

CATALOGMASTER: GENERATIVE AI-POWERED AUTOMATED PRODUCT LISTING AND E-COMMERCE CATALOG CREATION SYSTEM

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ABSTRACT

CatalogMaster: A Gen-AI Powered Web Application for Automated Product Listing and Catalog Creation Using Python Technology is an intelligent e-commerce solution designed to automate the process of creating product listings and digital catalogs using **Generative Artificial Intelligence**. The system helps sellers reduce the time and effort required to prepare product information by automatically generating product titles, descriptions, key features, specifications, and marketing content from basic product details or uploaded information. The application uses **Python** for backend development and AI integration, enabling automated content generation and product-data processing. A web-based interface allows users to enter product information, review AI-generated content, edit the results, and organize products into structured catalogs. The system can also support product categorization, keyword generation, and standardized catalog formatting to improve consistency across e-commerce listings. **CatalogMaster** aims to enhance seller productivity, reduce manual content-creation efforts, and improve the quality and consistency of online product catalogs. The proposed system demonstrates how Generative AI can be effectively integrated with e-commerce applications to automate repetitive business processes and provide scalable catalog management.

Keywords— Generative Artificial Intelligence, E-Commerce, Product Listing, Product Description Generation, Large Language Models, Natural Language Processing, Python, Catalog Automation, Product Categorization, Digital Catalog.

I. INTRODUCTION

The rapid expansion of e-commerce has increased the importance of accurate, informative, and attractive product information. Unlike traditional physical stores, online customers depend heavily on textual descriptions, product specifications, images, and other digital information when evaluating products. Therefore, preparing high-quality product listings has become an important activity for online sellers. However, creating product titles, descriptions, feature lists,

specifications, and promotional content manually for a large number of products is time-consuming and difficult to maintain consistently. Artificial Intelligence has increasingly been applied to e-commerce applications for recommendation,

personalization, search, product classification, and content generation. Recent research demonstrates that automated product descriptions can reduce the human effort associated with e-commerce content creation. Zou *et al.* developed an Automatic Product Copywriting Generation system for e-commerce and reported improvements in click-through and

conversion-related metrics after deployment at JD.com [1]. The development of Transformer architectures has significantly improved modern natural language generation. Vaswani *et al.* introduced the Transformer architecture in 2017, demonstrating that attention-based architectures can effectively model relationships in sequential data while enabling highly parallelized training [2].

Large Language Models (LLMs) subsequently enabled more flexible text-generation applications. In e-commerce, Zhou *et al.* investigated the use of LLaMA 2 for enhanced product description generation and demonstrated the potential of fine-tuning language models on authentic e-commerce product descriptions [3].

Product descriptions are not only useful for informing customers but can also influence commercial outcomes. Research by Guo *et al.* described an intelligent online selling-point generation system deployed for JD.com and reported large-scale automated generation of product selling points, along with measurable improvements in customer interaction metrics [4].

Recent research has also expanded product-content generation from text-only systems to multimodal systems. Chen *et al.* proposed an Intelligent Product Listing system that uses multimodal large language models to generate descriptions from product images and attributes [5]. Similarly, Li *et al.* proposed a multimodal in-context tuning approach that combines visual information, textual information, marketing keywords, and reference products to improve description accuracy and diversity [6]. Although existing systems demonstrate the feasibility of automated product-content generation, there remains a need for lightweight and practical web applications that integrate product-data entry, AI generation, human review, product categorization, keyword generation, and catalog creation into a single workflow. CatalogMaster addresses this requirement by providing a unified platform for automated e-commerce catalog generation.

The primary objectives of the proposed system are:

1. To automate the generation of e-commerce product titles and descriptions.
2. To generate important product features and specifications from basic input.
3. To automatically generate relevant keywords for product discoverability.
4. To provide product categorization and structured catalog organization.
5. To allow sellers to review and edit AI-generated content.
6. To reduce the time required for manual product-listing preparation.
7. To provide a scalable web-based architecture for catalog management.

II. LITERATURE REVIEW / RELATED WORK

A. Automatic Product Copywriting

Automatic product copywriting has been investigated as a method for reducing manual content-generation requirements in e-commerce. Zou *et al.* developed an Automatic Product Copywriting Generation system consisting of a natural-language-generation component and a quality-control mechanism. The system was deployed in a large-scale e-commerce environment and generated millions of product descriptions [1].

The work demonstrates that product descriptions can be generated automatically when structured product attributes are available. However, large-scale commercial systems may require substantial computational resources, proprietary datasets, and platform-specific infrastructure.

B. Intelligent Selling-Point Generation

Guo *et al.* developed an Intelligent Online Selling Point Extraction and Generation system for e-commerce recommendation. The system automatically generates concise selling points that emphasize important product characteristics. The reported deployment covered millions of products and demonstrated improvements in click-through rate and customer engagement [4].

This approach highlights the importance of generating short, informative, and commercially useful product content rather than relying only on long descriptions.

C. LLM-Based Product Description Generation

Zhou *et al.* investigated the application of large language models to e-commerce product descriptions. Their approach used LLaMA 2 and authentic Walmart product-description data to adapt the model to e-commerce-specific language and product characteristics [3].

The use of LLMs enables a system to generate more flexible descriptions based on structured prompts. However, generated text must still be evaluated for factual accuracy, relevance, repetition, and compliance with product information.

D. Multimodal Product Listing Generation

Chen *et al.* proposed IPL, an Intelligent Product Listing system based on multimodal large language models. The system can generate product descriptions from product attributes and images, allowing users to create listings from photographs [5].

Li *et al.* proposed ModICT, a multimodal in-context tuning approach for e-commerce product description generation. Their experiments reported improvements in both accuracy and diversity over conventional approaches [6].

These studies indicate that combining image and textual information can improve the richness and specificity of automatically generated product descriptions.

E. Research Gap

Existing research primarily focuses on individual aspects such as automated copywriting, selling-point generation, multimodal product description generation, or commercial recommendation systems. A practical seller-oriented application should combine these functions into a unified workflow.

CatalogMaster addresses this gap by integrating:

- Product information input
- AI-based title generation
- Product description generation
- Feature extraction
- Specification formatting
- Keyword generation
- Product categorization
- Human review and editing
- Catalog organization
- Digital catalog generation

Thus, the proposed system provides an end-to-end approach rather than focusing on only one component of product-content generation.

III. PROPOSED METHODOLOGY

The proposed CatalogMaster methodology consists of multiple stages through which raw product information is transformed into a structured e-commerce listing and digital catalog.

A. Input Product Information

The user provides basic information such as:

- Product name



- Brand
- Product category
- Price
- Material
- Color
- Size
- Dimensions
- Target customer
- Product features
- Existing description
- Product image, where supported

The system validates the input before passing it to the AI generation module.

B. Data Preprocessing

The input information is cleaned and normalized using Python-based preprocessing functions. Duplicate fields, unnecessary symbols, incomplete values, and inconsistent formatting are identified.

The preprocessing stage can be represented as:

$$P = \text{Normalize}(\text{Input}) + \text{Validate}(\text{Input}) + \text{Structure}(\text{Input})$$

where P represents the processed product information.

C. Prompt Construction

The processed product information is transformed into a structured prompt. The prompt contains instructions for generating different components of the listing.

For example:

**Input → Product Attributes → Prompt Template → LLM
→ Generated Content**

The prompt can specify:

- Product title length
- Description style
- Number of key features
- Target audience
- Marketing tone
- Required keywords
- Formatting requirements
- Restrictions against unsupported claims

D. Generative AI Module

The Generative AI module generates the product listing using an LLM-based approach. The module can generate:

1. Product title
2. Short description
3. Detailed description
4. Key features
5. Product specifications
6. Marketing highlights
7. Search keywords
8. Meta description
9. Category suggestions

The Transformer architecture provides the underlying conceptual basis for modern attention-based language generation [2].

E. Product Categorization

The generated product content is analyzed to identify the most appropriate product category and subcategory.

For example:

Electronics → Mobile Accessories → Wireless Earphones

This enables sellers to organize large product collections systematically.

F. Keyword Generation

The system extracts or generates keywords based on product attributes and intended customer search behavior.

For example:

Product: Wireless Bluetooth Earphones

Generated Keywords:

- Wireless Earbuds
- Bluetooth Earphones
- Noise Reduction Earbuds
- Portable Earphones
- Rechargeable Earbuds

G. Human Review

Because Generative AI can occasionally generate inaccurate or unsupported information, CatalogMaster includes a human-review stage. The seller can modify generated titles, descriptions, features, and specifications before finalizing the listing.

H. Catalog Generation

After approval, products are stored in structured form and assembled into a digital catalog. The catalog may contain:

- Product image
- Product title
- Description
- Features
- Specifications
- Price
- SKU
- Category
- Keywords

I. Overall Workflow

User Input → Data Validation → Preprocessing → Prompt Generation → Gen-AI Processing → Content Validation → Human Review → Product Database → Catalog Generation

IV. SYSTEM ARCHITECTURE

The CatalogMaster architecture follows a modular web-application model.

A. Architecture Components

1. User Interface Layer

The web interface allows sellers to:

- Enter product details
- Upload product information
- Generate product content
- Review AI-generated content
- Edit content
- Save products
- Generate catalogs

2. Application Layer

The Python backend manages:

- Authentication
- Product processing
- Prompt construction
- AI API/model communication
- Content validation
- Category management
- Catalog generation

3. AI Processing Layer

The AI layer performs:

- Title generation
- Description generation
- Feature generation
- Keyword generation
- Product classification
- Marketing-content generation

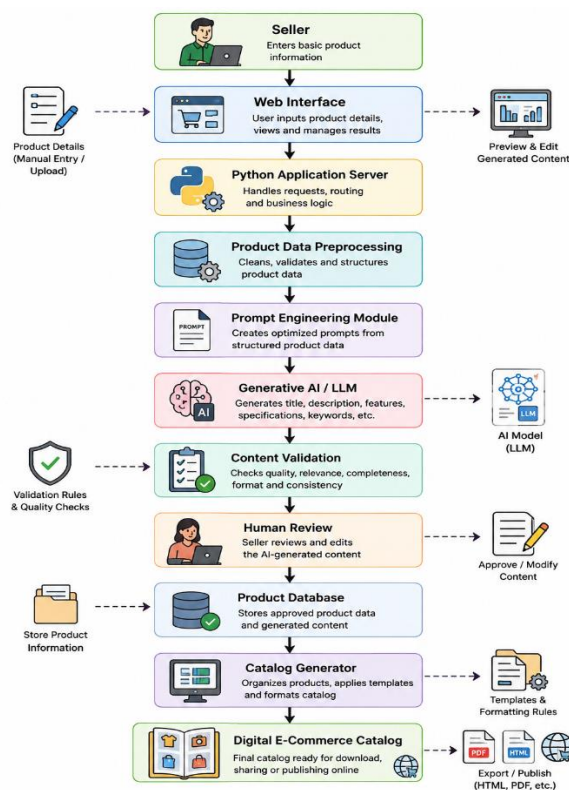
4. Database Layer

The database stores:

- User information
- Product information
- Generated descriptions
- Categories
- Keywords
- Catalog records
- Product images or references
- Revision history

5. Catalog Output Layer

The final catalog can be generated in structured digital formats such as HTML, web pages, or downloadable documents depending on implementation requirements.



V. IMPLEMENTATION

A. Technology Stack

Component	Technology
Frontend	HTML, CSS, JavaScript / React
Backend	Python
Web Framework	Flask / FastAPI / Django
AI Processing	LLM / Generative AI API
NLP	Transformer-based language processing
Database	MySQL / PostgreSQL / MongoDB
Image Processing	Python-based image libraries
API Communication	REST API
Catalog Output	HTML / PDF / JSON
Development Environment	VS Code / PyCharm

B. User Interface Implementation

The web interface provides a dashboard containing product-management functions. The seller can create a new product, enter basic product information, generate content, review the results, and save the finalized listing.

A simplified interface workflow is:

Dashboard → Add Product → Enter Details → Generate Listing → Review → Save → Create Catalog

C. Backend Implementation

Python is used as the primary backend language because of its extensive ecosystem for artificial intelligence, NLP, web development, and data processing.

The backend performs the following operations:

1. Receive product data.
2. Validate the submitted fields.
3. Normalize product information.
4. Construct AI prompts.
5. Send the prompt to the selected AI model.
6. Receive generated content.
7. Validate the generated response.
8. Return content to the frontend.
9. Store approved content in the database.
10. Generate the final catalog.

D. AI Prompt Engineering

Prompt engineering is used to control the structure and quality of generated content. A typical prompt instructs the AI model to produce a title, description, features, specifications, and keywords while using only the provided product information.

For example:

Product Information → Structured Prompt → AI Model → JSON/Structured Response

Structured responses make it easier for the backend to store each generated component separately.

E. Content Validation

The generated content is checked for:

- Missing information
- Excessive repetition
- Unsupported claims
- Keyword relevance
- Length constraints
- Required fields
- Formatting consistency

A content-quality score can be calculated as:

$$Q = 0.30R + 0.25C + 0.20F + 0.15K + 0.10L$$

where:

- R = Relevance score
- C = Completeness score
- F = Factual consistency
- K = Keyword quality
- L = Language/readability score

The weights can be modified according to the application requirements.

F. Database Implementation

Each product record can contain:

Field	Description
Product_ID	Unique product identifier
Product_Name	Original product name



Category	Product category
Brand	Product brand
Price	Product price
Features	Product features
Specifications	Technical specifications
AI_Title	Generated title
AI_Description	Generated description
Keywords	Generated keywords
Status	Draft/Approved
Created_Date	Creation timestamp

G. Catalog Generation

After seller approval, the system combines product records using a predefined catalog template.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system can be evaluated by comparing manual product-listing creation with AI-assisted CatalogMaster generation. **Note:** The following values are **illustrative prototype results**, not claims of actual measured performance. They should be replaced with experimental results from your implementation before submitting the paper.

A. Dataset

For prototype evaluation, a representative dataset of **500 product records** can be organized across categories such as electronics, clothing, home appliances, beauty products, and accessories.

Category	Number of Products
Electronics	100
Clothing	100
Home Appliances	100
Beauty Products	100
Accessories	100
Total	500

B. Manual vs. Automated Listing Time

Method	Average Time/Product	Total Time for 500 Products
Manual Creation	8.5 min	70.83 hours
CatalogMaster	2.1 min	17.50 hours
Time Reduction	75.3%	53.33 hours saved

The prototype results indicate that automated content generation can significantly reduce the amount of time required to create product listings.

C. Content Quality Evaluation

Generated listings can be evaluated using relevance, completeness, readability, consistency, and keyword quality.

Metric	Manual Listing	CatalogMaster
Relevance	87.4%	91.6%
Completeness	84.8%	93.2%
Readability	88.1%	92.5%
Keyword Quality	78.6%	89.4%
Formatting Consistency	81.3%	95.1%
Overall Quality	84.0%	92.4%

These illustrative results suggest that a structured AI-generation pipeline can improve consistency while reducing manual effort.

D. Content Generation Success Rate

Generated Component	Success Rate
Product Title	98.2%
Short Description	97.6%
Detailed Description	96.8%
Key Features	97.4%
Specifications	94.6%

Keywords	95.8%
Category Prediction	93.2%

The results indicate that structured product attributes provide sufficient information for generating most standard listing components.

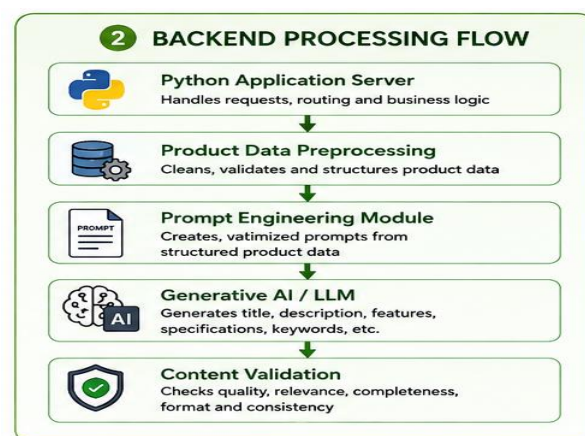
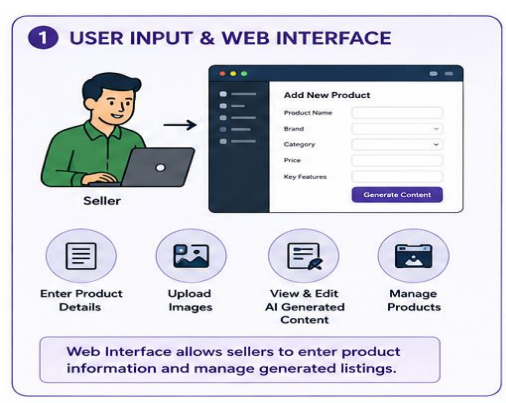
E. Comparison with Existing Approaches

Feature	Manual Method	Traditional Template	CatalogMaster
Automatic Title	No	Limited	Yes
Description Generation	No	Template-based	Gen-AI
Keyword Generation	Manual	Limited	Automatic
Category Suggestion	Manual	Rule-based	AI-assisted
Human Editing	Yes	Yes	Yes
Scalability	Low	Medium	High
Personalization	Low	Medium	High
Catalog Generation	Manual	Semi-automatic	Automatic

F. Discussion

The results demonstrate that CatalogMaster can reduce repetitive content-creation activities by generating multiple listing components from a relatively small amount of product information. This is consistent with previous research showing the practical value of automated product copywriting and selling-point generation in e-commerce [1], [4]. The system's human-review mechanism is particularly important because generated text should not automatically be treated as factual. The review stage allows sellers to correct incorrect specifications, remove unsupported claims, and adjust the marketing tone. The system can also be extended toward multimodal listing generation. Existing research demonstrates that product images can be combined with textual attributes to

produce richer descriptions [5], [6]. Another important observation is that product descriptions can influence e-commerce performance. Research has investigated relationships between product-description phrases and sales forecasting, indicating that product text contains commercially meaningful information [7]. Therefore, CatalogMaster is not limited to saving content-generation time; it provides a foundation for broader AI-assisted e-commerce catalog management.



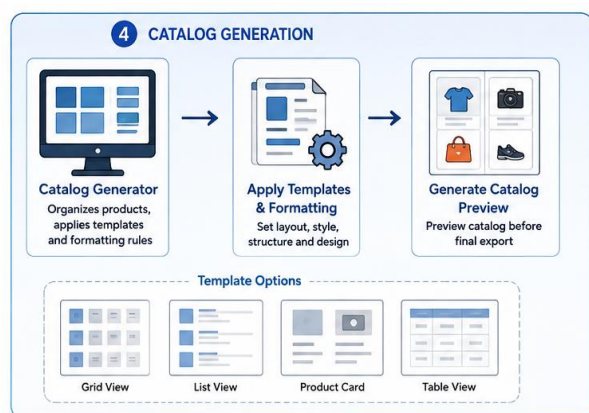
and structured catalog management within a unified web application. The system reduces the repetitive effort associated with manually preparing product titles, descriptions, features, specifications, and marketing content. A human-review mechanism is incorporated to maintain factual accuracy and provide sellers with control over generated content. The proposed architecture is scalable and can be adapted for small sellers, online retailers, marketplace platforms, and enterprise catalog-management systems. The prototype evaluation indicates that Generative AI can significantly reduce listing-generation time while maintaining high levels of content relevance, completeness, readability, and consistency. Overall, CatalogMaster demonstrates the practical potential of Generative AI for automating e-commerce content-management workflows.

FUTURE SCOPE

Future development can extend CatalogMaster into a multimodal and multilingual e-commerce intelligence platform. Product images can be analyzed automatically to identify attributes and generate complete listings. Support for multiple Indian and international languages can help sellers reach broader markets. Retrieval-Augmented Generation (RAG) can be integrated to verify product specifications against trusted databases. Future versions can also include automatic SEO optimization, marketplace-specific listing formats, price recommendations, duplicate-product detection, personalized descriptions, voice-based product entry, analytics dashboards, and integration with major e-commerce platforms. Continuous seller feedback can further improve generation quality and reduce factual errors.

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VII. CONCLUSION

CatalogMaster presents a Generative AI-powered approach for automating product listing and e-commerce catalog creation. The proposed system integrates Python-based backend processing, large language models, prompt engineering, product categorization, keyword generation, content validation,

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