Leveraging Machine Learning Models to Generate Product Descriptions in e-Commerce

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ABSTRACT

This study addressed the challenge of incomplete or inadequate product descriptions in e-Commerce by integrating Large Language Models (LLMs) and image-to-text technology. Collaborating with a national retailer, we proposed a new solution to improve the online shopping experience. Our methodology involved evaluating and enhancing product descriptions across various scenarios by utilizing computer vision and LLMs to iteratively generate and refine content, covering 111 thousand unique products. Additionally, we introduced a new scoring model to assess description quality, considering relevance, completeness, readability, and confidence score. As a result, our solution can improve 73% of products with unqualified descriptions or with only images. Our study offered a strategy for retailers to optimize product listings, ultimately enhancing competitiveness and customer engagement in e-Commerce.

Keywords: Product Description Generation, Image-to-Text, Optical Character Recognition, Image Captioning, Large Language Models

INTRODUCTION

In the realm of e-Commerce, the customer experience hinges significantly on the quality of product listings. These listings serve as virtual storefronts, providing customers with vital information about products they cannot physically interact with. In recent years, media outlets have highlighted the growing importance of product information quality in e-Commerce and its impact on customer satisfaction and sales. For example, Medium published a report[1] in 2023 emphasizing the lack of accurate product information can have a significant negative impact on engagement, sales, and customer satisfaction. Similarly, a WordPress developer posted an article[2] on Linkedin(2023) pointing out some benefits of accurate product information on e-Commerce, such as building customer loyalty, reducing product return rates and disputes, and differentiating from competitors. Product descriptions, in particular, play a crucial role in this regard, as they help customers understand and visualize the product, decide whether it's the target product, and ultimately influence their purchasing decisions.

However, retailers face several challenges in generating sufficient and effective product descriptions. First, human labor is generally competent for the description generation job but it would be a huge expenditure for big e-Commerce companies who list millions of products on their websites. How to satisfy this business requirement and also mitigate the cost is a key. Second, maintaining consistency and coherence across a vast array of product descriptions poses a significant challenge. With numerous products offering different features, specifications, and target demographics, ensuring that all product descriptions align with the brand voice, style guidelines, and marketing objectives can be daunting. Inconsistencies in tone, language, or messaging across product descriptions can confuse customers and undermine the brand's credibility and trustworthiness. Therefore, establishing and adhering to a consistent framework for product description creation becomes imperative but can be logistically challenging, especially for large e-Commerce platforms with diverse product offerings.

This study embarked on a collaboration with a national retailer in the United States, which grapples with incomplete product descriptions provided by its vendors. Shockingly, 33% of the retailer's stock-keeping units (SKUs) are absent from its websites due to incomplete descriptions, resulting in significant missed sales opportunities.

Inspired by the CNBC journal "On Amazon, eBay, and Shopify, AI is the new third-party seller"[3], in which eBay is working on tools to auto-generate item descriptions, our team decided to utilize the latest AI technology to solve the business problem stated above. This study proposes a solution (Fig1: Solution Framework)that leverages Large Language Models (LLMs) and image-to-text technology to create and enhance product descriptions. Additionally, a scoring model is developed to evaluate the generated content's quality. To streamline and automate this process, a cloud pipeline was architected on the Microsoft Azure platform to deploy the models effectively. The overarching goal is to ensure that each product is accompanied by a high-quality description, thereby facilitating better customer understanding and fostering a more satisfying shopping experience.

The research questions guiding this study are:

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[1] How the Lack of Product Information in E-commerce Affects Sales, Engagement and Customer Satisfaction | by Wireshape | Medium
[2] (4) The Significance of Accurate Product Details and Descriptions on E-commerce Websites | LinkedIn
[3] On Amazon, eBay, and Shopify, AI is the new third-party seller (cnbc.com)

How can Large Language Models and image-to-text technology be utilized to create and enhance product descriptions effectively?
What criteria can be used to evaluate the quality of generated product descriptions?
How can the proposed solution facilitate large-scale deployment for e-Commerce companies while effectively managing costs?
Answering these questions is vital as it not only addresses the immediate business problem faced by the retailer but also contributes to the broader understanding of how technology can be leveraged to enhance the e-Commerce customer experience.

The remainder of this paper is organized as follows: A review of relevant literature on e-Commerce product information quality and technology utilization is presented in the next section. Following that, the methodology section outlines the approach taken to address the research questions. Subsequently, the paper delves into the performance comparison and selection of appropriate models, as well as the development of rubrics to evaluate auto-generated product descriptions. Finally, the results and their impact on business metrics are discussed in the concluding section, along with avenues for future research.

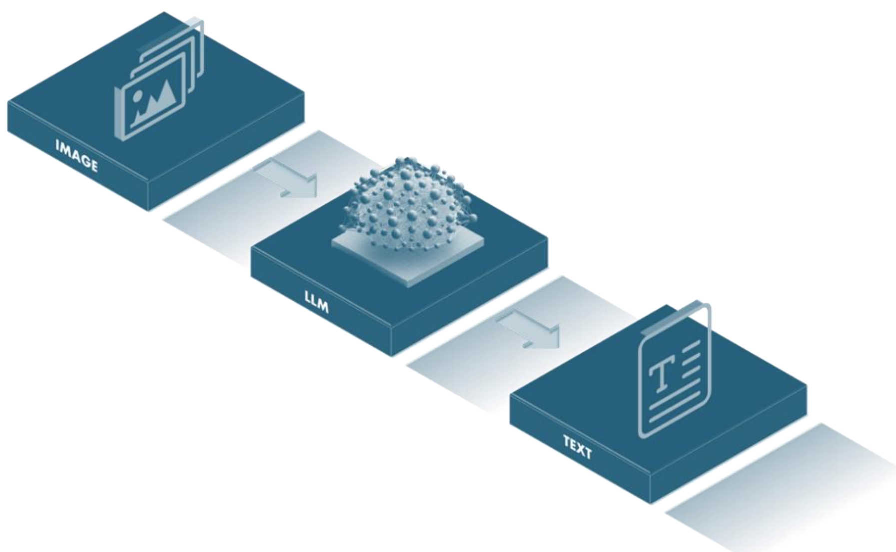

Figure 1: Solution Framework

LITERATURE REVIEW

This study proposes leveraging advanced AI technology like Large Language Models (LLMs) and image-to-text capabilities to address incomplete product descriptions faced by retailers. Besides, this study also developed a scoring model to evaluate content quality, contributing to assessing the effectiveness of AI-driven content generation methods. The past researches on relevant fields are discussed below.

Leveraging machine learning models for enhanced product descriptions has been an emerging research topic. For example, Abraham et al. (2023) proposed a solution combining Azure Computer Vision and ChatGPT to generate product descriptions based on the images and text data of products. It also designed a scoring model to access machine-generated content and achieved a promising performance on content quality. Part of previous works focused on generating descriptions based on provided product information, such as product names, features, and specifications. Large language models (LLMs) have played an important role in this field. For example, Nguyen et al. (2021) used the GPT-2 model and text paraphrasing to improve the quality of e-Commerce product descriptions. In another study, a LLaMA 2.0 7B language model was fine-tuned with a dataset of authentic products from Walmart, one of the largest e-Commerce platforms, and it effectively automates product description generation, reducing human workload and improving search functionality and sales (Zhou et al., 2023).

In addition to using text data as inputs, the field of extracting product information from product images has been researched. There are two main types of models for this task: optical character recognition (OCR) and image captioning model. OCR systems work on converting images of machine-printed or handwritten numerals, letters, and symbols into a computer-processable format. Deep learning models, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have been commonly used in OCR systems for character recognition (Chaudhuri et al., 2016). Li et al. (2023) proposed TrOCR. This end-to-end text recognition approach utilizes pre-trained image and text transformer models, achieving state-of-the-art results on printed, handwritten, and scene text recognition tasks.

Image captioning is the process of generating automatic textual descriptions for images using natural language processing (NLP) and computer vision. Arora et al. (2023) proposed a combined model of CNN and Long short-term memory (LSTM), which achieved notable performance on metrics like Bilingual Evaluation Understudy (BLEU). Li et al. (2023) introduced Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models (BLIP-2), a novel model that leverages frozen pre-trained image encoders, large language models (LLMs), and transformer encoder, achieving state-of-the-art performance on various vision-language tasks.

As content generation studies increase, the challenges surrounding evaluation methods for the produced content have become vital. Fukumoto et al. (2021) proposed evaluation axes for generated product descriptions, including linguistic correctness, relevance, trust, attractiveness, and politeness. This framework aimed to evaluate the quality and persuasiveness of generated content. Fukumoto et al. (2022) tailored evaluation methods focusing on motivating consumer purchases through automatically generated product descriptions. Drawing from prior research, the authors refined 17 evaluation items and categorized them into three axes: grammar, content, and attributes.

In conclusion, neural network models have been widely employed in text-to-text and image-to-text tasks and achieved satisfying performance. Accordingly, some evaluation methods for generated content have also been developed. Based on previous research, this study focused on contributing to the following three research fields. First, it applied and compared different machine learning models using the dataset from a major retailer in the United States. It demonstrates which model is capable of delivering promising results and the potentials of model applications. Second, it designed a solution with state-of-the-art models to help the retailer improve product listing information. The new solution delivered significant business benefits by generating high-quality product descriptions to enhance product discoverability and drive sales. Third, it proposed a new method for evaluating the generated product descriptions, and the method was tailored to meet the retailer's needs. This evaluation method considers crucial factors like readability, content relevance, and completeness. It can be utilized in assessing the quality and effectiveness of generated content for various applications.

Table 1: Literature summary

Study	**Contribution**
Abraham et al. (2023)	Proposed a solution combining Azure Computer Vision and ChatGPT to generate product descriptions from images and text data, with a scoring model to assess content quality.
Nguyen et al. (2021)	Used GPT-2 and text paraphrasing to improve e-commerce product descriptions.
Zhou et al. (2023)	Fine-tuned LLaMA 2.0 7B language model on Walmart product data to automate product description generation.
Chaudhuri et al. (2016)	Reviewed deep learning models like RNNs and CNNs for optical character recognition (OCR) in product images.
Li et al. (2023)	Proposed an end-to-end text recognition approach using pre-trained image and text transformer models.
Arora et al. (2023)	Proposed a CNN and LSTM combined model for image captioning, achieving good performance on metrics like BLEU.
Li et al. (2023)	Introduced a novel model leveraging frozen pre-trained image encoders, LLMs, and transformer encoder for vision-language tasks.
Fukumoto et al. (2021)	Proposed evaluation axes for generated product descriptions, including linguistic correctness, relevance, trust, attractiveness, and politeness.
Fukumoto et al. (2022)	Tailored evaluation methods focused on motivating consumer purchases through automatically generated product descriptions.

DATA

The dataset used in this study is from a major grocery store in the United States. It comprises a collection of 309,826 unique products spanning diverse categories such as apparel, food, and electronics. Each product within this dataset is associated with attributes including product names for internal use, alongside information required for listing on the retailer's website, encompassing product names, descriptions, features, and images.

Table 2: Dataset used in this study

Variable	Type	Description
ItemSku	Nominal	Stock Keeping Unit, a unique identifier for a product/item
Product Name	Nominal	Name of the product for internal purpose
Marketing Name	Nominal	Name of product for listing
Marketing Details	Nominal	Description of the product for listing
Marketing Feature	Nominal	Features of the product for listing
ItemDocumentNote	Nominal	View of the product image taken (i.e. front/back/left/right/top/bottom/tilt right/tilt left)
ItemDocumentValue	Nominal	URL to the product image

In the dataset, not every product has complete information in the fields such as Marketing Name, Marketing Details, Marketing Features, and ItemDocumentValue (which contains image URLs). A breakdown of the data reveals the following:

- There are 107,079(35%) products that have both images and descriptions.
- A total of 3,682(1%) products are equipped with images but do not have descriptions.
- Conversely, 51,961(17%) products have descriptions but are missing images.
- Additionally, there are 147,104(47%) products that lack both images and descriptions.

METHODOLOGY

The methodology employed in this study aims to enhance the representation of products available for sale on a retailer's online platform. Our approach encompasses four distinct analytical paths tailored to address various scenarios:

1. **Products with Both Images and Descriptions**: We initiated this process by employing a scoring model to assess the quality of existing descriptions. If deemed satisfactory, the description remains unchanged and is published on the retailer's website. However, if the evaluation indicates poor quality, we utilize the Image-to-Text model and generate the content relevant to the product image using the Optical Character Recognition (OCR) and image captioning capacities of the Azure AI vision. Subsequently, this content is refined using the Large Language Models (LLMs) to generate well-crafted product descriptions. This iterative process continues until a description attains a satisfactory score from the scoring model.
2. **Products with Images but without Descriptions:** Similar to the previous scenario, we employ Image-to-text models to extract information from images. Subsequently, LLMs are utilized to generate descriptions. In cases where satisfactory descriptions cannot be achieved through LLMs alone after a specific iteration, vendors are engaged to manually enhance the descriptions.
3. **Products without Images but with Descriptions:** Products without images are not qualified for being listed on the retailer's website and, hence, are reverted to the vendors.
4. **Products without Both Images and Descriptions**: Similar to the above scenario, products without both images and descriptions cannot be listed on the retailer's website. Vendors are requested to improve the product information.

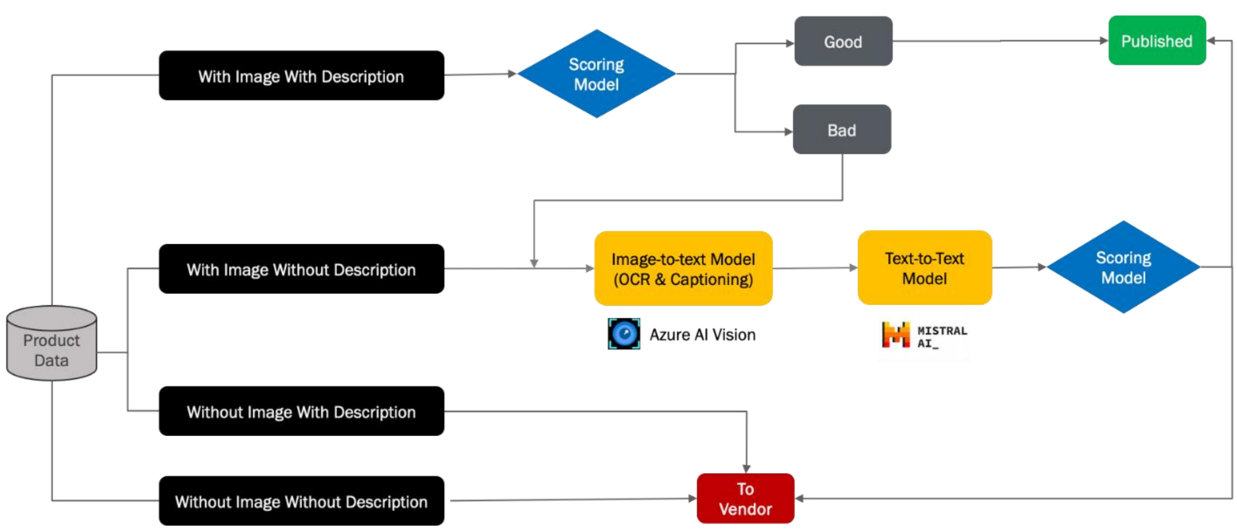

Figure 2: Analytics Workflow

Cloud Deployment:

We also migrated the entire analytical pipeline to Azure Cloud infrastructure, leveraging the following Azure Cloud Services.

1. **Azure Blob Storage Service**: All the product input data to the model are stored in Azure Blob Storage. Additionally, essential Python libraries like Azure Vision and OpenAI, which were not available with the default environment in ML studio, are imported into Blob Storage. Later, upon successful execution, the output (generated product descriptions) is also stored in Azure blob storage in the CSV format for further product listing needs.

2. **Azure Machine Learning Workspace**: We utilized the pipeline 'designer' feature in Azure ML Studio to architect an end-to-end solution to generate appropriate product descriptions for the respective SKUs. This solution seamlessly integrates input and output data from Azure Blob Storage.

3. **Azure Compute Instance**: A managed compute instance (Standard_F2s_v2) has been deployed within the ML Studio to execute the designed solution.

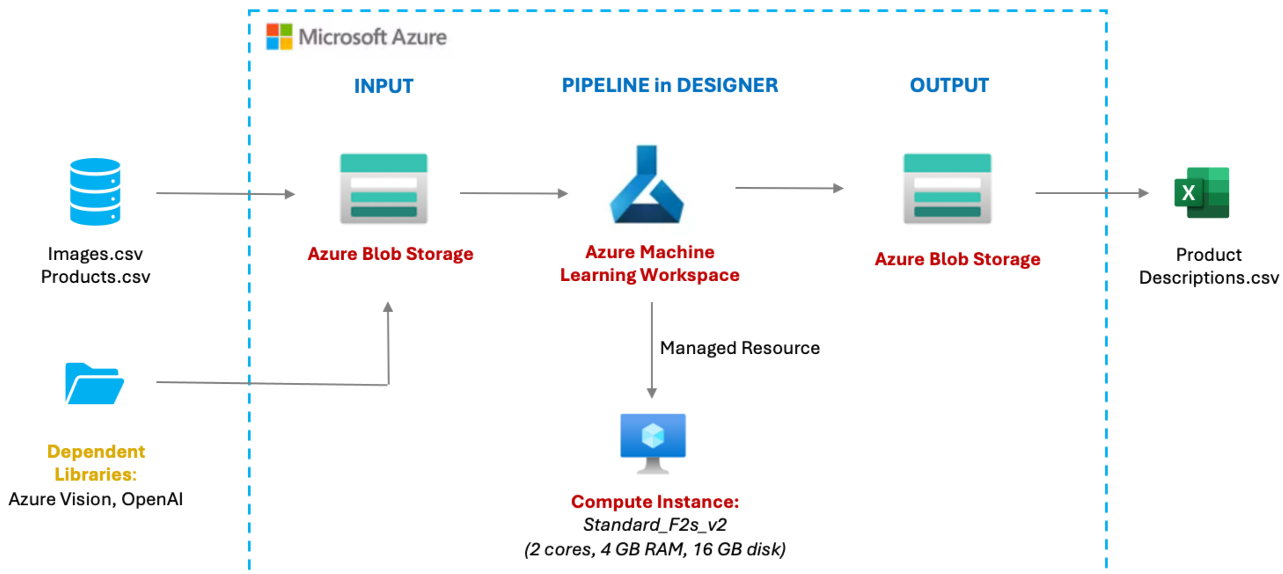

Figure 3: Cloud Deployment Architecture

MODEL(s)

This section introduces three major models we applied in this study, including the image-to-text model, text-to-text model, and the scoring model. Each model facilitates available state-of-the-art machine learning models, aiming to achieve the final goal of generating high-quality product descriptions.

Image-to-text Models:

Two types of models will be utilized for the image-to-text job - Optical Character Recognition (OCR) and Image Captioning.

1. **OCR:** This model extracts numerals, letters, and symbols from images, making it invaluable for interpreting product labels and other text captured in product images from various angles. In our project, images are input into a sophisticated OCR model, which processes these images to retrieve textual information.

Figure 4: OCR Model Example

2. **Image Captioning:** This model generates descriptive captions for images. In our application, product images are fed into an image captioning model, which then produces textual descriptions. These image descriptions are crucial for providing contextual information.

   In this research, we extracted 10 samples from each of the 8 types of product data and used these 80 samples to compare the performance of four trending open-source models. These open-source models include Salesforce BLIP & BLIP2-OPT, Microsoft Git-large-coco, and Unum Cloud uform-gen.

Figure 5: Image Captioning Model Example

In the end, we decided to deploy Azure AI Vision for the image-to-text job, even though it is not a free product. This decision was based on its ability to efficiently handle both OCR and Image Captioning simultaneously. Additionally, our trials demonstrated that it offers the highest accuracy and exhibits excellent compatibility with our subsequent cloud deployment strategies.

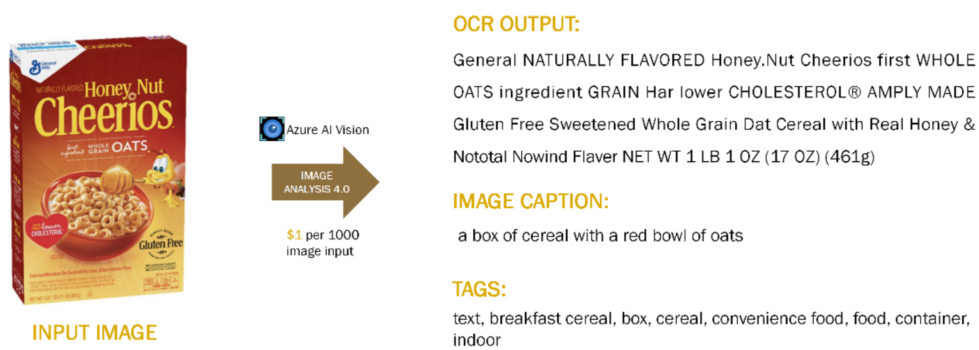

Figure 6: Azure AI Vision Example

Text-to-text Models (LLMs):

The text-to-text Models generate product descriptions by feeding available product information (Figure 7). This study compared four mainstream LLMs, including ChatGPT, Mixtral, Gemma, and LLaMA. Figure 8 shows the generated descriptions for a Yankee Candle from each LLM based on the inputs of vendor-provided product information and the text extracted from images through OCR and image-captioning. We conducted a small-size experiment where we chose 80 products across different product categories, and we found that “Mixtral 8X7b instruct” and “GPT-3.5 turbo instruct” have better performance based on human judgment. We also employed the scoring model introduced in the next section to evaluate the generated content. It turned out that Mixtral 8X7b instruct outperformed GPT-3.5 turbo instruct with a better pass rate. Therefore, we decided to use the LLM model Mixtral 8X7b instruct for the text-to-text task.

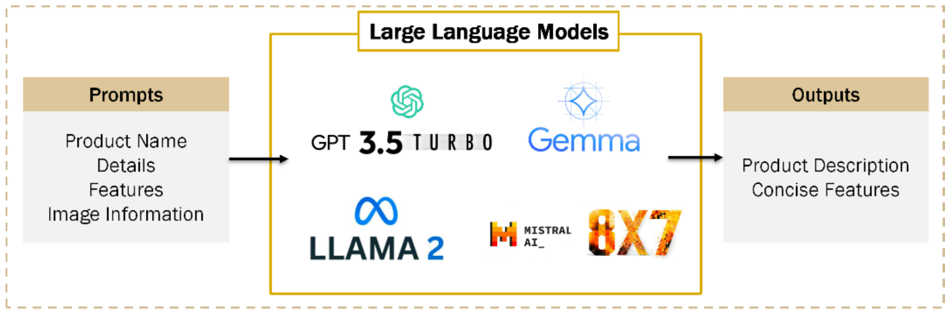

Figure 7: Generating Descriptions Using LLMs

Yankee Candle
Vanilla Cupcake

Model	Generated Product Description
Mixtral-8x7b instruct	Experience the delightful aroma of freshly baked vanilla cupcakes with Yankee Candle Signature Collection Small Tumbler Vanilla Cupcake. This 4.3 Oz. candle features an irresistible fragrance with top notes of vanilla icing and malted sugar, middle notes of cake batter and chocolate, and base notes of cocoa and vanilla bean. The combination of these scents creates a warm, inviting scent that is perfect for any room in your home...
Gemma-7b-it	Indulge in the irresistible aroma of freshly baked vanilla cupcakes, layered with layers of buttery icing. This fragrance is reminiscent of the sweet and decadent treats enjoyed on special occasions. Top notes of vanilla icing and malted sugar create a sweet and creamy first impression. The middle notes of cake batter and chocolate bring the sweetness to the forefront, while the base notes of cocoa and vanilla bean add depth and lingered sweetness...
Llama-2-70b-chat	Are you ready to indulge your senses in the sweetest way possible? Look no further than our Yankee Candle Signature Collection Small Tumbler Vanilla Cupcake! This delightful candle combines the rich, creamy aroma of vanilla cupcakes with hints of lemon and buttery icing, creating a mouthwatering scent that's sure to satisfy your sweet tooth...
GPT-3.5 turbo instruct	Introducing the perfect blend of sweetness and indulgence with the Yankee Candle Signature Collection Small Tumbler Vanilla Cupcake. This 4.3 oz candle has a decadent fragrance that will fill your home with the irresistible scent of vanilla cupcakes, enriched with hints of lemon and luscious buttery icing. The fragrance notes are carefully crafted to capture the essence of this classic treat, with notes of vanilla icing, malted sugar, and cake batter at the top, followed by chocolate and cocoa in the middle, and finished off with a touch of vanilla bean...

Figure 8: Comparison of Generated Text from Different LLMs

Scoring Model:

To score the existing and machine-generated product descriptions, we have developed a scoring model that evaluates the content quality. It follows a rubric encompassing fundamental aspects of a quality product description. Here is a detailed breakdown of the workings of the scoring model:

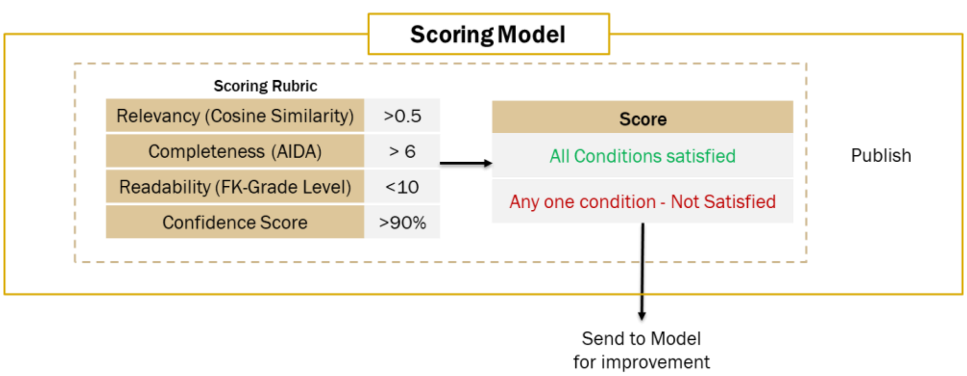

Figure 9: Scoring Model Framework

1. **Relevancy:** Relevancy is measured using cosine similarity, which calculates the angle between the input (product features) and the output (generated description) vectors. Scores above 0.5 indicate

that the description accurately reflects the product's features, ensuring the content is relevant and matches the intended product details.

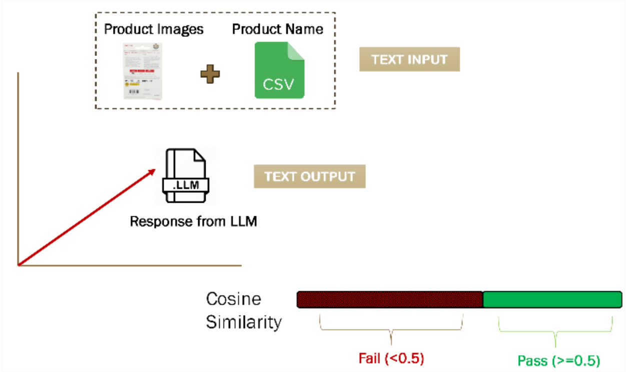

Figure 10: Cosine Similarity

2. **Completeness:** Completeness is evaluated through the AIDA framework (Attention, Interest, Desire, Action), assessing whether the description effectively engages customers at each stage of the buying process. High scores in all four areas indicate a powerful, compelling product narrative that drives customer engagement and conversions.

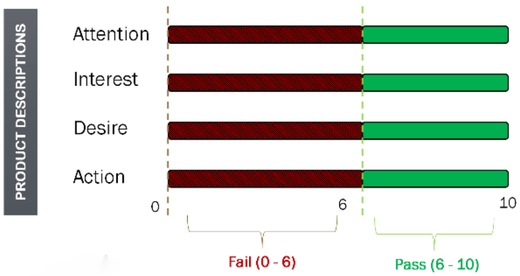

Figure 11: AIDA framework

3. **Readability**: Readability is gauged using the Flesch-Kincaid Grade Level, which determines the ease of text comprehension based on word and sentence length. Descriptions must achieve a score of 10 or lower, signifying they are easily understandable by an average 15-year-old student, making the content accessible to a broad audience.

$$\text{Readability} = 0.39 * (\text{words/sentences}) + 11.8 * (\text{syllables/words}) - 15.59$$

4. **Confidence Scores:** Confidence scores assess the reliability of the generated descriptions based on the language model's evaluations. Scores greater than 90% are required, reflecting high certainty in the accuracy and appropriateness of the descriptions, ensuring they meet quality standards and align with brand expectations.

Scoring Evaluation and Improvement Loop:

Descriptions are published only when they meet all the set benchmarks including relevancy above 0.5, completeness above 6, readability under a grade level of 10, and a confidence score over 90%. If any one condition is not satisfied (i.e., any individual score does not meet the threshold), the content does not pass the evaluation. It is either returned to the model for reworking or sent to vendors for additional product details before it can be published.

Limitations of the Scoring Model:

The scoring model's thresholds are derived from empirical trials and may require adjustment by business vendors to better align with specific operational needs. A significant limitation is the introduction of subjectivity when evaluating readability, relevancy, and completeness. Striking a balance between objective standards and subjective interpretations is vital for fairness and consistency in assessments. Moreover, the model relies on the confidence score provided by the same language models (LLMs) that generate the content, which could lead to biased scoring. There is an inherent conflict of interest when LLMs self-assess their output, raising concerns about the objectivity of the confidence scores.

RESULTS

Our study deployed an innovative text-generation approach using the Mistral Large Language Model (LLM), augmented with Azure AI's image-to-text capabilities. This section presents the results of this approach. Our research embarked on a two-phased assessment of product descriptions. The first phase applied our scoring model to the existing product descriptions. This initial scoring identified that only 40% of the product descriptions passed our quality assessment, indicating a significant scope for improvement.

The second phase addressed the shortcomings revealed in the first phase by employing our approach to generate new product descriptions. Subsequently, we re-evaluated the new descriptions using our scoring model, and we found a marked improvement in the quality of the product descriptions. 59% of products that previously failed passed the second evaluation after the refinement by our approach. Besides, we also applied our approach to products with only images for creating product descriptions. Eventually, our solution can improve 73% of products with unqualified descriptions or with only images (Figure 12).

The two-phase scoring results demonstrate the efficacy of integrating LLMs with image-to-text technology in the enhancement of e-Commerce product descriptions. By implementing this method, retailers can offer a more compelling and descriptive narrative to potential customers.

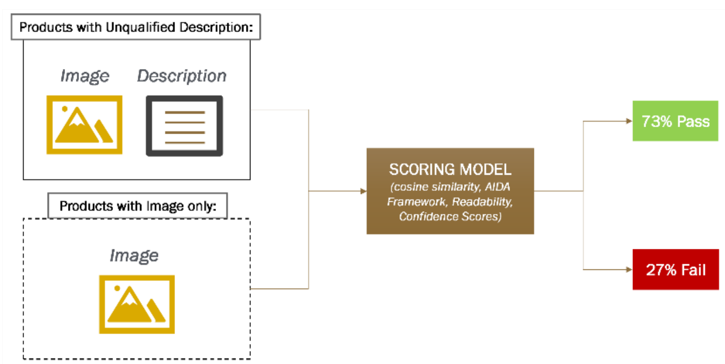

Figure 12: Scoring Results of Generated Descriptions

To further demonstrate our approach's capability, we sampled a variety of products, ranging from traditional Eastern European cuisine to authentic sports memorabilia and children's interactive game sets, and displayed the generated descriptions in Table 2. The generated descriptions reflect the product's core essence and offer consumers an informative and compelling narrative.

Table 3: Examples of Generated Results

ItemSku	Product Name	Generated Description
	KASIAS PIEROGI POTATO N ONION 14 OZ	Introducing Kasia's old-world goodness Pierogi - a delicious and nutritious meal that can be heated and served in just minutes! Made with all-natural ingredients from the heart of Europe, these potato and onion-filled dumplings are perfect for any meal. Simply pop them in the oven and enjoy a tasty, traditional meal without any hassle. Whether you're feeding a family or just craving a comfort food, Kasia's praha Pierogi is the perfect choice. Perishable, so keep them refrigerated or frozen until ready to cook. Net weight is 14 oz (397g) - enough to serve four. Give in to your cravings and indulge in Kasia's premium Pierogi.
	FOOD FOR THOUGHT SALSA BEAN & CORN MED 13 OZ	Introducing Food for Thought Salsa Bean & Corn Medium, a truly natural and delicious condiment perfect for any occasion. Made with intentionally selected and carefully sourced ingredients, our medium chipotle bean & corn salsa is a must-have for any kitchen or dining table. With its unique blend of spicy chipotle peppers and sweet corn, this salsa is the perfect addition to tacos, burritos, nachos, and more. The 13 oz. (368g) jar is perfect for sharing or keeping on hand for all your Mexican cravings. Try Food for Thought Salsa Bean & Corn Medium today and experience the difference of truly natural ingredients!
	PITTSBURGH STEELERS TABLE COVER	Introducing the Pittsburgh Steelers Table Cover, the perfect addition to your home decor! Featuring an intricate design featuring the famous Pittsburgh Steelers, this table cover is made with premium materials to ensure durability and functionality. With a black and yellow color scheme that matches the Steelers' uniforms, this table cover is sure to be a hit with your family and friends. The design showcases the Steelers' logos, including the Steeler helmet and the team's name in black letters, so you can show support wherever you go. Crafted from high-quality materials, this table cover is perfect for any occasion. The Steelers' logo adds a touch of uniqueness to your table cover, making it a one-of-a-kind addition to your home. If you're a fan of the Pittsburgh Steelers or simply looking for a functional yet stylish table cover, the Pittsburgh Steelers Table Cover is the perfect choice. Order now and experience the trustworthiness of our brand!
	CHAMPION 6PK CREW SOCK CH170 WH/BLK/GRY 6-12	Introducing the CHAMPION 6PK CREW SOCK CH170 WH/BLK/GRY 6-12 in our men's collection. These Happier Socks are proudly made by AUTHENTIC ATHLETICWEANT EST. 1919, a trusted brand in the athletic wear industry. These socks are a no-brainer for anyone on a hunt for the perfect sock. The 3-pack of socks comes in different colors: White/Black and Grey, catering to your fashionable taste. Each pair is a CREW ME 6-12, made of lightweight and breathable material for ultimate comfort. The 6-12-pair pack ensures that you'd have an ample supply to keep your feet cozy all year round. Our Champion socks are made of AUTHENTIC cotton, which is Certified Organic according to the Global Organic Textile Standard (GOTS). The 300 Thread Count fabric is soft, yet durable, providing the right balance of comfort and support. Give your feet the comfort they deserve with the CHAMPION 6PK CREW SOCK CH170 WH/BLK/GRY 6-12. Order yours today and experience the difference of a brand that's dedicated to bringing superior athletic wear to your daily life.

	ROBLOX 2 FIGURE GAME PACK ASRT 10725	Introducing the ROBLOX 2 FIGURE GAME PACK ASRT 10725, a one-of-a-kind item that's perfect for avid Roblox fans and collectors. Roblox Escape Room: Pharaoh's Tomb, a virtual game that immerses players in a world of mystery and puzzles. Featuring two exclusive figures, accessories, collector's checklist, and safety instructions, this set is sure to provide hours of entertainment for everyone. Each item is carefully crafted to accurately reflect the official description, ensuring a clear and concise product description. The set includes two figures, accessories, collector's checklist, and safety instructions. It's suitable for children aged six years and above, and it's not suitable for children under 36 months of age due to small parts that could become a choking hazard. It's important to retain any warnings or disclaimers that come with the product for future reference, as they contain essential information that could help ensure the toy's safety and quality. Whether you're a seasoned collector or a curious newcomer, the ROBLOX 2 FIGURE GAME PACK ASRT 10725 is the perfect addition to your collection. It's manufactured and distributed by Jazwares, and it meets the standards set by Roblox. With "Roblox" the Builder Logo, and "Powering Imagination" as among the labels on the packaging, you can trust that this product will provide endless hours of enjoyment for everyone in the family.

Business Impact

The project saw involvement from 6,139 suppliers and encompassed over 300,000 products, indicating the vast scale of its application. Moreover, it led to a 99% reduction in the original labor time and costs associated with the manual creation and refinement of product descriptions. This drastic decrease denotes a noteworthy leap towards optimizing resource allocation and streamlining the content generation process. It also underscores the potential of our model to be adopted across diverse industries that rely heavily on accurate and compelling product narratives.

CONCLUSIONS

In this study, we tackled the challenge of incomplete or inadequate product descriptions in e-Commerce. Through our research, we aimed to provide effective solutions to this problem by integrating Large Language Models (LLMs) and image-to-text technology, coupled with the development of a comprehensive scoring model. Our methodology addressed various scenarios based on the availability of product descriptions and images, with the ultimate goal of enhancing the quality of product listings on e-Commerce platforms.

We found that our proposed solution significantly improved the quality of product descriptions, as evidenced by the satisfied pass rate of our quality assessment. By leveraging LLMs and image-to-text technology, we were able to generate accurate and engaging product narratives, thereby enhancing the online shopping experience for customers. Moreover, the scalability and flexibility of our cloud-based analytical pipeline make it a practical solution for retailers operating in the e-Commerce landscape.

However, it is essential to acknowledge the potential strong assumptions and limitations in our study. One significant assumption is the reliability and accuracy of the LLMs and image-to-text models utilized in our methodology. While our research demonstrated promising results, there may exist inherent biases or inaccuracies in these models that could affect the quality of generated descriptions. Additionally, the subjective nature of some evaluation criteria, such as readability and completeness, introduces a degree of uncertainty in the scoring process.

Moving forward, future research could focus on addressing limitations in this study and refining the accuracy and reliability of the underlying models, as well as exploring alternative methodologies for evaluating product descriptions.

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