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Analysing the Capabilities of Generative AI to Determine Its Role in Customer Experience Management for Effective Product Development

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Abstract: Customer expectations are no longer confined to product quality or price offerings. Modern firms now emphasize the overall customer experience associated with acquiring a product or service, recognizing its significance in shaping customer satisfaction and loyalty. Since the technological scenario is changing rapidly, with generative AI (GAI) enhancing the capabilities of AI, the proposed research intends to examine the future transformational role and capabilities of GAI in customer experience management (CEM) for effective product management. A comprehensive analysis of AI and GAI's capabilities was conducted to identify the impact areas of traditional AI that are enhanced by GAI. The framework further mapped the functional enhancements offered by GAI across the core elements of CEM identified in the literature. This work highlighted GAI's capabilities to enhance customer understanding, experience design and experience measurement while also addressing its potentiality within the context of effective product management.

***Keywords*:** Customer experience management (CEM), Artificial intelligence (AI), Generative artificial intelligence (GAI), Customer experience (CX), Product management co-creation, Personalization

1. INTRODUCTION

AI was considered the primary tool of modern industrial revolutions that aimed at revolutionizing businesses by learning from data, identifying patterns and forecasting decisions through intelligent analysis and interpretation of data (Skilton, 2019). However, the introduction of GAI has further enhanced the capabilities of traditional AI by generating novel and related content. This capability is not restricted to the generation of specific content and allows multimedia content creation. Yi et al. (2020) deployed a GAI-based conversational agent and studied it in terms of the accuracy of its responses and its level of personalization. Furthermore, Beerbaum (2023) explained the GAI-based robotic process automation commitment to effectively imitating human interactions within a system. This indicates that GAI, along with the capabilities of traditional AI, may lead the innovation leap in major dimensions, impacting the entire management canvas.

Businesses are now looking to enhance the customer experience to improve the quality of their offerings through active customer involvement. With the development of digital technologies, customer experience is considered a key business driver and an objective for sustainable business growth (Johnston and Clark, 2008). With AI revolutionizing the entire business scheme, customer experience is now being considered a specific aspect of organisational offerings that directly impacts dimensions such as product development, image building and buying journey. Thus, businesses are formulating strategic approaches concerning the design, management and optimisation of their interaction with customers. Since the technological scenario is changing rapidly, with GAI enhancing the capabilities of AI, the proposed research intends to examine the transformational role and capabilities of GAI in customer management for effective product development.

1.1 Objectives and research questions

The objective of the proposed framework is to systematically identify the role of the enhancements offered by GAI in CEM, focusing on effective product management. Therefore, the following research questions are addressed by the study.

1. What are the core elements of the CEM journey?
2. What enhancements do GAI offer to traditional AI?
3. What role can these enhancements offer in the context of AI-assisted CEM?
4. What role can AI-assisted CEM play in product management?

2. METHODOLOGY

The introduction and incorporation of modern technologies, particularly AI and GAI, into industrial and business operations compels a shift in the comprehension and exploration of modern technologies. Li and Raymond (2023) explained that a more realistic and practical approach is to investigate the contextual capabilities of these technologies rather than analyse the concerned model or algorithm. Therefore, this work intended to map the functional enhancements offered by GAI for CEM in the context of product development. For this purpose, a comprehensive literature review was carried out.

Given that the research area is still emerging and exploratory, availability and access to direct and relevant resources was a significant challenge. The novelty of the research area required a broad and in-depth exploration of the topic to develop a

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foundational understanding. Therefore, a comprehensive literature review approach was adopted, incorporating diverse sources such as journal articles, conference papers and reports published in peer-reviewed journals. Several databases, including IEEE Xplore, SpringerLink and Google Scholar, were employed to access the literature. The inclusion criteria prioritised studies focusing on the capabilities of GAI, CEM and product management. Due to challenges in data availability, the selection and combination of keywords for efficient search querying also posed a significant challenge. Various similar terminology such as 'customer experience', 'customer engagement', 'user experience', 'customer interaction', 'customer-centric experience' and others were incorporated into the search strategy to capture diverse perspectives.

To effectively address the research questions, the findings were presented in four major themes – the CEM journey and its core elements, enhancements offered by GAI to the existing AI capabilities, the possible role of GAI across the core stages of CEM and the possible impact that GAI-backed CEM may offer in the context of product management.

3. CEM AND ITS CORE ELEMENTS

Customer expectations are no longer restricted to the price or quality of offerings and prioritise seamless buying or service acquiring experiences. Organisations have realised the importance of a customer-centric culture. Personalised experience generation is the core element of an immersive customer experience design. Understanding customers' insights and designing personalization strategies are crucial and require a strong grasp. It is an iterative process that requires constant monitoring and measurement for improvement. Therefore, it demands an agile, learning and adaptive culture to produce effective results. According to Lemon and Verhoef (2016), customer experience is a multidimensional phenomenon based on customers' responses to organisational offerings or other actions. In the advanced world of smart technology and social media, customer experience is considered a potent tool for gaining customer satisfaction in a highly commoditized market. Therefore, it is pertinent for service providers to consider a strategic approach towards designing and continuously improving the customer experience for sustainable growth. This strategic and cultural mindset, along with organisational capabilities to develop customer experiences, is referred to as CEM (Kuehnl et al., 2019). CEM has evolved to encapsulate the total customer experience, which includes the pre-, during and post-buying process or journey. This journey involves a series of steps to analyse and understand customer behaviour and inspirations (Datig, 2015).

3.1. Customer understanding

Ponsignon et al. (2017) explained that understanding customer needs is the most crucial element for designing an effective CEM. Designing activities and procedures to cater to customer needs is pertinent for designing an experience. It is fundamental to leverage customer data by identifying different patterns and trends relating to customer segmentations, behaviour, needs, preferences and expectations (Joel and Oguanobi, 2024). Customer data across internet platforms has been of great interest for businesses in the modern world for gaining insights into customer behaviour and preferences. This data provides them with the information to create value in many areas, such as designing marketing campaigns, creating market-oriented products and designing effective customer experiences (Kitchens et al., 2018).

3.2. Customer experience design

With the rapid emergence of digital platforms and the increasing popularity of social media, customer touchpoints are continually evolving, presenting more opportunities for engagement than ever before. Although it is challenging to account for all possible touchpoints, each of them presents businesses with substantial sales and engagement potential (Tarabasz, 2024). In this dynamic environment, it is crucial for businesses to anticipate future customer touchpoints and explore innovative pathways to effectively address them.

3.3. Customer experience measurement

Loureiro et al. (2020) explained that stimulating initial motivation in customers to collaborate as stakeholders may require certain emotional or monetary triggers that may diminish over time due to different social, behavioural and technological challenges. Personalisation schemes may also require constant updation due to changing customer behaviour or needs (Micu et al., 2022). Furthermore, customers' responses to touchpoints may change over time, and this change requires accounting. Therefore, it is essential that the CEM strategy accommodates the experientials to keep the stakeholders engaged and motivated. Thus, feedback collection and analysis have become a crucial part of CEM.

4. GAI ENHANCEMENTS TO TRADITIONAL AI

Ivanov et al. (2021) described the present and futuristic role of AI in enhancing the industrial productivity and overall growth of firms. Varying perspectives on these technologies are presented. For instance, the European Commission (2018) acknowledged its learning and perception capabilities by explaining that any system or programme that observes its environment learns from it and recommends learned actions based on the knowledge gained. Several industry giants (Google, 2023; McKinsey, 2023) interpreted AI capabilities as learning, prediction, reasoning, perception and adaptation based upon their experiences.

GAI offers to unravel an unimaginable future horizon through various models such as variational autoencoders, transformer-based architectures and generative adversarial networks by optimizing diverse AI capabilities. (Linkinen, 2024). To understand the enhancements offered by GAI, it is pertinent to these different GAI models, as they offer diverse capabilities and varied outputs.

4.1. Learning

Learning capability is pivotal for advanced machine learning models, such as variational autoencoders and generative adversarial networks. Their performance relies on understanding training data and simulating data patterns to create novel content that mimics training data patterns (Bao et al., 2022). This allows the formulation or extension of synthetic datasets with limited data instances. Since the range, relevance and accessibility of data is no longer an issue, the generalizability of AI models increases, which depicts the enhanced learning capabilities of AI (Sai et al., 2024). Further, this data mimicking and generation capability can address data privacy and bias concerns, which are often associated with AI systems (Zhang and Gosline, 2023). Moreover, GAI models can identify dependencies within data by assigning significance to parts of input through the attention mechanism. This helps extend the learning capabilities of AI systems to generate context-specfic output (Jackson et al., 2023).

4.2. Perception

Han et al. (2022) explained the capability of GAI to forge, enhance, alter or add to existing images and to create novel images that can play an important role in enhancing the perception ability of AI systems. Similar to the computer vision sphere, GAI has also revolutionised the perception capacity of the natural language processing (NLP) realm. For instance, NLP-based learning models, such as ChatGPT, generate humanistic content that is almost identical to human work (Rasul et al., 2023). Lingard (2023) stated that its ability has now improved to drafting long and complex sentences, representing its capacity to capture complex writing patterns and language semantics.

4.3. Forecasting

Similarly, researchers such as Jackson et al. (2024) and Kar et al. (2023) reported GAI's potential to better forecast the capabilities of AI systems across diverse spheres of business, education and health. They explained that GAI models possess a tendency to create more plausible and realistic projections that can help reduce risks and increase opportunities.

4.4. Reasoning

Furthermore, this potential to generate realistic and complex future scenarios enhances the reasoning abilities of AI systems (Bojic et al., 2024). Continuous learning and improvement are one of the primary features of GAI models. Along with prior data, GAI uses dynamic information to refine its output and improve model efficiency over time (Kaldaras et al., 2024).

4.5. Adaptability

Generator and discriminator join to formulate a progressing and learning system capable of absorbing new data and varying operational contexts. This depicts the enhanced adaptability feature offered by GAI models, which is crucial for their operation in the realm of modern and advanced operating environments (Zhu et al., 2021).

4.6. Perception

Dwivedi et al. (2023) described the human-like capability of GAI models to generate user-friendly interactions with the external environment. Models using transformer architecture have transformed interaction capabilities by generating contextual and concise responses (Bansal et al., 2024).

5. ROLE OF GAI IN CEM PROCESS

GAI has enhanced the capabilities of AI to allow organisations to automate certain tasks effectively and improve organisational processes. To analyse the capabilities of GAI in CEM, this work draws upon the key areas of CEM identified in the literature (as explained in Section 2). These domains incorporate customers' understanding and experience design and measurement.

5.1. GAI's role in customer understanding

Opinion mining and sentiment analysis are widely used to gain an understanding of customers and categorise them based on their features. This helps organisations better understand their customer base and formulate more relevant and definitive strategies (Peppers and Rogers, 2016). Algorithms such as hierarchical clustering, neural networks, fuzzy theory, K-means and evolutionary algorithms exhibit advanced capabilities to learn and segment customers (Li et al., 2023).

5.1.1. Mimicking customer data

Formulation and usage of relevant and quality customer datasets are daunting due to data privacy concerns, infrastructural limitations and biasness. Hence, Gupta et al. (2024) described the importance of GAI in addressing this limitation, as it facilitates the creation of synthetic datasets by learning and capturing the essence of the training data. This not only helps enhance the amplitude of the information to be processed but also addresses several data compilation-related issues, e.g. biasness and generalizability. Its enhanced capability to contemplate complex trends from existing data allows it to generate more generalised synthetic datasets that address all the identified real-world complexities (Chamola et al., 2024).

5.1.2. Complexity reduction

Moreover, Cao et al. (2023) identified that unlike most traditional AI models, GAI has the capability to process unstructured data originating from multiple sources and in varying formats. This reduces effort in processing and structuring data. The concatenation of multiple data formats helps make more functional and comprehensive datasets from which to learn. These enhancements unleash a dynamic learning potential by continuously embedding incoming data with minimal need for data pre-processing. This capability provides a better understanding of the situational and behavioural factors that improve the contextual understanding of the interactions.

5.1.3. Enhanced contextual understanding

GAI utilises probabilistic reasoning (Taniguchi et al., 2022), which can be used to recognise hidden variables and dynamically predict behavioural and situational changes, allowing pre-emptive and timely adjustments to customer experience strategies. Consequently, more personalised and engaging experiences are generated.

5.2. GAI's role in experience design

Correia and Venciute (2024) elucidated that AI models can play a crucial role in this endeavour by analysing high-engagement touchpoints, identifying potential physical and emotional triggers and recognising common distractions that influence customer behaviour. These insights are then used to construct customer personas, which serve as a foundation for understanding customer needs and preferences.

5.2.1. Adaptive and dynamic scenario generation

GAI extends this capability with its advanced learning abilities, which allow it to analyse key patterns in both structured and unstructured data across various channels (Bojic et al., 2024). Through scenario-based analysis, GAI can simulate different hypothetical situations, enabling businesses to develop adaptive and dynamic personas tailored to diverse interaction contexts. Its capabilities go beyond predetermined pathways, instead tailoring each interaction to provide a relevant and intuitive user experience (Samoili et al., 2020). This adaptive approach allows deeper insights, design personalised and relevant responses and craft tailored layout designs that enhance customer experience across channels. Ultimately, GAI's capacity to dynamically adapt to customer needs offers an unprecedented opportunity to meet evolving expectations, thereby strengthening customer engagement. Such highly personalised engagements also foster collaborative relationships (Kang et al., 2016).

5.3. GAI's role in experience measurement

AI has enabled organisations to design and deliver automated and dynamic touchpoints that keep records of user interactions (Gao and Liu, 2023).

5.3.1. Multidimensional feedback collection

The coalescence of GAI's enhanced learning, perception and reasoning capabilities enables it to gather, integrate and process user feedback with engagement data based on multiple behavioural and emotional dimensions. This interpretation of explicit user actions not only infers underlying sentiments and motivations but also facilitates the simulation of various hypothetical scenarios (Jackson et al., 2024). These scenarios can be used for testing and verifying these responses, ensuring a comprehensive performance measurement leading to optimisation of the user experiences. Moreover, its ability to generate adaptable and context-specific prompts, as explained by Bansal et al. (2024), can enhance the acquisition of meaningful and relevant customer feedback.

5.3.2. Performance benchmarks

Further, it facilitates the calculation and benchmarking of performance indicators that are both relevant to customer requirements and contextually aligned to organisational objectives (Bandi et al., 2023). Such a performance evaluation can also lead to predicting future areas of concern.

6. AI-ASSISTED CEM AND PRODUCT DEVELOPMENT

AI technology-assisted dynamic CEM can play a critical role in enhancing product development by ensuring the alignment of products with customer needs and market trends.

6.1. Customer-centric innovation

Businesses are compelled to explore unique ways to improve their acceptance and enhance their sales by offering customer-centric offerings. This approach requires them to gain a deep understanding of customer preferences and expectations with regard to their offerings. The CEM journey involves a series of steps to analyse and understand customer behaviour (Datig, 2015). It allows the collection of pertinent information relating customers' physical and emotional responses towards the organisational offerings at various stages of the customer journey (Marquez et al., 2015). Multi-dimensional data analysis using GAI not only allows organisations to develop effective CEM strategies but also provides a foundation for understanding preferences with regard to certain features of the products. Studies such as Wang et al. (2023) proposed a social media mining approach to access relevant customer data for product planning and improvement. They argued that efficiently monitoring user experience can help organisations evaluate existing products and provide leads for innovative customer-centric product solutions.

6.2. Rapid prototyping and product improvements

Some organisations have begun involving customers as collaborators in areas such as product design and customer experience design. This collaborative approach to co-creating value by lending a more active role to customers in the value creation process is based on the demand point of view (Albinsson et al., 2016). Verma et al. (2013) further explained that the main idea of co-creation is to gain a competitive advantage by developing market-oriented offerings and boosting the chances of the acceptability of these offerings. Such a collaborative design and development process using intelligent platforms and real-time feedback loops can assist in developing market-oriented offerings and boosting the chances of the acceptability of these offerings. Jaakkola and Alexander (2013) explained the role of customer engagement in effective value co-creation. By integrating AI-driven CEM strategies, companies can offer customers a more engaging role to align their products with customer preferences. CEM can also be utilised by companies to evaluate their product designs using multiple touchpoints and real-time feedback mechanisms. Continuously monitoring customer interactions, behaviour and sentiments can help businesses identify potential design issues early in the development process (Gao and Liu, 2023) and accelerate the innovation cycle through data-driven design improvements before production.

6.3. Personalisation and customisation

The effectiveness of CEM is heavily reliant upon the analysis of acquired customer behaviour and preferences data, which can also play a vital role in identifying and offering customised products to customers. Quan et al. (2023) highlighted the opportunity presented by data-assisted product design to accurately elucidate customer requirements and evaluations relating to product management. They discussed how customer data can be better utilised by AI-driven engines to design personalised products. Furthermore, Mourtzis et al. (2018) proposed a model for gathering and managing customer feedback for product system design to sense market needs and offer targeted products and product services.

7. RISKS AND CHALLENGES

Despite its benefits, several challenges hinder the widespread adoption of GAI. The challenge of low employee competency and technical knowhow to run and incorporate GAI tools is a big concern. Non-technical users may struggle with utilising the benefits offered by GAI in this context, which is a strong rationale for requiring different training initiatives so that people are prepared to work and incorporate AI tools within their work domain (Felten, Raj and Seamans, 2023).

Its perception as a potential replacement for their roles develops a sense of job insecurity among the workforce (Bhargava et al., 2021). Such perceptions can lead to trust issues and resistance against change, which can only be mitigated by the continuous upskilling of employees who boast both their technological skills and confidence (Jain, 2021). One of the conclusions derived from the literature review is that leaders must engage in change by encouraging learning and providing reasons why GAI tools can help improve employees' work rather than replace it (Walt, Kroon and Fourie, 2015). In addition, the issue of algorithmic complexity remains a challenge. LLMs, including GAI such as GPT-4, function as 'black boxes', and it is challenging to explain how decisions are made to non-expert users. This lack of transparency can lead to mistrust (Chui et al., 2018). Although Zhang and Gosline (2023) explained that the data mimicking and generation capability of GAI can address data privacy and bias concerns, the associated concerns with AI systems are difficult to eliminate completely.

4. CONCLUSION AND LIMITATIONS OF WORK

Research suggests the importance of realizing the capabilities of modern disruptive technologies. However, the spectrum of their capabilities has yet to be comprehensively investigated in varying contexts. For that purpose, this work highlighted the potential transformative role and functional GAI enhancements within CEM for product management. It was also elaborated that GAI-enhanced CEM can provide support for effective product management.

However, given the multidimensional nature of CEM and product management, a more rigorous categorisation of its constituent elements could offer more nuanced insights into areas of critical importance. Furthermore, this work primarily focuses on evaluating the functional enhancements on offer and does not encompass the full scope of its applications in the context of CEM for product management. To address this gap, future research should undertake a detailed and systematic literature review to carry out an in-depth assessment. Such an approach would enable a holistic comprehension of how GAI can transform CEM practices for effective product management.

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