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Transforming Digital Marketing with Generative AI

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Abstract: The current marketing landscape faces challenges in content creation and innovation, relying heavily on manually created content and traditional channels like social media and search engines. While effective, these methods often lack the creativity and uniqueness needed to stand out in a competitive market. To address this, we introduce MARK-GEN, a conceptual framework that utilises generative artificial intelligence (AI) models to transform marketing content creation. MARK-GEN provides a comprehensive, structured approach for businesses to employ generative AI in producing marketing materials, representing a new method in digital marketing strategies. We present two case studies within the fashion industry, demonstrating how MARK-GEN can generate compelling marketing content using generative AI technologies. This proposition paper builds on our previous technical developments in virtual try-on models, including image-based, multi-pose, and image-to-video techniques, and is intended for a broad audience, particularly those in business management.

Keywords: generative AI; deep learning; e-commerce; digital marketing

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1. Introduction

Digital marketing refers to the use of digital channels, platforms, and technologies to promote and advertise products, services, or brands to a target audience [1]. It encompasses a wide range of online tactics and strategies aimed at reaching and engaging potential customers on the internet. The most common marketing methods are through social media [2–4], search engine optimisation (SEO) [5], and email marketing [6], where businesses have taken advantage to capitalise on their continuous growth and create opportunities for success.

Various aspects of digital marketing have been studied previously. These include strategies, business contributions, impact on customers, issues, and future directions [7–9]. Researchers have explored the effectiveness of different digital marketing strategies, such as social media marketing and SEO, in reaching and engaging target audiences. Additionally, studies have examined the role of digital marketing in enhancing business growth, improving brand visibility, and driving sales [10]. Moreover, digital marketing's impact on customer behaviour, including online purchasing patterns and brand loyalty, has been a subject of investigation [11]. Researchers have also addressed various challenges and issues, such as privacy concerns and fraudulent ads [12–14].

However, there is currently a gap in both research and applications of utilising new technologies to enhance digital marketing, particularly with the emerging generative AI technologies. By exploring and suggesting new ways in which technology can be incorporated into marketing strategies, businesses can take advantage of a wider range of tools and techniques to achieve their goals. This encourages the development of more effective and efficient marketing strategies. Unfortunately, some businesses find it challenging to implement new marketing strategies due to their complexity and the need for skilled resources [15] and the lack of a clear framework [16]. Furthermore, only a handful of articles suggest how generative AI can be used for marketing [17–19], but do not delve into the details.

We are committed to tackling the challenges mentioned above and focusing on how businesses can use generative AI models in a straightforward manner to achieve their marketing objectives without relying heavily on pre-trained tools or existing APIs. Specifically, we seek to answer the following question: What steps must businesses take to develop a generative AI model that can assist them in achieving their marketing goals? To address this question, we propose a new framework called MARK-GEN, a conceptual framework that leverages generative AI models as a new approach to digital marketing. It outlines steps that are easily understandable for businesses, making it simpler to implement in their own environment.

We present a conceptual framework together with two case studies. We hope the conceptual framework provides clear steps that businesses need to follow to create a generative AI model that is ready to perform its function, and the case studies demonstrate how specific businesses can follow the framework to create a desired generative AI model to achieve their marketing objectives.

This work builds on our previous technical developments in virtual try-on models, including image-based [20], multi-pose [21], image-to-video [22], and others as systematically reviewed in [23]. Details of this will be discussed in the following sections, particularly with the two case studies in Sections 4 and 5.

For the purpose of model transparency and results reproducibility, we have made the complete projects for both SVTON [20] and FashionFlow [22], the models used in the case studies, available on GitHub, including the descriptions of methods, source code, model checkpoints, installation instructions, datasets, and illustrations of generated examples. The repositories for the projects are as follows: https://github.com/1702609/SVTON; https://github.com/1702609/FashionFlow (accessed on 6 July 2024).

2. Background

In this section, we will discuss the various methods that businesses commonly use to achieve their marketing goals. We will focus on how businesses market themselves on online platforms through social media, search engines, and email. Additionally, we will try to understand the impact of these marketing approaches on the customers, identify the challenges that businesses face during the process, and explore the ways to overcome these challenges.

2.1. Personalisation in Digital Marketing

When consumers perceive an advertisement on an online platform as more personalised, it leads to a positive attitude toward the brand and a stronger intention to click the advertisement [24]. The perceived relevance of the personalised advertisement acts as a middleman, connecting the personalised experience to positive outcomes by influencing consumers' attitudes and intentions. Furthermore, the enjoyment of personalised ads is minimally affected by one's attitude toward online platforms [24]. This means people who dislike online platforms will not let that affect their interest in the personalised ads shown on the platform.

Individuals who hold a positive view of personalised advertisements on digital platforms perceive them as a convenient means of accessing valuable product information that meets their needs [25]. Moreover, these individuals tend to have a more favourable attitude towards sponsored ads displayed on their screens and demonstrate a higher willingness to engage with and make purchases through those specific advertisements. However, there are certain groups of online users who may not be receptive to digital marketing. For instance, according to [13], men who spend a lot of time online tend to have negative attitudes towards advertising on these platforms, while college-aged users are more likely to be influenced by marketing content than any other age group. However, there are ways to address this issue. Advertisers can capture their attention and positively impact their attitudes towards marketing by posting ads at strategic times and aligning with users' behaviour patterns [13].

Personalisation can be a successful or unsuccessful marketing approach depending on the circumstances, which is referred to as the "personalisation paradox". Optimal results are achieved when a moderate level of personalisation is employed to encourage customer engagement with advertisements. However, when personalisation becomes overly intrusive or compromises customers' privacy, it may evoke feelings of vulnerability. When consumers feel vulnerable, it diminishes its effectiveness and reduces advert click-through rates [12,13].

2.2. Recommender System

A recommender system is a tool that provides personalised recommendations to potential customers based on their interests and relevance [26]. This method involves personalisation since the aim is to display content that is tailored to each customer's preferences. There are three types of recommender systems: collaborative filtering, content-based, and knowledge-based [27].

Collaborative filtering recommends content based on the opinions of other people who share similar interests [28]. The system recommends items based on the purchase history of similar users, assigning weights to each item to prioritise recommendations. A content-based approach suggests content that is comparable to what a user has previously liked [29]. This method examines the attributes of the items (e.g., genre, cast) to identify patterns of preference, which are then recommended to the user. The knowledge-based approach provides content based on the knowledge of the user profile [30]. To utilise this approach, companies must ask customers about their interests and preferences to accurately recommend products or services.

2.3. Social Media Marketing

Businesses have taken advantage of social media for digital marketing, capitalising on its continuous growth and creating opportunities for success. Extensive research indicates that advertising through social media enables businesses to achieve their marketing goals and strategies by fostering better customer engagement and interactions [2,3]. Social media marketing has been proven to be just as effective as traditional advertising platforms such as TV and radio [4].

The impact of digital marketing on social media goes beyond personalisation alone. The effectiveness of digital marketing is influenced by factors such as informativeness and creativity. When digital marketing materials are informative and creative, consumers tend to view the advertisements positively. By providing high-quality information about a product's advantages, these advertisements assist consumers in making well-informed purchasing decisions. Additionally, the significance of advertising creativity is closely linked to the basic human desire for novelty, uniqueness, exceptional experiences, and imaginative content [31].

Social media's effectiveness in digital marketing can be attributed to three key attributes [32]. Firstly, network capability allows users, including businesses and consumers, to have control over the generation, organisation, and sharing of information within a large community. Secondly, image transferability refers to social media's ability to coordinate strategic advertising elements across different cultures, creating a consistent brand image. Finally, personal extensibility facilitated by social media overcomes distance barriers, enabling transportation or communication and fostering global interactions.

Including corporate brand names in social media marketing content can result in higher engagement, particularly in the form of likes, from business-to-business social media users compared to business-to-consumer users [33]. Business users seek to establish a connection with corporate brand names and showcase their identities and loyalty by expressing their approval through liking such posts. It is worth noting that obtaining a significant number of likes and comments for a social media marketing post is important, as it contributes to increased influence and sales [34].

Specific resources like social media marketing strategy, organisational culture, strategic leadership, organisational learning, social network, and innovation orientation are responsible for driving success in the realm of social media marketing [35]. When these resources are harmoniously combined, they can increase marketing success. It is crucial for CEOs and managers to control those aforementioned resources. They must have a comprehensive understanding of the business model, which they can effectively align and leverage the resources, maximising their impact on social media strategy and, ultimately, driving improved business performance.

Electronic word of mouth (E-WOM) stands out as a highly effective social media marketing method that capitalises on the power of user-generated content [36]. By encouraging customers to share their experiences, reviews, testimonials, photos, and videos related to the brand or product, businesses can foster a sense of authenticity and trust among their audience. The phenomenon of E-WOM finds new life on social media platforms as satisfied consumers become brand advocates, promoting the brand irrespective of their consumption level or loyalty. Leveraging E-WOM allows companies to tap into vast social media communities, where content spreads rapidly and reaches a wide audience [36].

Online influencer marketing (OIM) is a strategic collaboration between businesses and influential individuals who possess a substantial following on social media platforms [37]. The primary goal of OIM is to leverage the influence of these individuals to promote the products or services offered by the business to their engaged audience. OIM allows businesses to connect with a specific target audience, leveraging the influencers' credibility to strategically position their products or services in a way that resonates authentically with the audience. The creative and authentic content produced by influencers not only enhances the brand's image but also captivates the audience, leading to a higher level of customer trust and, ultimately, better effectiveness in reaching and retaining customers [37].

Recommender systems are utilised by social network platforms to provide users with personalised recommendations for friends, pages, groups, and content that align with their interests, connections, and online activity [38,39]. These systems are designed to analyse user data, such as likes, comments, and shares, to identify patterns and preferences. As a result, businesses can take advantage of this technology to ensure that their marketing content is directed towards users who are more likely to engage with it [40]. This approach can increase the visibility and reach of marketing efforts, resulting in improved brand awareness and customer engagement.

2.4. Search Engine Marketing

The other common digital marketing strategy is Search Engine Marketing (SEM). SEM refers to the overall strategy of marketing a website or business through search engines. As the majority of web users retrieve information using search engines [41], gaining good visibility on these platforms is crucial for businesses. SEM involves various tactics to improve a website's visibility in search engine results pages (SERPs) and attract more visitors [42]. SEM includes two main components, which are Search Engine Optimisation (SEO) and Pay-Per-Click (PPC). SEO is the process of optimising a website's content, structure, and technical aspects to make it appear in the highest organic (non-paid) rank in the search engine when the customer types in relevant keywords [43,44]. PPC is a form of online advertising where advertisers bid on specific keywords, and their ads appear on the top of the SERP when someone searches for those keywords [44–46].

It is reported that 60–86% of search engine users click on the link in the organic rank in the SERP when conducting online queries, whereas only 14–40% of search engine users click on the sponsored links in the non-organic rank [47]. It turns out that SEO can generate more traffic for the same keywords than PPC. The reason why some companies choose PPC is because it is cheaper to pay for ads than invest in SEO efforts; implementing SEO can be expensive, especially for a large number of keywords, while paid ads allow companies to control their spending more precisely. Each search engine (like Google, Yahoo, Bing) has its own rules and requirements for ranking websites. What works for one search engine may not work for another. SEO programs must adapt to these different rules, making them more complex and costly. SEO does not guarantee consistent high rankings on SERPs. Search engines often change their ranking algorithms, forcing SEO specialists to continually adjust their strategies, which can be unpredictable and costly.

Search engines can utilise a technique called retargeting, which engages users who have previously interacted with a company's website or app. Tools like Google AdWords utilise this technique to enable businesses to reconnect with previously interested customers through search engine and partner site advertisements [48]. An example of retargeting could be that a user visits an online store and views a specific product without making a purchase; they may later encounter adverts for that product while browsing other websites or social media platforms [49]. Companies achieve this through the use of cookies, which is a small text file that stores information about user preferences and browsing behaviour, allowing them to recognise users across different platforms and target them with relevant adverts [50].

SEM is a highly effective strategy for businesses that are mindful of their customers' privacy and aim to avoid any potential mistrust. This approach allows businesses to concentrate solely on enhancing their website's visibility on search engines while targeting particular keywords that customers enter in their search queries. However, one could argue that search engine websites still collect customer data [51], making the privacy advantage of SEM counterintuitive.

2.5. Email Marketing

Email marketing is a digital marketing strategy that involves sending targeted emails to a group of customers with the goal of building relationships, promoting products or services, and driving engagement and conversions. It has long been a cornerstone of the digital marketing toolbox due to its cost-effectiveness and ability to deliver personalised content to a segmented audience [6]. One of the key advantages of email marketing is its versatility; it can be used for various purposes, such as sending newsletters, product announcements, promotional offers, or transactional messages [52].

Including a customer's name in email content can offer significant benefits for businesses [6]. Personalised emails can make a lasting impression on the customer, even if the message does not explicitly promote a product. Rather, the content establishes a personal connection with the customer, which can be a powerful tool for businesses.

2.6. Concerns with Digital Marketing

Intrusiveness has a negative impact on both the perceived usefulness and attitude towards digital marketing. In other words, when users perceive adverts as intrusive, it affects how useful they find the ads and their overall attitude towards them [13,25].

Furthermore, privacy concerns affect both the perceived usefulness and ease of use of personalised adverts. While both privacy and intrusiveness concerns contribute to creating negative perceptions of personalised marketing, the effect of intrusiveness concerns is indirect, whereas privacy concerns have a direct impact on the intention to purchase products advertised on online platforms [25].

It is crucial for companies to openly collect data from online platforms rather than doing so covertly. Open data collection practices establish trust between companies and online users, consequently increasing the likelihood of users clicking on advertisements. Consequently, improving the growth and effectiveness of digital marketing would involve enhancing consumer trust and aligning it with their perceived information and data privacy [12].

It is reported that 72% of customers are willing to discontinue their association with a company if they suspect that their privacy is being compromised [53]. This underscores the criticality for companies to handle collected data in a transparent manner and provide clear explanations on how it benefits them to retain customer trust. The main problem associated with the existing framework is the significant risk of customer attrition due to privacy concerns. It is crucial for a business to consider how they can safeguard customer data for marketing purposes and maintain their trust. This can be achieved by developing a clear framework aimed at ensuring transparent data handling and customer trust preservation in businesses.

2.7. Generative AI

Up to this point, we have discussed the different approaches that businesses can utilise to market themselves in the online realm. In this section, we will investigate which methods are more commonly used and effective in the business community. There is a considerable amount of research that compares various digital marketing tools and discusses their effectiveness, such as [54,55].

Search engine marketing distinguishes itself from other marketing methods by its distinct reliance on search queries rather than customer information. Unlike conventional approaches, SEM is centred around understanding and catering to what customers are actively seeking online [56]. The primary objective for businesses engaging in SEM is to secure prominent rankings on search engine results pages, thereby enhancing visibility and attracting potential customers [56]. What sets this method apart is its inherent undisputed popularity with users where many of them begin surfing the internet using a search engine. It is uniquely positioned as one of the most prominent and effective digital marketing strategies [57].

Email marketing is a highly efficient and speedy tool for conducting marketing campaigns that can be tailored to the needs of individual customers. Research has shown that it is a preferred method of communication for many consumers due to its low intrusiveness, and it is often more cost-effective than other marketing methods [58]. Additionally, email marketing allows marketers to reach a wider audience with minimal effort, reducing time and distance barriers. It also provides a safer way to promote products and services, as it helps mitigate legal and brand risks [59]. By using email marketing, businesses can gain a competitive advantage and increase their customer engagement and sales.

Social media marketing is a personalised approach that businesses use to engage with their customers, much like email marketing [60,61]. It creates a platform for businesses and customers to meet and share interests, creating a sense of community and building customer loyalty. By leveraging social media data, businesses can target their marketing more effectively, ensuring that the right message reaches the right audience. Overall, social media marketing is an essential component of any modern marketing strategy.

Using the generative AI marketing approach differs greatly from the aforementioned methods. With AI-powered tools, businesses can generate marketing content in different formats, such as audio, images, and video, with remarkable speed and efficiency. One of the primary benefits of using AI models for marketing is that they reduce the amount of human effort required to create marketing material. Previously, creating marketing content was a time-consuming task that required specialised skills such as photo editing, video editing, and graphic design. But with AI models, businesses can streamline the process, reduce costs, and allocate resources more effectively.

AI-powered marketing tools can also help small businesses that do not have a large number of employees. These businesses can use AI models to create marketing content quickly and efficiently without having to hire additional staff or outsource the work, which can be expensive.

Since the development of generative AI technologies is still in its early stages, there is currently a research gap in business studies on how these newly emerged models can support businesses, particularly in digital marketing. While there have been studies reported, such as in [17,19,62], they largely focus on high-level organisational decision-making and provide generic examples, lacking specific studies on digital marketing.

In the next section, we introduce a conceptual framework on how generative AI models can be utilised for marketing purposes. We demonstrate how these models can quickly synthesise content and enhance marketing efforts. Our claims are supported by two case studies in the fashion industry, illustrating each step of the proposed framework and how it serves the purpose of digital marketing for businesses.

3. Proposed Framework

Figure 1 shows the iterative process with seven stages: defining the marketing aim, data collection, data processing, model design, model training, model evaluation, and deployment. MARK-GEN improves non-technical audiences' comprehension of how generative AI can be used for marketing.

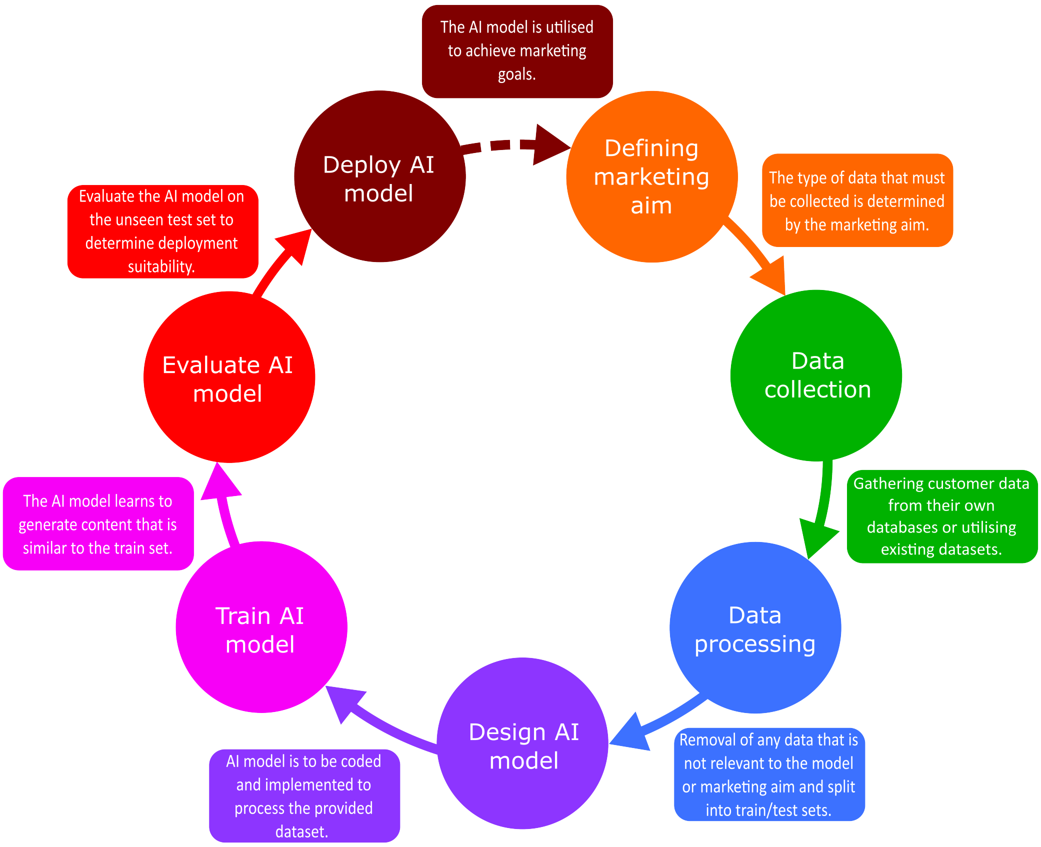


Figure 1. The conceptual framework of MARK-GEN for digital marketing with generative AI, with its iterative steps of defining marketing aim, data collection, data processing, model design, model training, model evaluation, and deployment.

3.1. *Defining Marketing Aim*

Establishing a clear marketing aim for the generative AI model is crucial for any business. This involves taking the time to consider what the business wants to promote and what it hopes to achieve with the help of the generative AI model. It is important to think about the message the business wants to convey through its marketing content and how it will benefit its customers. By doing this, the business can set expectations for what the generative AI model needs to produce in order to meet its marketing goals. This initial step is vital as it sets the tone for the subsequent processes in MARK-GEN and ensures that the rest of the actions are aligned with the overall objective. By carefully defining their goals at the campaign's outset, businesses can maximise their chances of success and achieve their desired outcomes.

3.2. Data Collection

The successful training of a generative AI model requires the gathering and collection of a significant amount of data [63]. It is crucial to expose the model to a diverse dataset that exhibits high variability to ensure optimal performance in real-world scenarios. The dataset needs to represent actual situations and scenarios; otherwise, it may result in the generative AI model performing poorly. Therefore, it is essential to collect data that accurately reflects the variability and complexity of the environment the model will operate in to ensure accurate and reliable results.

If businesses want AI to produce personalised marketing content, they must collect substantial customer data for the generative AI model to learn [64,65]. However, it is imperative to remember that gathering public data from customers should only be performed after obtaining prior consent to comply with legal regulations such as GDPR, the EU AI Act, and other international privacy laws to avoid ethical and confidential problems. Furthermore, businesses can maintain trust with customers by avoiding unethical practices and protecting personal data [53].

Alternatively, businesses can utilise publicly available datasets for the purpose of training their generative AI model if the authors of the dataset allow for commercial use. This method presents a significant advantage as it eliminates the need for laborious collection and organising big data, thereby expediting the process of moving onto the training phase. However, businesses may need to modify existing datasets (i.e., adding supplementary data) to achieve their marketing aim.

3.3. Data Processing

It is crucial for organisations to filter and process the data that is relevant to their marketing aim and ensure seamless integration with the generative AI model. For example, if a business gathers data from social media sites, it can present challenges due to its unstructured nature, which includes a combination of videos, text, and images [62]. Proper organisation of these data is essential to facilitate the training of a generative AI model.

For supervised learning, the dataset must include a reference for the ground truth. This involves having a collection of input data paired with their corresponding accurate output data that the generative AI model strives to generate based on the provided inputs.

It is necessary to divide the dataset into two portions: the train set and the test set. This division allows for training the model and then measuring its performance. Typically, a common split ratio is 7:3 or 8:2, which means allocating 70% or 80% of the data for training and the remaining 30% or 20% for testing the model's capabilities.

3.4. Designing Generative AI Models

There are various generative AI models [18,66] that can be developed to allow businesses to fulfil their marketing objectives. These include variational autoencoders (VAEs) [67] which learn a low-dimensional representation of input data by compressing them into a latent space and generating new samples from it. Generative adversarial networks (GANs) [68], which consist of two neural networks, a generator and a discriminator, compete against each other to produce increasingly realistic outputs.

The loss function of the GAN is formulated as:

$$\begin{aligned} L_{\text{GAN}}(x, z) = &\mathbb{E}_x[\log D(x)] \\ &+ \mathbb{E}_x[\log(1 - D(G(z)))] \end{aligned} \tag{1}$$

where G represents the generator; D represents the discriminator; x represents the ground truth; and z represents the noise input for the generator.

Transformers [69] and diffusion models [70] have become increasingly popular in recent years and are used interchangeably. Transformers have comparable performance with other state-of-the-art models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [71]. They use self-attention to estimate the relevance of each item in the input data to other items, with the most relevant part having the greatest impact on the output. Each of these models offers unique capabilities and advantages for generating data, images, text, or other content to support marketing efforts. Diffusion models work by iteratively refining a sample from noise to the desired output.

There are two steps for diffusion models to work—the forward and reverse processes. The forward process can be depicted as follows:

$$x_t = \sqrt{1-\beta_t} \cdot x_{t-1} + \sqrt{\beta_t} \cdot \epsilon_t, \epsilon_t \sim \mathcal{N}(0, I) \tag{2}$$

where at each time step t, the noisy data x_t are created by introducing noise to the data from the preceding time step x_{t-1}. The noise level at time step t is indicated by β_t. Gaussian noise, denoted as ϵ_t, is incorporated into the data at each time step. The reverse process is presented as follows:

$$x_{t-1} = \mu_\theta(x_t, t) + \sqrt{\beta_t} \cdot \epsilon_t, \epsilon_t \sim \mathcal{N}(0, I) \tag{3}$$

where the generative AI model $\mu_\theta(x_t, t)$ is used to predict the noise of x_t and subtract it to obtain x_{t-1}, which looks more plausible.

Coding the AI framework from scratch requires a thorough understanding of the underlying technologies and programming languages. However, it provides more flexibility and control over the development process. Developers can customise their models to suit the specific needs of the marketing aim. On the other hand, cloning repositories from popular platforms like GitHub [72] and Hugging Face [73] can save developers a lot of time and effort. They can simply download pre-existing codes and adjust them to fit their needs. Popular machine learning libraries like PyTorch [74], TensorFlow [75], and Caffe [76] are commonly used to develop generative AI models. These libraries provide a wide range of functionalities and tools to facilitate the development process.

3.5. Training Generative AI Models

In the realm of supervised learning for generative AI models, the goal is to guide the model in generating outputs that closely match the ground truth. During the training phase, the generative AI model generates outputs based on the input it receives from the train set. The train set also has the ground truth (i.e., desired output), where the generated samples are compared. This comparison serves as a measure of the model's performance. If the generated outputs closely resemble the correct outputs, it signifies that the model has effectively captured the essence and patterns of the intended data.

During training, the model's parameters are gradually refined to produce the best outcome. These parameters consist of numerical values (weights and biases) that dictate how the model generates its outputs. Through an optimisation process, these parameters are fine-tuned to ensure that the generated content becomes increasingly aligned with the desired outputs.

The optimisation process involves training the generative AI models in multiple epochs. An epoch refers to one complete pass through the entire train set during the training of a neural network or other iterative learning algorithms. During each epoch, the algorithm processes the entire dataset, typically divided into smaller batches, to update the model's parameters in order to minimise a predefined loss function. The goal of training is to iteratively adjust these parameters to improve the model's ability to make accurate predictions, classifications, or generation.

When training an AI model, hyperparameters need to be set to ensure that it performs well. Hyperparameters are different from the model's internal parameters, which are learned from the data to optimise its weight and bias. These hyperparameters include settings like the number of epochs (i.e., the number of times the model iterates through the dataset), number of hidden layers, optimisation algorithms, and learning rate. It is crucial to experiment and find the optimal hyperparameter value. Setting it too high or low can lead to overfitting and poor performance.

Training a model for a higher number of epochs can potentially enhance its learning and performance. However, if epochs are excessively increased, it may result in overfitting. Overfitting occurs when the model performs well on training data but fails to generalise on new data [77]. The hidden layers of a model are responsible for learning the underlying patterns in data, and adding more layers can lead to better performance. However, too many layers can also result in overfitting.

During the training process of a model, the choice of optimisation algorithm used is crucial to the model's performance. Popular optimisation algorithms, such as Adam [78] and SGD [79], work by adjusting the model's internal parameters to reduce the error between the predicted output and the actual output. The learning rate is another important hyperparameter that can impact the performance of these algorithms. It determines the extent to which the internal parameters of the neural network are modified during each iteration of the training process. If the learning rate is too high, the model may overshoot the optimal values, whereas if it is too low, the model may take longer to converge.

Different hyperparameters need to be set depending on the type of neural network a business is using. For a CNN, important hyperparameters to consider are the number and size of kernels, stride, padding, and pooling [80]. Kernels are used to extract features from the input data, and increasing the number and size of kernels can result in better performance. For an RNN, crucial hyperparameters include the number of recurrent units, the type of RNN cell (i.e., long short-term memory (LSTM [81]) or gated recurrent units (GRU [82])), sequence length, and dropout rate [83]. Recurrent units capture temporal dependencies in sequential data, and choosing an appropriate type and number of units is essential for effective modelling. Transformers require hyperparameters such as the number of attention heads and hidden dimension size [69].

3.6. Evaluating Generative AI Models

As mentioned in Section 3.3, the dataset is split into a train and test set to train and evaluate the model. The generative AI model's effectiveness can be evaluated by passing data from the test set. It serves as a benchmark to assess how well the model generalises to new, unseen data. The test set will allow businesses to measure the model's ability to make accurate predictions on previously unseen examples.

The test set is used to determine if the generative AI model depends too much on memorisation or overfitting of the training data. It is important for the model to learn meaningful patterns and representations that can be applied to new situations rather than simply memorising the data.

If the generative AI model achieves high accuracy and performs well on the test set, it indicates that the model has learned to generalise effectively and can be considered successful in its intended application. However, if the model performs poorly on the test set, it suggests that it might be overfitting or lacking the ability to handle unseen data, prompting further refinement or improvement of the model before deployment.

Before finalising the evaluation, businesses should consider whether the trained model meets their marketing goals and can effectively work with real-world data. Depending on their assessment, they may need to make minor adjustments to align the model with their marketing objectives and data collection.

3.7. Deploying Generative AI Models

A business can finally achieve its marketing aims by deploying its trained model. The generative AI model relies on real-world data input from the business in order to generate marketing content that allows them to achieve marketing objectives. By leveraging the capabilities of AI, the business can create marketing campaigns that are both efficient and effective, saving time and resources while simultaneously increasing the potential for success.

It is important to note the following:

1. The framework aims to provide guidance for the digital marketing process, and there is no strict order to follow the stages in the process. This allows the unique demands of each project to be adapted and, therefore, ensures that specific marketing objectives can be addressed in the most efficient manner possible.
2. The process is iterative, meaning that steps can be repeated as necessary to refine and enhance outcomes. This enables continuous improvement and optimisation, allowing for adjustments based on new data, insights, or changes in the market.
3. Furthermore, the framework is only conceptual, and the process can be rolled back to previous stages at any time, ensuring a high degree of adaptability and responsiveness in their digital marketing efforts.

After deploying the AI model, businesses can use various methods to quantitatively assess the effectiveness of their marketing approach. One approach is to compare data from before and after the deployment of generative AI. This comparison can help determine if the AI model increased sales and if the business has gained new customers while retaining existing ones.

Businesses can analyse different data sources to measure quantitative performance. These include sales data (e.g., total sales, sales growth, average transaction value), customer data (e.g., number of new customers, customer demographics), and engagement data (e.g., website traffic, click-through rates). Survey data, such as customer ratings, can also be valuable.

If the comparison indicates improvements, it suggests that using a generative AI model for marketing has a positive impact on customers' hedonic value. However, if the effects are negative, it could be due to issues such as poorly defined marketing objectives or the AI model generating unconvincing marketing material. In such cases, it may be necessary to revisit certain steps of the framework. For example, if the trained model does not produce satisfactory content, technical stakeholders may need to go back to the training or designing AI model stage. It is possible to go further back; for instance, if the dataset is not diverse enough for marketing purposes, stakeholders may need to go back to the data collection stage.

In order to protect customer privacy, it is essential for the business to delete any data uploaded by the customer and any generated content that refers to them at the appropriate time. For example, the right moment to delete customer data and generated content would be when the customer closes the webpage or when it exceeds an appropriate timeout limit. If a customer wishes to upload new data, old data should be deleted.

In the next two Sections 4 and 5, we present two case studies to demonstrate how the MARK-GEN framework can be utilised to achieve marketing objectives using generative AI models.

There are various AI models that create opportunities for fashion industries to market their products [23]. In the case studies we conducted, we explored how generative AI can be utilised to market fashion products. By harnessing the power of generative AI, fashion companies can create unique and customised content that resonates with their target audience. Our case studies highlight the potential benefits of using generative AI in the fashion industry, demonstrating how it can help businesses stay competitive in an ever-changing landscape.

Generative AI can be applied in the fashion industry in various ways, including image-based virtual try-on models [84,85]. These models can accurately synthesise an image of a person wearing desired clothing. Additionally, facial makeup transfer allows the model to transfer makeup from a reference image to a source image [86]. Another application is pose transfer, which changes the posture of a person to show different viewing angles of fashion products [87,88]. As research in generative AI continues, there is potential for even more ways in which these tools can benefit the fashion industry.

There are also non-generative AI models that can be useful for fashion businesses. For instance, there are models that can extract clothing items from random photos and find similar products sold in the store [89]. Attribute recognition is another helpful feature, automatically associating keywords with clothing items and making it easier for customers to find the fashion product they want using a search query [90]. Another useful example is the complementary recommendation, where the model recommends which fashion item matches with other products or scenes [91,92].

We selected fashion as the focus for our case studies because it presents a complex problem, and it would be interesting to demonstrate how MARK-GEN can be utilised to leverage generative AI to market clothing products. However, it is essential to note that MARK-GEN is not limited to the fashion industry and can be applied across various other sectors, including product recommendations in retail, property demonstration in real estate, personalised itineraries in travel, hotel promotions in hospitality, and driving experiences in the automobile industry, just to name a few.

4. Case Study 1: Virtual Try-On

The online fashion sector is undergoing an extraordinary surge, as many people are embracing online shopping like never before. During the COVID-19 pandemic especially, purchasing clothes online has become a widespread trend worldwide. This situation opens up possibilities for businesses to use images of their product to create personalised content using generative AI models. Fashion companies can now make a profound impact on customers by using a virtual try-on model that can fuse the images of the clothing and customers. Businesses can make this tool available on their website for customers to experiment with or use to produce tailored adverts so that customers can enjoy a personalised experience and swiftly assess how the garment would look on them. This tool will also mitigate hesitations and uncertainties associated with the inability to physically try on clothing prior to making a purchase [93]. Additional benefits include higher customer satisfaction rates, reduced returns resulting in a lower carbon footprint, and increased business sales.

In this case study, we demonstrate the development of a virtual try-on system for Clothing Ware, a fictional e-commerce platform that specialises in fashion retailing, using our previously developed generative model SVTON [20].

4.1. Marketing Aim

The company is dedicated to providing a unique shopping experience for its customers through the use of virtual try-on technology. This innovative technology enables customers to virtually try on different clothing items by merging their images with the clothing images. By doing so, customers are able to see how the clothes look on them before making a purchase, resulting in a more satisfying shopping experience.

The company plans to take this technology further by integrating it with customer data to generate personalised ads for third-party websites. This approach aims to resonate with customers on a personal level and increase their interest in the business. By analysing customer data, the company will be able to recommend clothing items that are more likely to appeal to individual customers, resulting in a higher success rate for the business.

4.2. Data Collection

In order for the virtual try-on model to function effectively, it must be trained on a dataset that includes pairs of people wearing clothing. This will enable the model to learn how to apply the image of the clothing to the person in a realistic way. The dataset should include a diverse range of individuals wearing different types of clothing, allowing the generative AI model to accurately learn how clothing is applied to the person's body.

The VITON dataset [85] consists of 16,253 images of professional women models. Each image shows the frontal view of the model from the head down to the hips and is paired with a standalone image of the clothing that they are currently wearing. The dataset has been divided into two subsets: a training set containing 14,221 image pairs, and a separate testing set containing 2032 pairs. Each pair within the dataset consists of an image of a woman and the corresponding clothing she is currently wearing. The images in the VITON dataset exhibit uniform dimensions, with a height of 256 pixels and a width of 192 pixels.

The authors of the VITON dataset have recently made it unavailable to the public due to copyright issues. However, there is an alternative dataset called the VITON-HD dataset [94], which has the same structure as the VITON dataset but with a higher resolution of 1024 pixels for height and 768 pixels for width.

Having a large dataset is beneficial as it allows the model to handle a wide range of clothing and postures. If more specific requirements are needed, such as focusing on lower-body clothing, a custom dataset can be developed following a similar structure as the VITON dataset.

4.3. Data Processing

Data processing plays a critical role in ensuring that the dataset remains appropriate. In this case study, our focus is solely on promoting upper clothing. Therefore, any items displaying lower-body attire should be excluded. This removal process is essential to harmonise the dataset with our marketing objectives in an efficient manner.

It is important to split the dataset into two separate sets—the train set and the test set. Fortunately, the VITON dataset is already divided. This separation is crucial because it allows the model to learn from the train set and then evaluate its performance on the unseen test set.

4.4. Model Design

The complete project of SVTON [20] can be found at its GitHub repository (https://github.com/1702609/SVTON, accessed on 6 May 2024), including the source code, model checkpoints, and illustration of generated examples. It uses the PyTorch library to perform virtual try-ons. Figure 2 shows how this model enables the creation of images featuring individuals adorned in preferred clothing items. These images can then be utilised as personalised marketing material.

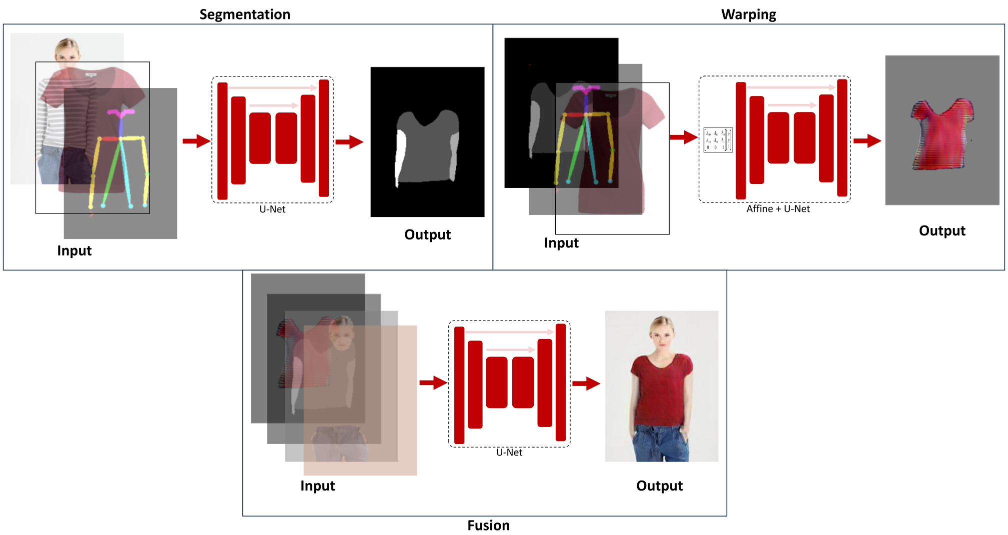


Figure 2. A high-level illustration of the SVTON model. The model comprises three modules: segmentation, warping, and fusion. The segmentation module creates body segments that match the target garment. The warping module uses an affine transform to initially warp the garment, and then an AI model carries out further refinement. Finally, the fusion module combines all the processed images and generates the virtual try-on image. More technical details of the model can be found in [20].

SVTON consists of three modules: a segmentation module to predict the appropriate body segment that complements the target garment, a warping module to geometrically manipulate the image of the target garment to fit within the person's torso, and a fusion module to fuse the warped garment with the person. All modules utilise an encoder–decoder generator, U-Net [95], to complete their tasks. The U-Net consists of three components: an encoder, a decoder, and skip connections. The encoder consists of several layers of downsampling convolutions, while the decoder has upsampling convolutions, and the skip connections allow information to flow better between the encoder and decoder layers. We recommend that interested readers refer to the SVTON paper for the full details of the implementation and hyperparameters of the model.

The warping and fusion modules have utilised a GAN [68] to synthesise high-quality images. This framework consists of two neural networks, the generator and the discriminator, engaged in a competitive learning process. The generator aims to create realistic data, such as images, from random noise or conditional data, while the discriminator's role is to distinguish between genuine data and the synthetic data generated by the generator. During training, these networks engage in a back-and-forth competition, improving the quality of the generated content.

The segmentation module uses a U-Net to predict and generate the segment of the torso and arms that complements the chosen garment. The predicted segment serves as a guide for the subsequent modules, informing how the garment should be positioned and how the arms should be generated.

The warping module manages the adjustment of the garment to properly fit the upper body of the person. First, the module performs a geometric transformation on the clothing image by rotation, resizing, and translation. Second, the U-Net generates natural wrinkles and other details to make a garment look more realistic as if someone is wearing it.

The fusion module merges the person's image with the warped clothing. In this step, binary masks are produced, which represent what part of the image needs to be preserved or generated. The U-Net model uses this information to blend the person's image with the adjusted garment and realistically generate the arm. This process ultimately yields a final try-on image. More details of the model can be found in our previous paper [20].

4.5. Model Training

The generative AI model will go through a training phase using the train set. The primary objective of this phase is to show the generative AI model of the methods of appropriately fitting individuals with specific garments. This process involves refining the model's parameters to grasp the intricate techniques of placing clothing images on people. The model gradually learns by observing numerous examples from the train set. As the model processes these examples, it discerns the underlying patterns that dictate the correct application of garments to achieve a visually appealing and realistic appearance.

The optimisation of the model's parameters is a crucial element of this training process. Parameters act as the fine-tuning knobs that influence how the model generates its output. Training each module for several epochs and using a sophisticated optimisation procedure, these parameters are adjusted to align the model's output with the expected outcomes. In this case, the optimisation process revolves around enabling the model to effectively interpret and replicate the behaviour of fitting clothing on individuals.

4.6. Evaluation

By utilising an unseen test set, the business can evaluate the generative AI model's performance in a context beyond its training data. This assessment serves the critical purpose of identifying if the model has become too fixated on the training data to the extent of overfitting, a phenomenon that could hinder its performance because it learned too closely about the training set.

In this case study, the generative AI model will encounter unseen combinations of clothing and individuals (i.e., data it has not been trained on). The test set will show the model's ability to generate convincing try-on images. The fidelity and precision of the generated try-on images are assessed by comparing them against the ground truth. Also, the business can subjectively evaluate the appearance of the try-on images and decide if they are fit to be shown to the customers.

This evaluative process equips businesses with actionable insights into the model's performance. Depending on the outcome, they can make informed decisions on whether adjustments or refinements are necessary to enhance the model's capabilities.

4.7. Deployment

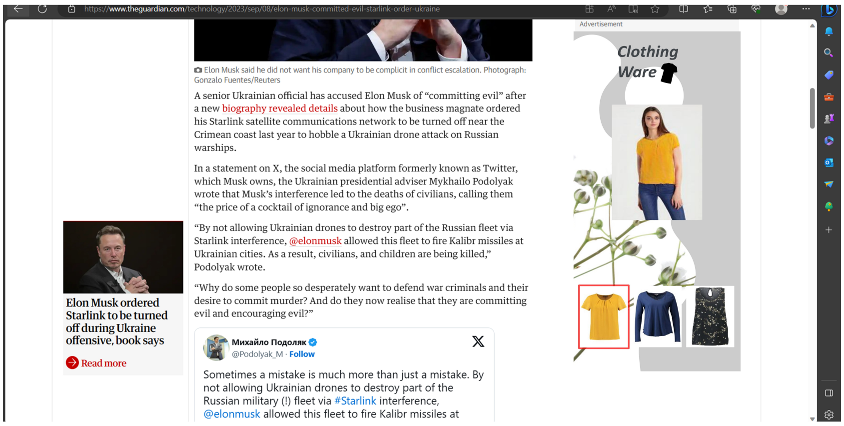
Upon the successful completion of both the training and testing phases, the model will be primed and ready to assist the business in reaching its marketing objectives. Specifically, the model will leverage customer data to synthesise personalised virtual try-on images, which will serve as eye-catching advertisement banners on both third-party websites. Also, the business seeks to integrate the model on its own website, where customers can experiment with compatible clothing products. Through this innovative approach, the business hopes to give customers the opportunity to experiment with various clothing products that align with their unique preferences, ultimately driving sales and enhancing overall customer satisfaction.

4.8. Summary

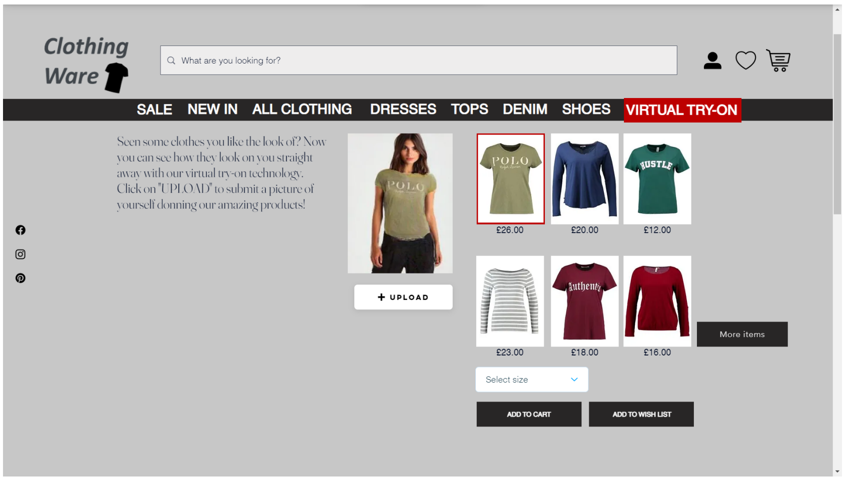
Figure 3 presents a compelling display of synthesised try-on images generated by SVTON, attesting to the remarkable quality achieved by the model. These images possess such high fidelity that they can readily serve as captivating marketing material when shared with customers.

Figure 3. Virtual try-on images synthesised by SVTON. The results show clothing products being accurately synthesised on the person while preserving clothing details.

Virtual try-on images can be leveraged by businesses as advertisement banners. Figure 4a shows how the try-on images are displayed on third-party websites as advertisement banners. This is possible by gathering relevant image data about their clients from social media platforms or through customer uploads. This method will provide the most personalised experience when customers view and interact with the advertisement banner because it directly involves them. Moreover, the advertisement banner enables customers to swiftly switch between clothing products by selecting the other two displayed at the bottom, thus increasing their engagement and promoting experimentation with more products.



(**a**)



(**b**)

Figure 4. Virtual try-on on two applications for a fashion online retailer. (**a**) An advertisement banner on a third-party website. The right side of the webpage shows a model or customer wearing a selected clothing product. (**b**) A website featuring virtual try-on technology. This allows customers to upload a photo of themselves and see how the clothing looks on them.

Virtual try-on can also be a tool on the business's website to allow customers to experiment with clothing products virtually, as shown in Figure 4b. This personalised and immersive experience holds the potential to impact customers' perceptions and engagement with the business. As a result, customers are more likely to feel confident in their purchasing decisions, leading to increased conversion rates and customer satisfaction.

5. Case Study 2: Image-to-Video Generation

Recently, there has been a notable upswing in the employment of generative AI models to generate impressive, lifelike images and videos of an array of subjects, including landscapes and people. This technology has been harnessed by popular mobile apps, such as "Lensa: AI photo editor, camera" [96], to empower users to produce highly engaging and widely shared content. The success of these mobile apps can be attributed, in no small part, to the incorporation of diffusion models [70], which have revolutionised the way in which machines synthesise images and videos. In this case study, we aim to demonstrate how diffusion models can be beneficial for the marketing domain in businesses and how they benefit both the customer and the business.

5.1. Marketing Aim

Assuming the marketing aim is to incorporate an image-to-video model to feature their clothing products on individuals, the primary objective is to offer customers a comprehensive view of the apparel in a seamless and uninterrupted way, which they believe will provide ample details to prospective customers. They aspire to condition the generated video using static images of professional human models. Essentially, the image-to-video model generates subsequent frames from the still image to create a smooth, consistent, realistic video. Clothing Ware believes using this generative AI model would increase efficiency in terms of time and cost compared to filming professional human models posing in their clothing products and increase hedonic value (i.e., pleasant experiences and pleasures) for customers.

5.2. Data Collection

In order to assist the image-to-video model in learning how to create videos from still images, it is necessary for the business to collect video data. The video dataset should feature a diverse range of individuals wearing different types of clothing to enable the generative AI model to accurately learn how to produce realistic and seamless movements in a video, regardless of the person's appearance or attire in the still image.

The Fashion dataset [97] features professional women models who pose at various angles to showcase their dresses. There is a vast range of clothing and textures available, offering a multitude of possible appearances. This dataset includes 500 videos for training and 100 for testing. Each video consists of approximately 350 frames. The video resolution is set to 512 pixels in height and 400 pixels in width.

5.3. Data Processing

Data processing plays a critical role in ensuring that the dataset remains appropriate and high-quality. In this case study, the business is solely on promoting upper clothing. Therefore, any items displaying lower-body attire should be excluded. This removal process is essential to harmonise the dataset with its marketing objectives in an efficient manner.

The dataset will be divided into two sets: the training set and the testing set. The Fashion dataset has already been separated accordingly. The train set will help optimise the model to synthesise videos with natural garment flow and relevant poses whilst retaining vital detail from the conditioning image. The test set will evaluate the model's performance in generating spontaneous videos.

5.4. Model Design

The complete project of our image-to-video model FashionFlow [22] is available from GitHub (https://github.com/1702609/FashionFlow, (accessed on 6 May 2024)). FashionFlow is a video diffusion model designed to generate short videos based on a single input image, as shown in Figure 5. Leveraging the power of diffusion models, it excels in producing accurate and visually captivating video sequences.

Diffusion models operate on a fundamental principle: they simulate the gradual, controlled diffusion of information or noise across an image or video frame [70]. The first step is to add Gaussian noise in consecutive steps, where the image gradually becomes unrecognisable. The second step is for the model to learn to perform a series of diffusion steps, during which it incrementally refines the image by reducing noise and enhancing details.

FashionFlow employs a denoising diffusion U-Net for progressively removing noise from a video until it appears natural and viable [98]. It also integrated an additional module that enables the conditioning of the video with a desired image. This module leverages an encoder to transform the desired image into a feature vector, which then uses a cross-attention mechanism [69] to influence the U-Net in several layers. In essence, this technique ensures that the generated video is consistently aligned with the conditioning image.

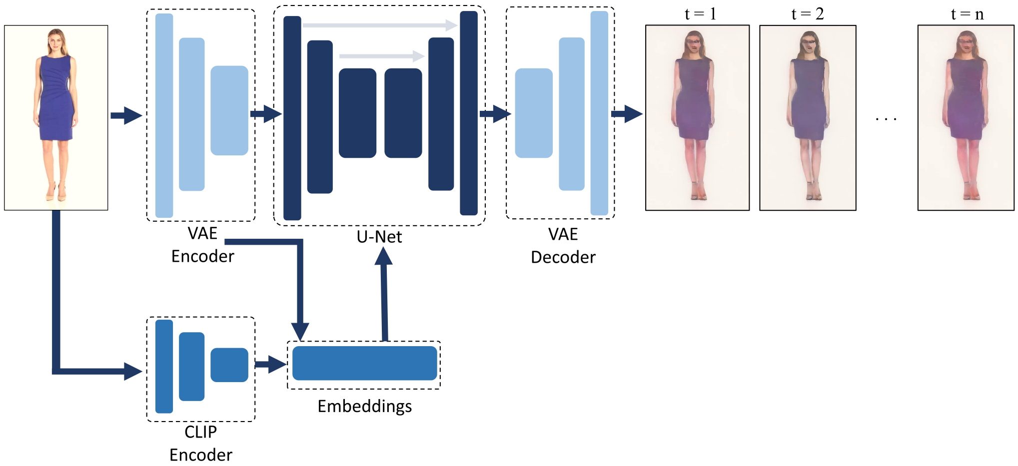


Figure 5. The process diagram of our FashionFlow model [22]. The model uses a latent diffusion model to denoise the latent space of a video. Each frame of the latent space is processed by a VAE decoder to generate the final video. The video is conditioned in two ways: locally and globally. Local conditioning involves adding a VAE-encoded image as the first frame of the noisy latent, while global conditioning involves using cross-attention layers to influence intermediate features with the conditioning image throughout the layers of the latent diffusion U-Net. Please refer to our original paper for more details.

5.5. Model Training

During the training phase, the generative AI model will use the train set to learn how to capture important details from still images and generate subsequent frames that result in smooth and believable movements. The model gradually learns by observing numerous examples from the train set. As the model makes progress, it understands the underlying patterns that dictate the smooth movements in a video and what important characteristics to capture from the still image.

The training process will fine-tune the model's parameters. Each parameter's value will influence how the model produces its output. By using an iterative and optimisation procedure, the values of each parameter are adjusted to align the model's output with the desired results. In this situation, the optimisation process focuses on helping the model capture information from still images and create a video with seamless movements.

5.6. Evaluation

In order to evaluate the true efficacy of a generative AI model, it is important to utilise an unseen test set. This enables businesses to detect any instances of overfitting, wherein the model simply memorises details from the training set rather than learning patterns, resulting in poor performance on the test set. By analysing the model's performance using unseen data, any potential issues can be identified and addressed.

In this scenario, the generative AI model is tasked with generating a video using an unfamiliar image. The efficacy of the model will be assessed by the test set, which will evaluate its ability to produce a compelling video while retaining the details of the still image. As the resulting video will contain random movements, the business needs to evaluate subjectively to determine whether they are satisfied with the outcome and believe the video will contribute to their marketing objectives. Depending on the business's evaluation of the model's output, they may opt to retrain the model or deploy it to real-world customers to serve their marketing aim.

5.7. Deployment

When the generative AI model has undergone rigorous training and evaluation phases, the business can use the model to synthesise video from still images to showcase their clothing products from multiple angles, thus assisting customers in making informed purchase decisions. This innovative approach not only enhances the visual appeal of the products but also aligns with the business's marketing goals. By offering dynamic and engaging content, the business can captivate its audience, drive higher user engagement, and ultimately boost sales and brand visibility in the highly competitive fashion industry.

5.8. Summary

The results of FashionFlow can be observed in Figure 6. The results show fluidity in the movements of the video while precisely capturing the colours from the corresponding image. While the reconstructed face could be further improved, we acknowledge that the capability of the diffusion model needs to be enhanced to achieve this goal.

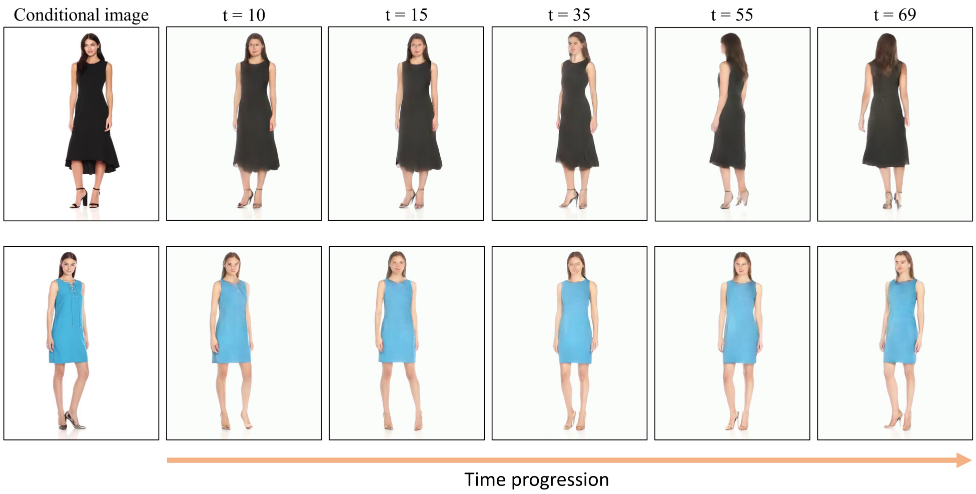


Figure 6. Video synthesised by FashionFlow. A conditional image was used as input for a generative AI model, which then animated the image into a video. The variable *t* represents the index of the video frame. We ordered *t* from left to right to showcase the consistent and smooth movements. The videos also show that the skin and clothing colours are accurately captured from the conditioning image.

The image-to-video model used by the business is shown in Figure 7. This model displays the clothing from different angles in a continuous manner, providing customers with a better idea of how it looks. Additionally, it is possible to generate a short video from a virtual try-on image (Section 4), which can offer even more personalised and informative information about the clothing product on a customer's body.

This powerful tool can enhance the hedonic value for customers. Improved hedonic value can lead to greater customer satisfaction [99]. Also, the implementation of such a model can serve as a strategic marketing tool, attracting new customers and retaining existing ones. The use of image-to-video models has the potential to revolutionise the way in which businesses present their content to consumers and should be considered a valuable addition to any marketing strategy.

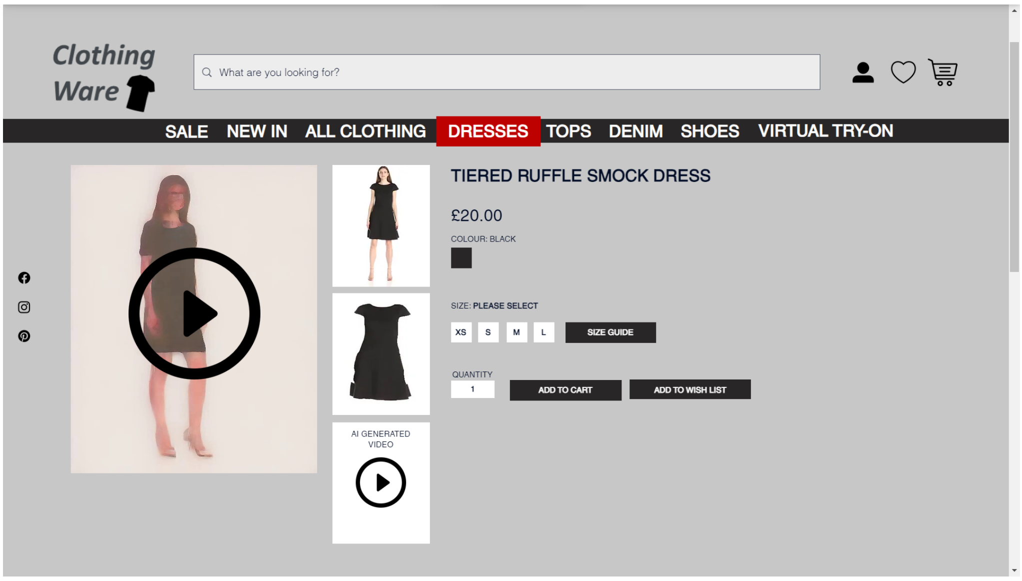


Figure 7. The website showcases the generated video. Customers would enjoy seeing models pose with the product from different angles, making it a cost and time-efficient option for businesses.

6. Discussions

While exploring the many advantages of using generative AI in marketing, it is important to also consider its drawbacks. One key issue is that the output from these models may not be the true resemblance of the users, leading to inaccurate or misleading results [100].

A significant drawback of MARK-GEN is its lengthy training process for deep learning algorithms, including many generative AI models. This extended training duration could lead to inefficiency when trying to align with marketing objectives that require adaptability to new scenarios. Deep learning models demand several weeks or even months to finalise their training before it is deployed [101]. MARK-GEN is not suitable for businesses that seek to constantly change their marketing aim and expect the generative AI model to quickly adapt to new situations.

Many generative AI models, including the ones in our case studies, rely on GPUs or other hardware AI accelerator chips for training and inference. This means that businesses need to invest in expensive hardware to make these AI models work. While renting servers with AI accelerator chips is a more affordable option, using generative AI for marketing always comes with a fee.

Gathering and processing extensive datasets for training and evaluating generative AI models poses significant difficulties and challenges. This phase alone can occupy as much as 80–90% of the time allocated for generative AI development [63]. To illustrate, the VITON dataset used in Section 4 contains a significant 16,253 pairs of images. Collecting voluminous amounts of data through web crawling presents challenging obstacles. The processing and refinement of data require additional time and resources, which makes it an unattractive option for some.

Another limitation of this work lies in the quantitative evaluation of objectives, including data collection quantities, customer hedonic value or impact, residuals of model fitting, and iteration management. It is important to note that this is a common issue for marketing research generally, not solely to digital marketing with generative AI. Given that the application of these emerging technologies in this field is still in its early stages, and the potential unique opportunities offered by generative AI to this quantitative issue remain unclear, we leave this as a subject for future research.

7. Conclusions

In this study, we introduced MARK-GEN, a conceptual framework that leverages generative AI models to create marketing content. We detailed the essential stages for successfully implementing this framework and explained how businesses can benefit substantially from its utilisation. This approach offers a novel method that diverges significantly from traditional marketing techniques, providing new opportunities for businesses to enhance their marketing campaigns.

Through two case studies in the fashion industry, we demonstrated how businesses can follow the MARK-GEN framework to produce effective marketing content. Specifically, we showcased how image-based virtual try-on and image-to-video models can enhance marketing strategies in the fashion sector.

We chose to use fashion applications for our case studies because they heavily rely on images, presenting a challenging problem. However, it is important to note that MARK-GEN is not limited to the fashion industry, and its implications go beyond that. Various businesses can benefit from generative AI to create marketing materials, such as posters and chatbots in retail, property demonstrations in real estate, personalised itineraries in travel, hotel promotions in hospitality, and virtual experiences in entertainment, to promote their products or services.

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