI in the early stages of product development, particularly in design and ideation.

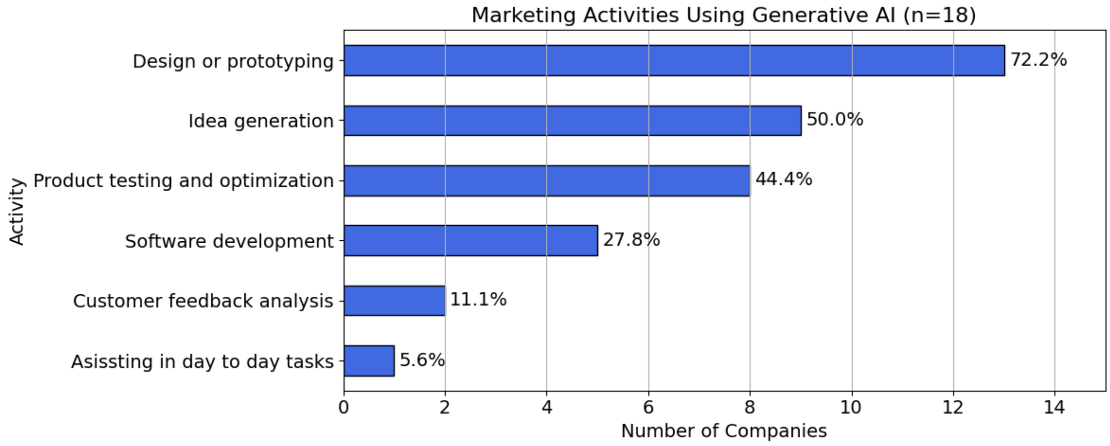

Figure 18. Product development activities using generative AI among the responding companies.

In Figure 19, results for the perceived impact levels of generative AI on time-to-market for new products are shown. The majority of respondents, representing 60.9% of the population, reported a moderate impact (level 3). The mean and median impact levels are 2.91 and 3.0, indicating a central tendency towards moderate impact. Interestingly, 17.4% of respondents responded both a level 2 and level 4 impact, suggesting a rather wide spectrum of perceived impact of generative AI on time-to-market for new products. Only 4.3% respondents indicated no impact (level 1) and no respondents reported a level 5 which indicates significant increase in time-to-market speed. As a result, although there has been a positive impact generative AI on time to market for new products, this impact seems to be moderate.

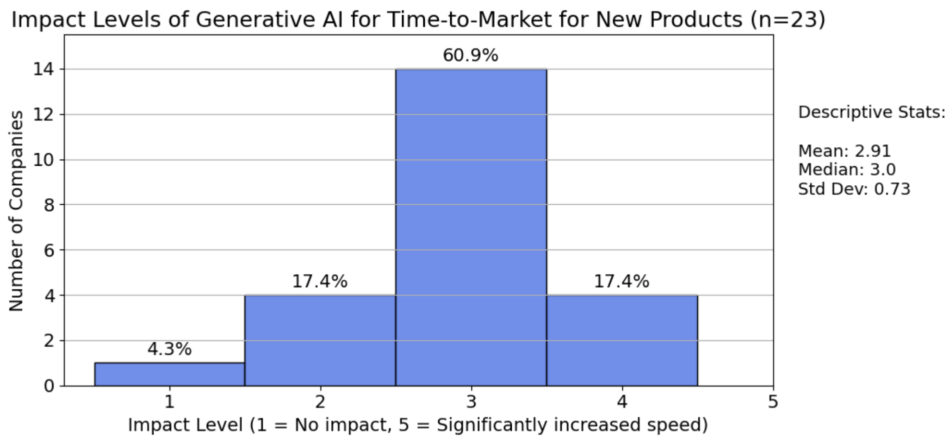

Figure 19. Perceived impact of generative AI on time-to-market for new products.

Figure 20 illustrates the perceived impact of generative AI on product innovation, as reported by 23 respondents. The majority of respondents, representing 65.2% of the population, indicated a moderate level of agreement (level 3) regarding the impact of generation AI on product innovation. The mean and median levels for agreement are 2.91 and 3, respectively which supports this central tendency. On the other hand, 8.7% of respondents strongly disagreed (level 1) and another 8.7% of respondents disagreed (level 2), suggesting that a portion of the population did not perceive a positive impact of generative AI. Conversely, 17.4% of the respondents agreed (level 4) which indicates a positive perception. No respondents strongly agreed with level 5. The data indicates that while most companies see a moderate positive impact of generative AI on product innovation, there is a notable minority that has had a negative view.

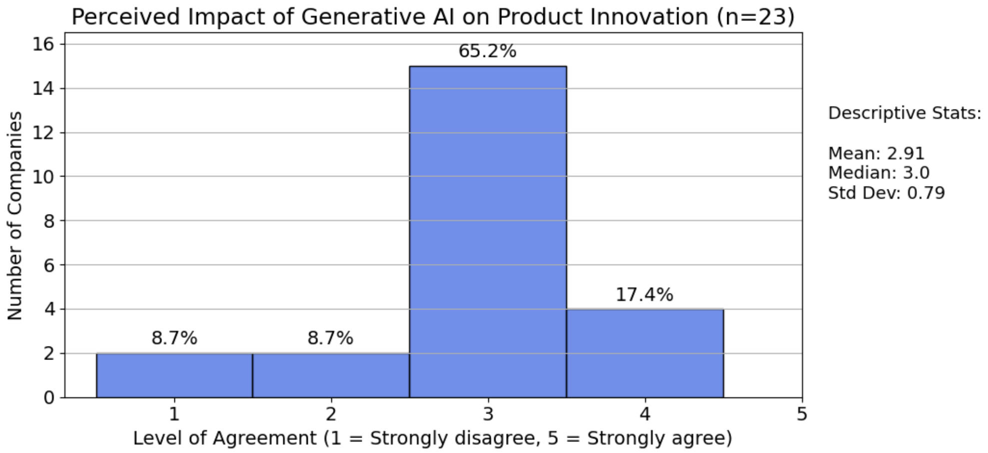

Figure 20. Perceived impact of generative AI on product innovation.

In Figure 21, the impact of generative AI on the product quality and features across three contribution areas according to 23 respondents is shown. The areas studied were ‘Reducing time-to-market’, ‘Enabling new features’ and ‘Improving product quality’. For ‘Reducing time-to-market’, 69.6% of respondents reported a positive impact, while 30.4% reported no effect. In ‘Enabling new features’, 43.5% reported a positive impact, and a larger proportion, 56.5% reported no effect. Lastly, in ‘Improving Product Quality’, 52.2% reported a positive impact, and 47.8% reported no effect. It is worth mentioning that no respondents reported a negative impact across any of the three areas.

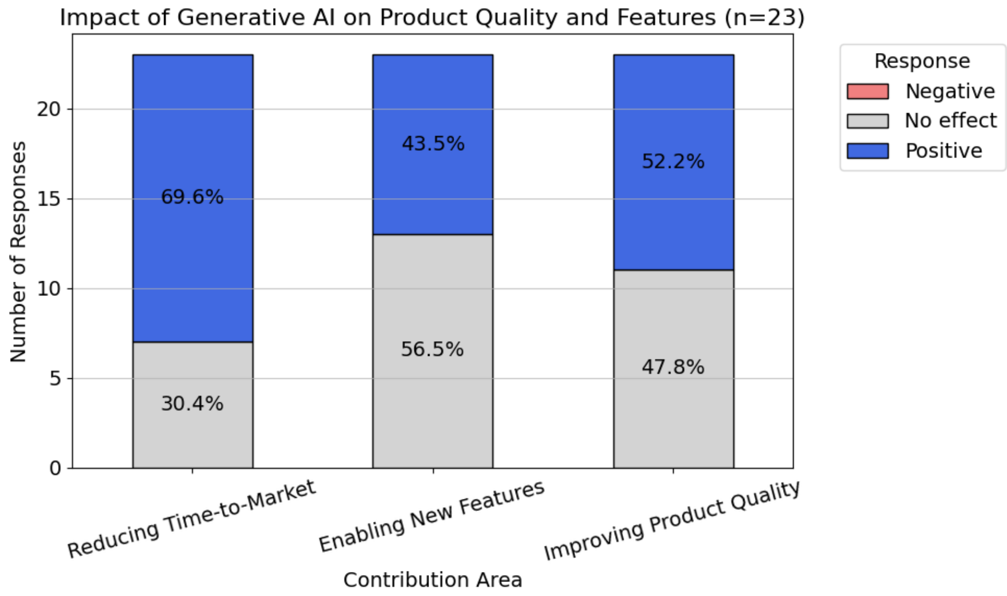

Figure 21. Perceived impact of generative AI on product quality and features.

In order to analyse the correlation between the generative AI integration level with time-to-market speed improvement, product innovation, product new feature development and product quality impact some of the responses were mapped to numerical values as shown in Table 7 for relevant questions. In these questions there were positive, neutral and negative response possibilities. Positive responses were assigned to score 1 whereas neutral responses and negative responses were assigned as score 0 and -1 respectively.

Table 7. Numerical mapping of responses of product development for correlation analysis.

Q: In which ways as generative AI contributed to product quality or new features? [Reducing time-to-market]	
Actual Response	**Numerical mapping**
Positive	1
Neutral	0
Negative	-1
Q: In which ways as generative AI contributed to product quality or new features? [Enabling new product features]	
Actual Response	**Numerical mapping**
Positive	1
Neutral	0
Negative	-1
Q: In which ways as generative AI contributed to product quality or new features? [Improving product quality]	
Actual Response	**Numerical mapping**
Positive	1
Neutral	0
Negative	-1

Since there was a separate question that was analysing time-to-market speed improvement with Likert chart pointing system (level 1: no effect, level 5: significant speed increase), these levels will be re-scaled to be able to combine with the first question from Table 7. The scaling will be done by applying equation (1) to the replies of the question with Likert chart pointing system.

$$X_{new} = \frac{X_{old} - 1}{5} \quad (1)$$

Here, X_{new} is the new score whereas X_{old} is the old score. After applying this scaling, the “no effect” response will have score of 0, while “significant speed increase” response will have score 1.

Based on this mapping, a regression plot is drawn and shown in Figure 22. In Figure 22 the respondent population sizes (*n*) for corresponding questions, Pearson correlation coefficient (*r*) and p-values are also shown where the higher Pearson correlation coefficient indicates the higher level of correlation and p-value indicates statistical significance. In this work, it is assumed that when p < 0.05 results are statistically significant, 0.1 < p < 0.05, results are marginally significant and p > 0.1 results are not significant.

Generative AI integration has clear positive correlations between time-to-market speed improvement, new feature development and product quality improvement. On the other hand, there isn't a significant correlation between generative AI integration and innovation.

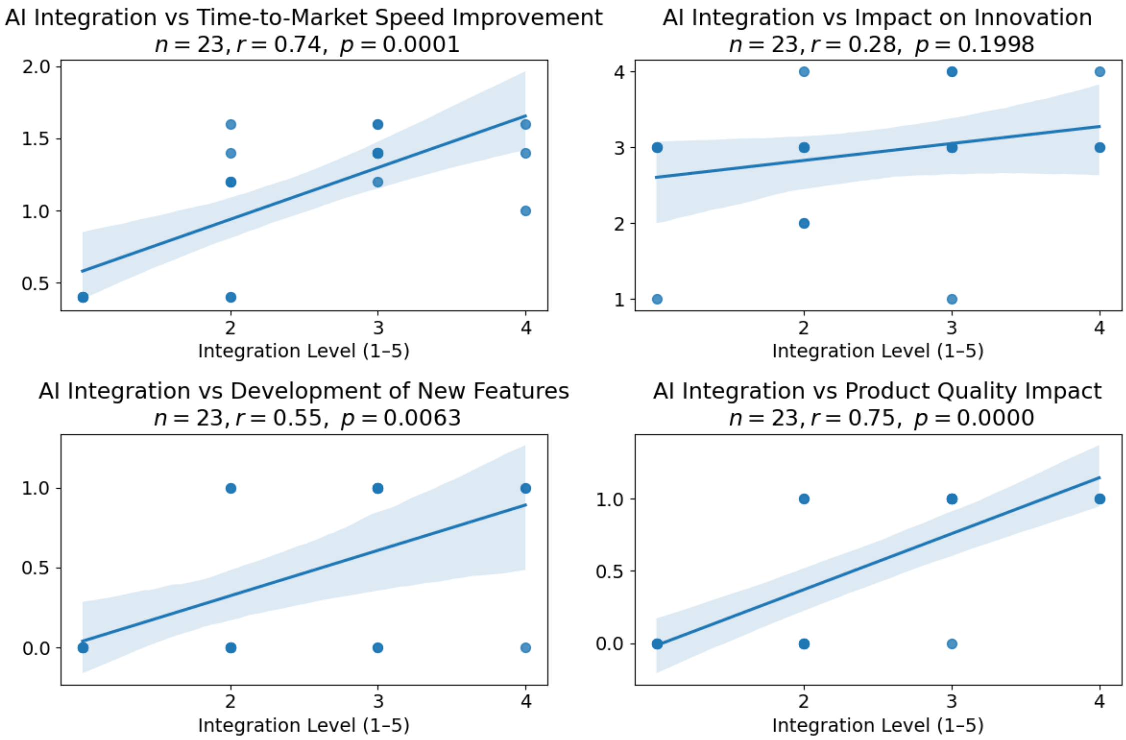

Figure 22. Linear correlation analysis between AI integration level with time-to-market speed improvement, product innovation, product new feature development and product quality impact.

There were 14 responders who replied to open-ended question about generative AI impact on product quality and features. The open-ended question has been analysed by using thematic grouping of the replies. Based on the manual analysis of the responses in total 7 themes were chosen then the frequency of appearance of these themes in the responses were counted. The results are shown in Figure 23.

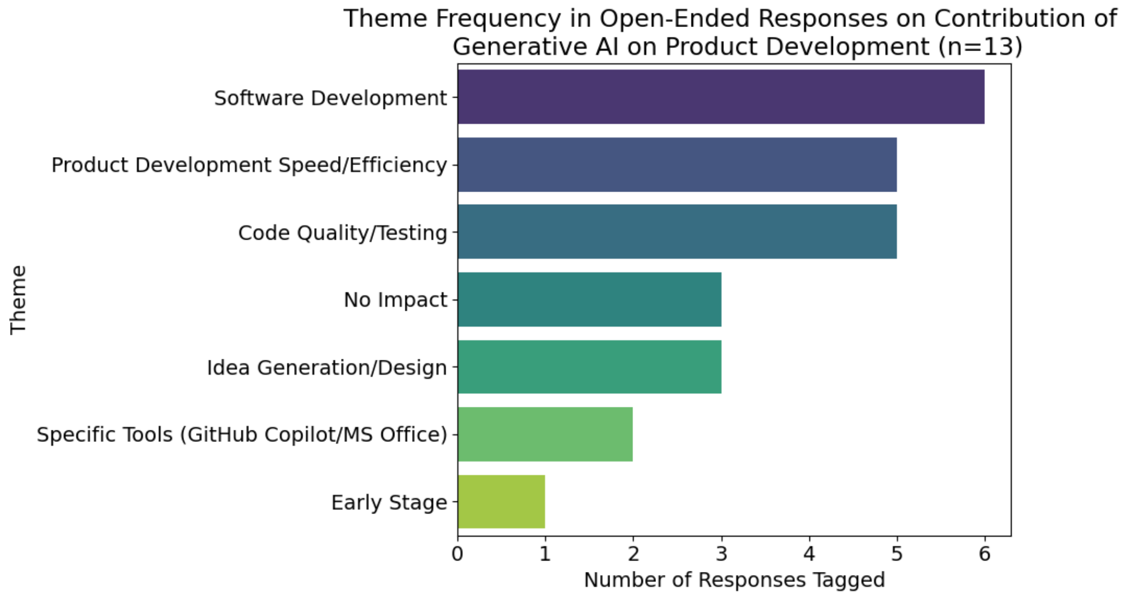

Figure 23. Theme frequency analysis for the contribution of generative AI on product development.

‘Software Development’ emerged as the most frequently mentioned theme, with 6 tagged responses. In addition to this, ‘Code Quality/Testing’ was tagged in 5 responses. These two themes indicate that the responders have been using generative AI in software development area extensively. ‘Product Development Speed/Efficiency’ was tagged in 5 responses whereas ‘Idea Generation/Design’ had received 3 responses. ‘No impact’ was seen in 3 responses, while ‘Specific Tools’ and ‘Early Stage’ appeared in 2 and 1 responses, respectively.

The figure indicates that software development product development and quality improvement are the most prominent areas where respondents perceive generative AI is contributing considering the product development area. On the other hand, some respondents reported no impact and the early stages adoption.

In addition to thematic analysis, open-ended responses about the product development were also analysed using sentiment analysis. Similar to marketing strategies analysis, the sentiment analysis was done using the VADER model. The sentiment analysis results are shown in Figure 24. The analysis revealed that the most of responses were classified as positive, indicating a generally favourable perception of generative AI tools in product development. Smaller portion of responses were neutral and, which can be reflecting the early-stage experimentation or uncertain outcomes and lack of positive impact on product development and quality despite investing in the use of generative AI.

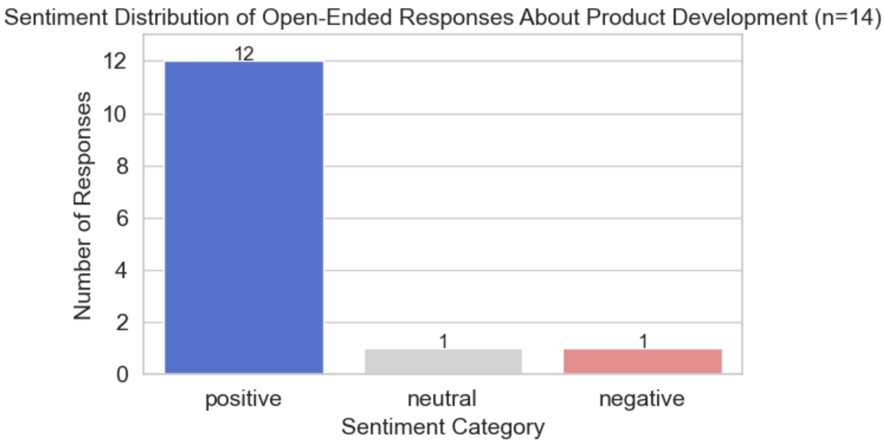

Figure 24. Sentiment analysis for open-ended responses about use of generative AI in product development.

In order to dive deeper on the impact of generative AI on the product quality, another open-ended question was constructed. This question was specifically designed to analyse how the overall quality of AI-assisted products compared to those developed without AI differs.

In Figure 25, the thematic analysis for this question is shown. The most prominent theme is ‘Quality Slightly or Significantly Improved’ with 11 tagged responses. This indicates a strong perception that generative AI contributes positively to product quality. ‘Domain-Specific Effectiveness’ is the second most frequent theme, with 5 responses. This suggests that improvements may be associated with the application domain. 'Early-stage Technology / Trust Issues' and 'Human-AI Collaboration' both appear with around 3 responses each, indicating that while there are quality improvements, there are also concerns about the maturity of AI technology and the need for effective human-AI collaboration. 'Improved Efficiency / Speed' also had around 3 responses, pointing to the ways AI accelerates development which is not directly related to product quality. Finally, 'Quality Depends on Tool / Usage' is the least frequent theme, with approximately 1 response, suggesting that the quality of AI-assisted products is perceived to vary based on the specific tools and how they are used.

These results indicate a general perception that AI has a positive impact on product quality, with a significant number of respondents observing improvements. However, the analysis also reveals concerns about the technology's maturity, the importance of human-AI collaboration and the domain-specific nature of AI's effectiveness.

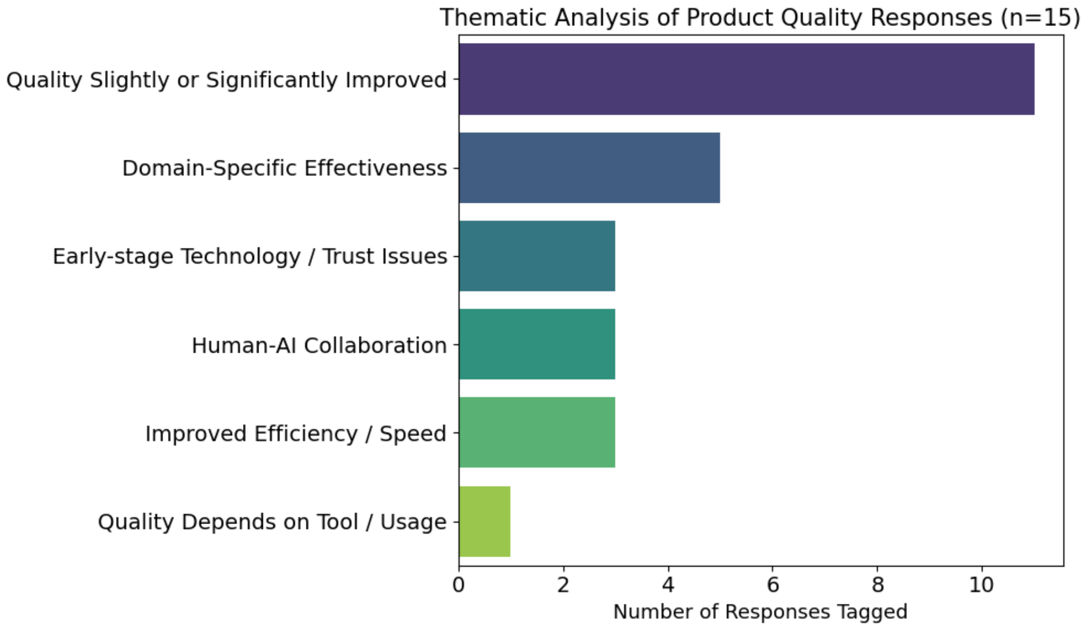

Figure 25. Theme frequency analysis for the contribution of generative AI to product quality.

The responses for the generative AI contribution for the product quality, were also analysed using sentiment analysis with VADER model. The results are shown in Figure 26. Number of responses with positive sentiment is 10 which indicates that the generative AI contributes positively to the product quality in general. There were 3 neutral and 2 negative sentiments indicating generative AI had no effect or negative effect on product quality.

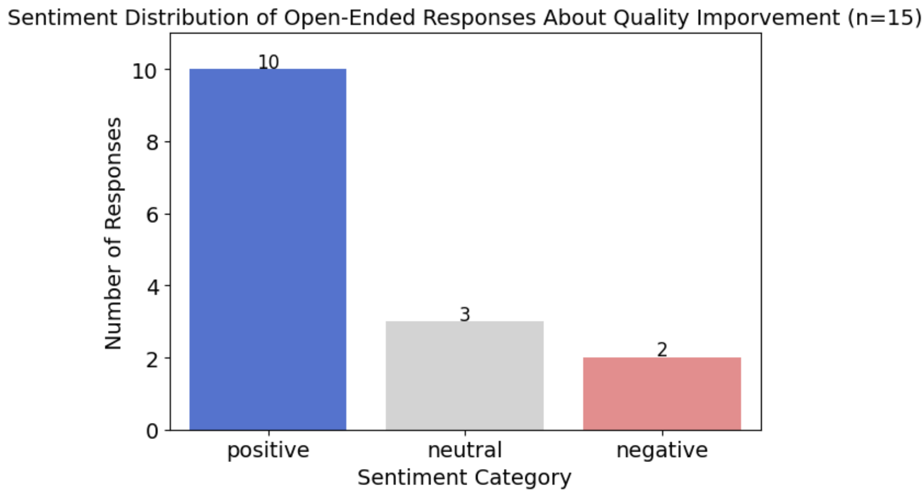

Figure 26. Sentiment analysis for open-ended responses about contribution of generative AI in product quality.

4.4 Impact of Generative AI in Competitive Landscape

In Figure 27, the perceived impact of generative AI on the responder's company's position within the competitive landscape of e-commerce industry, based on 49 responses is shown. The data reveals distribution skewed towards lower impact levels. A significant portion of respondents (34.7%) indicated a level 1 impact which indicates a minimal influence of generative AI on the competitive landscape. Closely following, 38.8% of the respondents reported a level 2 impact which suggests a moderate impact. The mean and median impact levels are both 2, reinforcing this trend towards lower perceived impact.

A smaller percentage, 18.4% of respondents, reported a level 3 impact, indicating a more noticeable influence. Only 8.2% of respondents reported a level 4 impact which indicates significant impact. There were no reports with impact level 5 that indicates a significant impact on competitive landscape.

The data suggests that while generative AI is perceived to have some influence on companies' competitive positions, this influence is generally perceived as low to moderate. A significant majority of respondents reported minimal to moderate impact, with only a small fraction indicating a substantial influence.

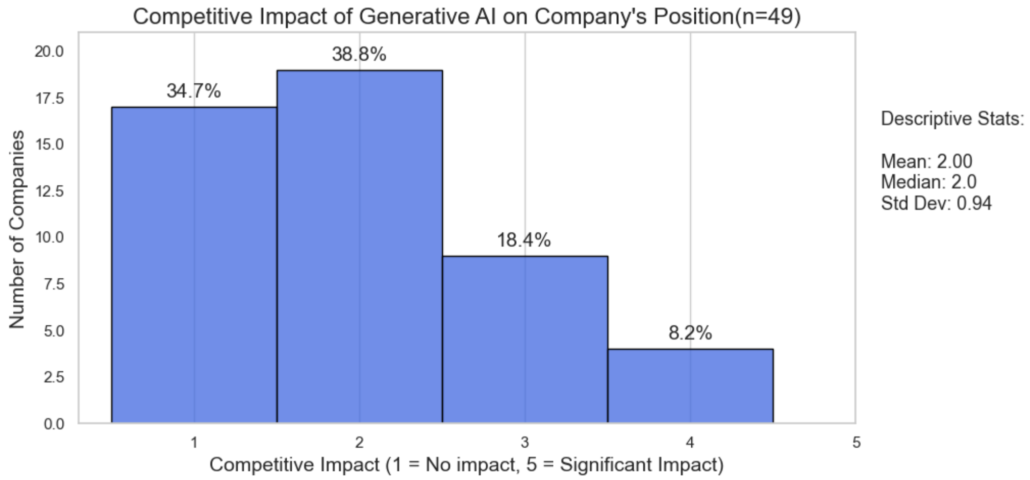

Figure 27. Impact of generative AI on the responder's company's position within the competitive landscape.

Figure 28 shows the perceived impact of generative AI on barriers to entry to the market within the e-commerce industry. The data reveals a clear majority, 63.3% of respondents, believe that generative AI has lowered barriers to entry to the market. On the other hand, 18.4% of respondents reported 'No effect,' suggesting they do not perceive generative AI as having significantly altered the existing barriers. Additionally, 18.4%, responded 'Unsure,' indicating a lack of clarity or a neutral stance on the issue. No respondents reported that generative AI has raised barriers to entry.

The data strongly suggests that the general perception among respondents is that generative AI has lowered barriers to entry in their industries. While a significant portion remains either neutral or unsure, the majority believe that generative AI is making market entry easier. The absence of any respondents reporting raised barriers further reinforces this result.

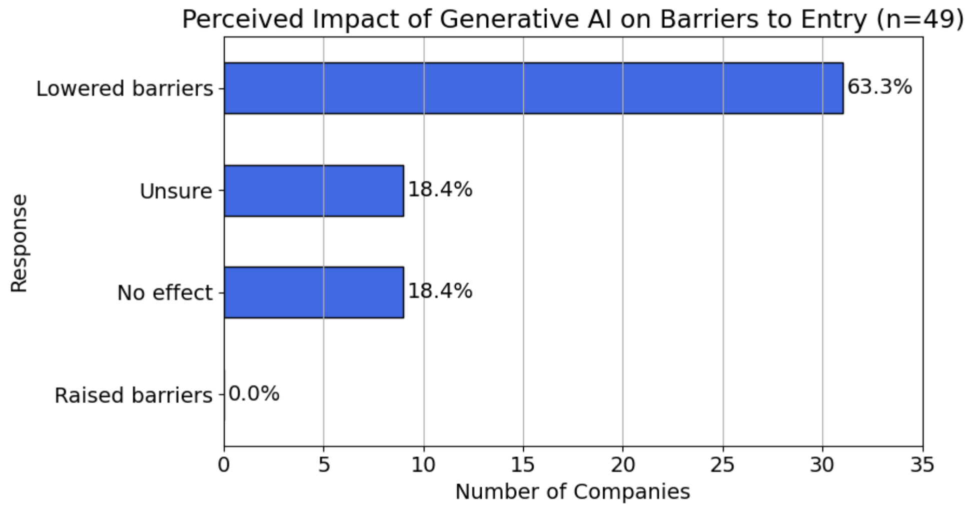

Figure 28. Perceived impact of generative AI on barriers to entry to market.

In Figure 29, the perceived change in ability to compete with larger organizations is shown based on the responses from 49 responders. The data reveals that the majority of responders (61.2%) reported “No difference”. A considerable portion of the responders (32.7%) reported slight change in their ability to compete with larger organizations thanks to generative AI. Only 6.1% of respondents reported 'Yes, significantly,' indicating a perception of a major improvement. No respondents reported 'No,' meaning no one perceived a decrease in their ability to compete.

The data indicates that the general view among respondents is that generative AI has not significantly changed their ability to compete with larger companies. While about a third of responders reported a slight improvement, only a small fraction believes generative AI has significantly enhanced their competitive position.

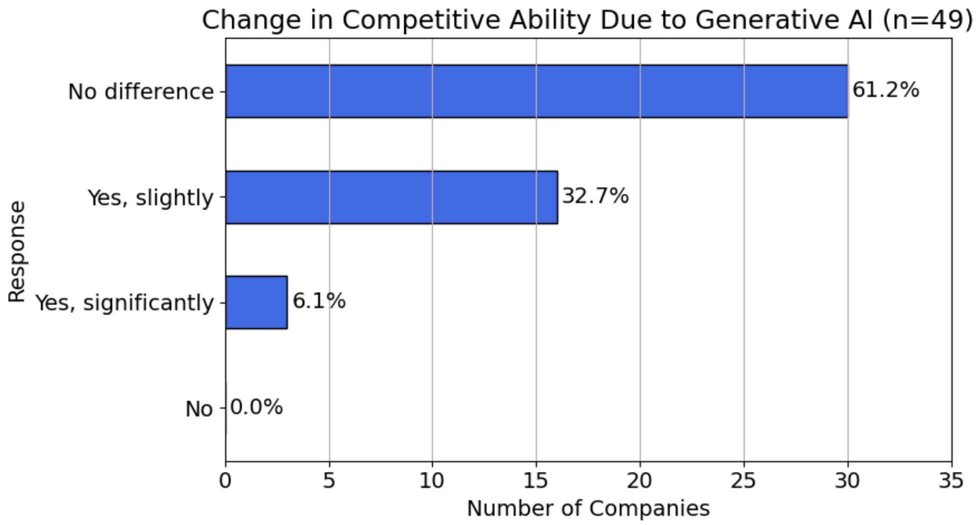

Figure 29. Perceived impact of generative AI on the ability to compete with larger organizations.

Figure 30 shows the impact of generative AI on the overall level of competition within the respondents' industries, based on responses from 49 companies. The data reveals strong perception that the generative AI increased the competition in e-commerce business landscape as 77.6% respondents reported slightly increased competition in the industry. A smaller percentage, 20.4% of respondents, reported no effect of generative AI on the industry-wide competition. Only 2.0% of respondents reported significantly increased competition due to generative AI. No respondents reported a decrease in the level of competition. The data strongly suggests a universal understanding among respondents is that generative AI has led to a slight increase in the overall level of competition within the e-commerce industry landscape. While a small fraction perceives no change, the majority believe that generative AI is intensifying competition. The absence of any respondents reporting decreased competition further reinforces this trend.

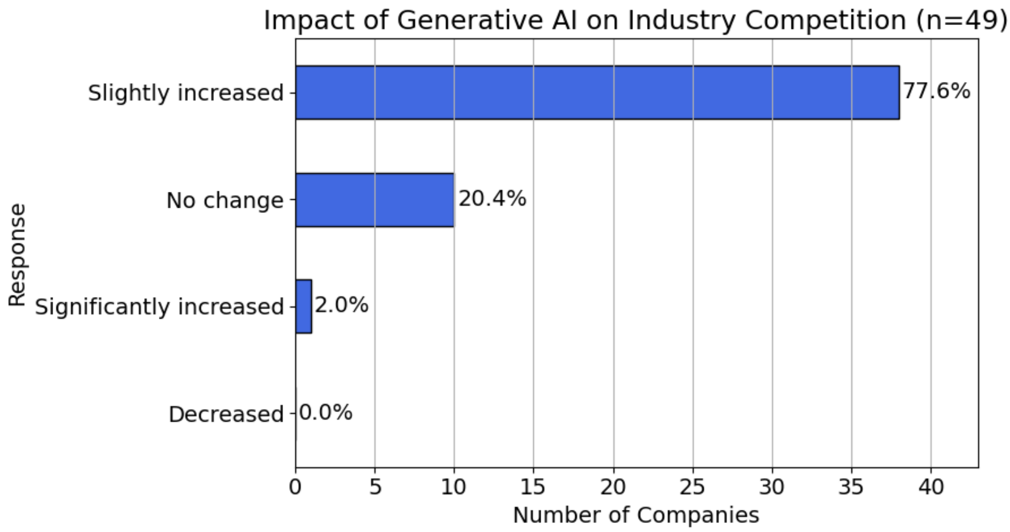

Figure 30. Impact of generative AI on the overall level of competition within the respondents' industries.

In Figure 31, the impact of generative AI on e-commerce market saturation is shown based on responses from 49 companies. The data reveals a distribution skewed towards lower impact levels. Majority of respondents (53.1%) indicated a level 2 impact, suggesting a moderate influence on market saturation. There were 20.4% of respondents who indicated level 1 and level 3 impact. Only 6.1% of respondents reported a level 4 impact. It is worth noting that, no respondents reported a level 5 impact, indicating significantly increased saturation. The mean and median impact levels are 2.12 and 2.0, respectively. This reinforces the trend towards lower impact on market saturation. Therefore, while generative AI is perceived to be influencing e-commerce market saturation, it is not yet seen as a major factor of saturation within the surveyed companies.

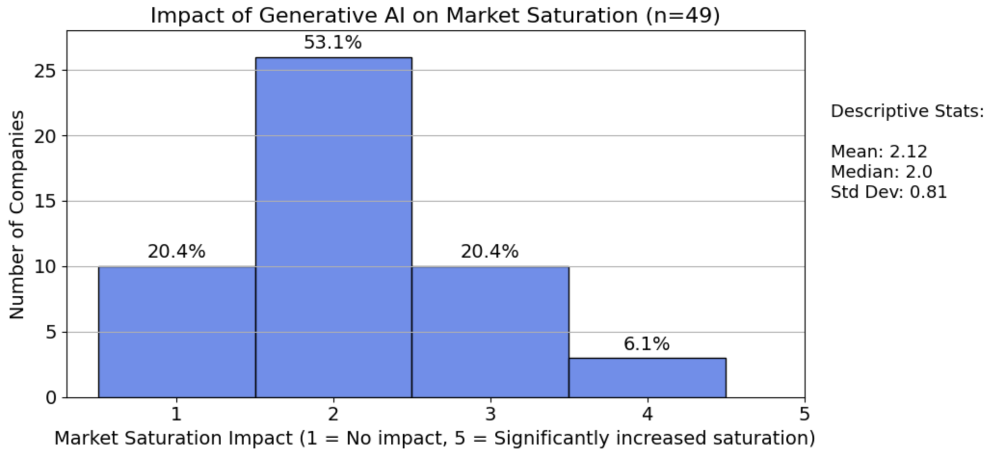

Figure 31. Perceived impact of generative AI on market saturation.

In Figure 32, adaptation of competitive strategy of responding companies in response to generative AI is shown. It is seen that 63.3% of companies made decision to adapt their competitive strategy due to generative AI, whereas 36.7% of the responding companies opted not to do that. These results suggest that generative AI is perceived as a significant factor in influencing competitive strategy of responding companies.

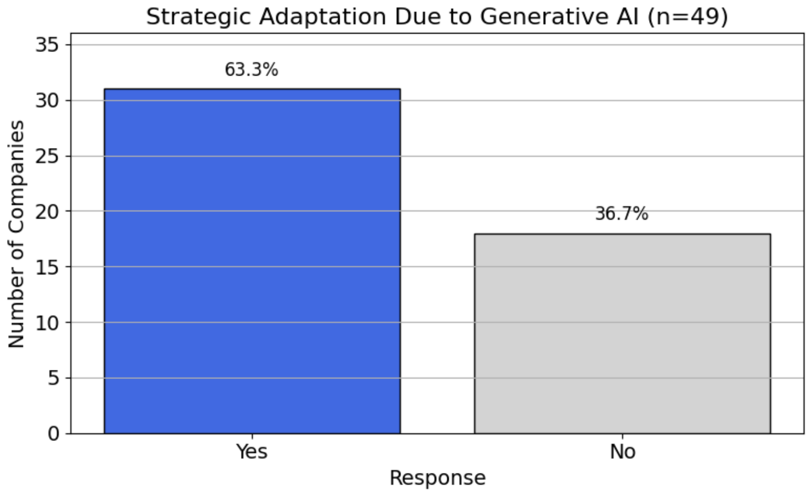

Figure 32. Adaptation of competitive strategy of responding companies in response to generative AI.

In order to further analyse how the companies have adapted their strategy an open-ended question was placed in the survey. This question was answered by the companies who decided to adapt their competitive strategy due to generative AI. The responses to the open-ended question are first analysed with a thematic grouping of the replies. After manual analysis of the responses total 7 themes were chosen and the frequency of appearances of these themes in the responses were counted. These results are shown in Figure 33.

The analysis results reveal that ‘Future intentions & Pilot Projects’ is the most prominent theme with 15 tagged responses. This suggests that companies are actively exploring and implementing generative AI in product development and conducting pilot projects to understand its potential in their competitiveness. The second most frequent theme is ‘Marketing & Sales Applications’ with 15 tagged responses. This indicates that a significant number of responding companies are focusing their strategic adaptation on using generative AI within their marketing and sales activities. ‘Competitive Response’ is the third most frequent theme with 11 responses. This highlights the fact that companies are leveraging generative AI as a strategy to stay competitive or gain competitive advantage. Following this ‘Product Development/Innovation’ appears with 8 responses suggesting that smaller but still considerable number of responding companies are integrating generative AI into their product development and innovation processes. The least frequent themes were ‘Employee Training & Skill Development’ and ‘Efficiency & Internal Process Improvement’ with 5 and 4 tagged responses, respectively. This suggest that some small number of companies are recognizing there is a need to upskill their employees to utilize generative AI effectively and generative AI may be useful tool to improve internal operation efficiency.

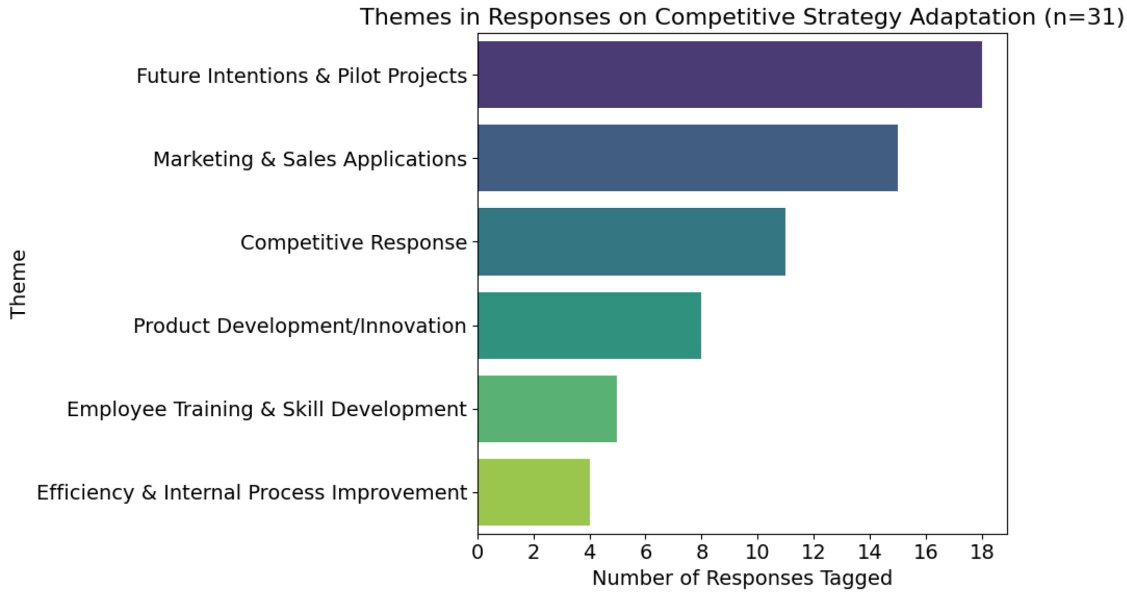

Figure 33. Theme frequency analysis for the competitive strategy adaptation.

Unlike the previous open-ended questions, the topic of how the companies adapted their strategy in response to generative AI was not analysed using sentiment analysis since it is not well suited for that. This is because the focus of responses was mainly descriptive, detailing the strategic changes rather than expressing positive or negative sentiment towards these adaptations. Instead, a word cloud analysis of the responses was done on the responses to better understand the specific strategic adaptations being reported.

In Figure 34, the word cloud is shown for this topic. The word cloud reveal that ‘AI’ and ‘generative AI’ is very prominent, meaning that it is the central topic which is natural considering the question. Several other frequent words such as ‘Marketing’ and ‘decided’ provide further information into the nature of the strategic adaptations. ‘Marketing’ seems to be a key area where companies are integrating AI into their strategies while ‘decided’ implies that companies have actively made choices regarding AI integration. The terms ‘company’, ‘explore’ and ‘future’ also stands out, implying that responding companies are actively exploring generative AI’s potential as their strategy. In addition, words ‘competitive’ and ‘competition’ highlight the context of adapting to stay competitive or gain competitive advantage in the market. The smaller word 'ecommerce' indicates the area where the strategy adaptation of the companies may be happening similar to larger word 'Marketing' and smaller word 'product development'. Some smaller words such as 'tools', 'ideas', 'areas', 'cases', 'art', 'efficiency' and 'customer service' indicate that diverse applications are considered by the responding companies in their strategic adaptation.

Figure 34. Word cloud analysis for the competitive strategy adaptation.

4.5 Reliability, Validity and Limitations of the Study

Several potential limitations should be considered when interpreting the results of this study. The findings are based on the experiences and perspectives of the 49 participating small to medium sized e-commerce businesses. While efforts were made to collect responses from a representative sample, a larger, more diverse sample could provide potentially more comprehensive and generalizable data.

The scope of this study is specifically focused on the implications of generative AI on marketing strategies, product development and competitive landscape within the small to medium sized e-commerce businesses. Consequently, the results may not be directly applicable to other sectors or larger enterprises. Different industries may exhibit varying levels of AI adoption and experience different effects. Additionally, larger enterprises may possess more resources and different organizational structures, which could influence their implementation and outcomes related to generative AI. Therefore, caution should be taken when interpreting these findings to areas outside the defined scope.

Furthermore, the data collection method was via an online survey that relies on self-reported data. As a result, the responses might include personal bias (Podsakoff et al., 2003). Participants may provide answers that they perceive as socially desirable, potentially overestimating the positive impacts of generative AI or misreporting the limitations and negative aspects of it. While survey included measures to mitigate biases such as ensuring anonymity and framing questions neutrally, the potential for response bias remains a limitation.

It is also important to acknowledge that the data reflects the experiences and views of the survey respondents. While the participants posses experience in their respective fields, variations in their level of expertise and experiences towards generative AI may influence the data. For example, respondents primarily involved in marketing roles may provide different perspective than those working on product development. Furthermore, technological infrastructure in the respondents' organizations may affect their experience with generative AI. The study did not explicitly control for these factors, which could introduce variability in the results.

5 Conclusions

5.1 Influence of Generative AI on Marketing Strategies

The first research question explored the impact of generative AI too integration on the marketing strategies of small to medium e-commerce businesses. The result analysis reveals that while awareness and initial adoption exists, the integration of generative AI into core marketing strategies remains at an early stage for most responding SMEs. Findings show that about half of the surveyed businesses utilize tools with integrated generative AI. However, deeper integration such as developing custom tools is far less with 18.4% of respondents. For those companies that are currently not using generative AI, a significant portion (14 out of 26), have short-term plans for adoption, mainly targeting marketing activities.

The analysis on the data related to marketing strategies was done based on maximum 23 respondents. The primary application of generative AI in marketing according to respondents identified by 95% of them, is content creation. This aligns with the widely recognized capabilities of generative AI to automate and improve text and image generation (Kshetri et al., 2024; Reisenbichler et al., 2022). Significant number of respondents (about 77%) reported efficiency gains in this area. This suggests that SMEs are successfully utilizing generative AI for operational benefits in marketing content creation supporting the findings of Hartmann et al. (2024). The thematic analysis further reinforced this as ‘Efficiency Gains’ was the most dominant theme in open-ended responses.

However, the impact on other important marketing areas, such as personalization and customer engagement, appears significantly less pronounced at this stage. The average perceived impact on personalization was relatively low, with mean value being 2.17 out of 5. In addition, close to 70% respondents reported that they had seen minimal to no improvement in this area utilizing generative AI. Similarly, 36.4% of respondents reported that they are not using generative AI in customer engagement with 50% reporting minor role in that area. These results are contradicting with some studies that highlight the potential of generative AI in marketing content personalization (Garde, 2024; Lee et al., 2024). This may be due to the complexity of implementing advanced personalization which requires deeper data integration and potentially exceeding the current capabilities or resources of smaller businesses. This is supported by the discussion above which was majority of SMEs currently do not use more advanced type of generative AI such as custom tool development. This is further supported by the finding prominent of ‘Learning Curve’ theme in the open-ended questions.

The effect on marketing costs was varied. Nearly 40% of the respondents saw cost reductions whereas 47.8% saw no change. This suggests that potential savings highlighted by some studies such as Sinha et al. (2023) are not universally realized and may be reduced by the implementation and tool costs.

The impact on overall marketing performance was moderate, with 50% reporting slight improvements and 13.6% reporting significant gains. On the other hand, 36.4% reported seeing no noticeable difference. The positive correlation found between the level of AI integration and marketing effectiveness ($r=0.51$, $p<0.05$), content personalization ($r=0.63$, $p<0.01$) and content creation efficiency ($r=0.48$, $p=0.05$) shows that deeper integration tends to provide better results. It is worth mentioning that the weak correlation with cost savings ($r=0.16$, $p>0.1$) reinforces the above discussion about the variability in financial impact.

The dominant positive sentiment towards generative AI in marketing, despite moderate performance impacts and challenges like the learning curve, suggests that SMEs recognize the potential even if the full benefits are yet to be realized.

5.2 Influence of Generative AI on Product Development and Innovation

The second research question studied the ways generative AI tools influence product development and innovation processes within small to medium e-commerce businesses. Among the companies that are currently not using generative AI, a small portion (3 out of 26), have short-term plans for adopting generative AI in product development and innovation. Considering the organizations that are already using generative AI (23 companies), integration level of generative AI in product development and innovation is moderate (mean integration level 2.39 out of 5), with most SMEs still in the early stages of adaption.

The primary applications of generative AI identified are concentrated in the initial technical stages of product development such as ‘Design or prototyping’ (72.2%) and ‘Idea Generation’ (50%). This aligns with literature suggesting generative AI’s usefulness in boosting creative and conceptual work (Booth et al., 2024; Bouschery et al., 2024; Marion et al., 2024). Additionally, significant number of respondents selected ‘Software Development’ (27.8%) in multi response question and high frequency themes ‘Software Development’ and ‘Code Quality/Testing’ in open-ended responses highlight the perceived value of generative AI as a coding assistant (Friedman, 2022).

The study found moderate positive impact of generative AI on reducing time-to-market for new products (mean value 2.91 out of 5), with around 70% reporting a positive contribution in this area. This aligns with thematic analysis of open-ended questions as the second most frequent theme was ‘Product Development Speed/Efficiency’. This indicates that generative AI can accelerate development cycles as discussed by Marion et al. (2024). Similarly, 52.2% noticed a positive impact on improving product quality and sentiment analysis on the contribution of generative AI on product quality was mainly positive.

On the other hand, the influence of generative AI on the innovation was mixed. The average perceived impact on innovation was moderate (mean value 2.91 out of 5). However, 17.4% of respondents did not agree on the benefits of generative AI on product innovation. Also, correlation analysis revealed no statistically significant relationship between the level of generative AI integration and the perceived impact on innovation ($r=0.16$, $p>0.1$). This contrasts with the significant positive correlations found between integration level and time-to-market speed ($r=0.57$, $p<0.01$), new feature enablement ($r=0.5$, $p<0.05$) and product quality ($r=0.55$, $p<0.01$). This suggests that while generative AI is utilized for operational efficiencies and incremental improvements in product development, its role as a driver for significant innovation is not major or requires more than simple tool adoption. This could reflect a focus on improving the efficiency rather than transformative change or it can be linked to challenges identified in thematic analysis such as 'Early-stage Technology/Trust Issues' and the need for effective 'Human-AI Collaboration' (Booth et al., 2024; Colombo et al., 2023).

5.3 Influence of Generative AI on Competitive Strategies of E-commerce SMEs

The third research question was about understanding how generative AI has affected the competitive dynamics of small to medium e-commerce businesses, specifically concerning barriers to entry and market saturation. The findings of this study indicate that while SMEs perceive generative AI as an influential force, its role in fundamentally reshaping the competitive landscape is currently viewed as more incremental rather than transformative. The overall impact on competitive positions of responding companies was moderate (mean impact level 2 out of 5). This suggests that although generative AI is beginning to shape competitive conditions, it has not yet led to widespread or disruptive changes in market positioning across the responding businesses.

A key finding is that the significant portion of the respondents (63.3%), believe that generative AI lowers barriers to entry into e-commerce market. This aligns with the potential of AI to automate foundational business tasks such as generating product descriptions or initial marketing materials and potentially helping for new entrants to the market (Belém et al., 2020; Opuszko et al., 2024; Reisenbichler et al., 2022). This also aligns with the broader understanding on AI democratizing certain capabilities (Kshetri et al., 2024). On the other hand, 18.4% of the respondents did not perceive any effect from generative AI on the barriers to entry whereas another 18.4% was unsure of the effect. This implies that traditional barriers for e-commerce businesses related to logistics, capital investments or brand recognition as explained by Savrul et al. (2014), may not be overcome solely by the use of generative AI.

Interestingly, while generative AI may be lowering the barriers to entry to the market, it is mainly perceived that generative AI does not lead to major increase in the competition since 77.6% of respondents reported a minor increase in the competition. This is also backed by the results of moderate increase in the market saturation (2.12 mean score out of 5). This suggests that generative AI may be currently helping existing small to medium e-commerce businesses operate more efficiently or compete more effectively, rather than causing a significant number of new competitors in the market. However, its impact on the ability of SMEs to compete with larger organizations remains limited. Most respondents (61.2%) observed no change while 32.7% reported a slight improvement in their ability to compete with larger organizations. This suggests that despite the accessibility of generative AI tools, the technology has not yet significantly reduced the structural advantages such as scale, data and resources that larger e-commerce organizations hold as reported by Laudon & Traver (2016). Therefore, while generative AI is incrementally changing the competitive landscape, its role in levelling the competition with larger players remains constrained.

Despite the moderate direct competitive impact felt so far, many responding organizations are already adjusting their strategies in response to generative AI. A majority (63.3%) reported making changes in their competitive strategy to stay competitive. Thematic analysis reveals that these changes are mainly focuses on future planning and experimentation since the analysis showed ‘Future Intentions & Pilot Projects’ as most frequently appearing theme in the open-ended responses. This analysis also revealed that the focus area is on the ‘Marketing & Sales Applications’ showing a need to utilize generative AI to provide ‘Competitive Response’ to changing dynamics. Applications in ‘Product Development/Innovation’ are also considerable aligning with the observed trends by Marion et al. (2024) and Booth et al. (2024). However, lower frequency themes such as ‘Employee Training & Skill Development’ suggests a potential gap in strategic focus that might limit the long-term and full potential of generative AI.

5.4 Managerial Implications and Recommendations

In this study the aim was to explore how generative AI is influencing the operations of SMEs in the e-commerce sector with particular focus on marketing strategies, product development and the competitive landscape. The results show that while the direct transformative effects of generative AI are still emerging, SMEs are actively exploring and adoption these tools with the main intention of improving efficiency, enhancing marketing content creation and keeping the pace with technological trends.

For companies currently in the process of integrating generative AI into their operations, the findings offer practical guidance. First, the clearest benefits were observed in marketing related activities, particularly in marketing content creation. SMEs are encouraged to prioritize these areas in their AI adoption efforts, as they present the lowest barriers and fastest efficiency gains. However, a successful implementation requires appropriate training and resource allocation. A strong attention should be pain on building internal capabilities, as many survey participants highlighted challenges related to the learning curve and insufficient expertise.

In product development and innovation, generative AI shows the most potential when used as a support tool, especially in design, prototyping and coding. However, the technology does not replace the need for strategic innovation planning. Managers are advised to approach AI as a complement to human creativity where collaboration between teams and AI systems leads to most effective outcomes. It is also important to address the issue of trust in AI generated content by establishing clear validation processes to ensure the quality and reliability.

Considering the competitive landscape, while generative AI may lower barriers for certain operational processes and enable more agile ways of working, it has not fundamentally shifted the competitive dynamics for most of the responding organizations. According to results, rather than creating entirely new market entrants, the technology is currently helping existing players operate more effectively. SMEs are suggested to focus on using AI to offer unique customer experiences, build stronger brand marketings and enhance personalization rather than solely aiming to match competitor efficiency.

The study also points to areas that require more attention in the future. Particularly, the lack of emphasis on employee training and skill development could become a barrier to sustainable AI integration. Companies need to ensure that their teams are not only equipped to use generative AI tools but also understand their strengths and weaknesses in addition to their strategic relevance to businesses.

These insights are valuable not only for participating SMEs to this study bit also for other companies facing similar challenges. The adoption of generative AI should not be treated as a one-time implementation, but rather as part of a broader transformation in how organisations approach digital tools, data use and decision-making. Future projects should also involve continuous monitoring of AI developments and competitor behaviour as the pace of change in this field is extremely fast. In the long term, SMEs that are able to align their technological initiatives with strategic goals and that actively engage their workforce in the process are more likely to experience meaningful and sustainable benefits from generative AI.

5.5 Future Research Directions

In the marketing domain, future research could benefit from longer studies to track how generative AI integration evolves over time within SMEs. Such studies would help clarify whether observed benefits, such as improved personalization or cost-efficiency become more pronounced with organizational maturity and experience. Additionally, developing robust return of investment assessment frameworks customized to SMEs could support more informed decision making. This framework for instance might include both directly measurable quantities such as conversion rates and intangible assets such as brand alignment and creative differentiation.

Considering product development, a key area for future research involves examining successful cases of innovation driven by generative AI. Qualitative deeper studies into these SMEs could help identify effective strategies, tools and collaborative practices. Furthermore, investigating how human-AI collaboration is structured in these companies focusing on task division, validation processes and creative workflows could provide practical guidance for organizations seeking to adopt similar approaches.

From a competitive and strategic perspective, empirical research is needed to quantify how generative AI impacts market entry barriers for new e-commerce companies. Comparative studies could evaluate whether startups using AI tools are able to reduce time-to-market and operating costs relative to those using traditional methods. Additionally, future work could explore how SMEs leverage their agility to adopt more customized and specialized generative AI solutions in order to compete resource-rich competitors.

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Appendix 1. Survey

Section 1: Business Demographics

1. **Which industry best describes your business?**
    - Retail
    - Technology
    - Services
    - Fashion
    - Home Goods
    - Health & Wellness
    - Food & Beverage
    - Other (Please specify)
2. **How many employees work at your company?**
    - Micro (1–19 employees)
    - Small (20–99 employees)
    - Medium (100–499 employees)
3. **How many years has your company been in operation?**
    - Less than 1 year
    - 1-3 years
    - 3-5 years
    - 5-10 years
    - More than 10 years
4. **What is the current annual revenue range of your business?**
    - Less than $100,000
    - $100,000 - $500,000
    - $500,000 - $1 million
    - $1 million - $5 million
    - More than $5 million

6. **What is your role within the company (optional)?**
   - Owner/Founder
   - Marketing/Advertising
   - Product Development
   - Technology/IT
   - Operations
   - Other (please specify)
7. **Does your business currently use any generative AI tools (e.g., ChatGPT, Midjourney, DALL-E) in daily operations?**
   - Yes
   - No

If you answered Yes to previous question, please proceed to Section 2. Otherwise, please answer questions 8 and 9 and proceed to Section 4.

8. **Are there any short-term plans to use generative AI tools and in what areas?**
   - Yes, in marketing
   - Yes, in product development and innovation
   - Yes, in other areas (please specify)
   - No plans to use generative AI

Section 2: Impact on Marketing Strategies

1. **To what extent has your company integrated generative AI tools into its marketing strategies?**
   - Scale: 1 (Not at all) – 5 (Fully integrated)
2. **What types of marketing activities has generative AI been used for in your company?**
   - Content creation (e.g., product descriptions, blogs)
   - Ad campaign personalization
   - Social media management

- Customer engagement and support
- Other, please specify:

3. **How has the use of generative AI impacted your marketing content creation process?**
    - Greatly improved efficiency
    - Somewhat improved efficiency
    - No noticeable change
    - Decreased efficiency
    - Not applicable
4. **How would you rate the impact of generative AI on your company's ability to personalize customer interactions?**
    - Scale: 1 (No change) – 5 (Significantly improved)
5. **Since implementing generative AI, how has your marketing cost been affected?**
    - Significantly decreased
    - Slightly decreased
    - No change
    - Increased
    - Not applicable
6. **Has generative AI improved your marketing performance in terms of reach, engagement or conversions?**
    - Yes, significantly
    - Yes, slightly
    - No noticeable difference
    - No
7. **How important is generative AI in your customer engagement strategy (e.g., chatbots, personalized messages)?**
    - Major role
    - Minor role
    - No role

- Not sure

8. **Can you share any specific examples or experiences of how generative AI has impacted your marketing strategies, either positively or negatively?**
   - Open-ended:

Section 3: Influence on Product Development and Innovation

1. **To what extent has your company used generative AI in product development or innovation?**
   - Scale: 1 (Not at all) – 5 (Extensively)
2. **Which product development areas has generative AI contributed to?**
   - Idea generation
   - Design or prototyping
   - Product testing and optimization
   - Customer feedback analysis
   - Other, please specify:
3. **How has generative AI impacted the time-to-market for new products?**
   - Scale: 1 (No impact) – 5 (Significantly increased speed)
4. **Do you feel that generative AI has led to more innovative products within your company?**
   - Scale: 1 (Strongly disagree) – 5 (Strongly agree)
5. **In which ways has generative AI contributed to product quality or new features?**
   - Reducing time-to-market
     - Negative, No effect, Negative
   - Enabling new product features
     - Negative, No effect, Negative
   - Improving product quality

    - Negative, No effect, Negative

6. **Are there any other ways generative AI has contributed to product quality or new features in your organization?**
    - Open-ended:
7. **How do you perceive the overall quality of AI-assisted products compared to those developed without AI?**
    - Open-ended:

Section 4: Effect on Competitive Landscape

1. **How has generative AI influenced your company’s position within the competitive landscape?**
    - Scale: 1 (No impact) – 5 (Significant impact)
2. **Do you believe generative AI has affected the barriers to entry in your industry?**
    - Lowered barriers
    - Raised barriers
    - No effect
    - Unsure
3. **Has generative AI changed your company's ability to compete with larger companies?**
    - Yes, significantly
    - Yes, slightly
    - No difference
    - No
4. **How has generative AI affected the overall level of competition in your industry?**
    - Significantly increased
    - Slightly increased
    - No change

- Decreased

5. **To what extent has generative AI impacted market saturation in your industry?**
   - Scale: 1 (No impact) – 5 (Significantly increased saturation)
6. **Has there been a decision to adapt your company's competitive strategy in response to generative AI?**
   - Yes
   - No
7. **If you answered yes to previous question, how has your company's competitive strategy adapted in response to generative AI?**
   - Open-ended: