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Article

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GOOD PRACTICE FOR PRODUCT MANAGEMENT DECISION-MAKING: USING AMAZON'S DATASET AND CHATGPT

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Abstract
This study examines how Chat Generative Pre-trained Transformer (ChatGPT) can be effectively utilised as a good practice to analyse Amazon reviews within the creative and cultural industry category of Design, particularly Arts, Crafts & Sewing. By focusing on specific products and reviews extracted from a dataset containing over 800,000 products and nearly nine million reviews, ChatGPT identified common themes and customer issues such as software problems and product reliability. When we compared ChatGPT's results with those from manual data reviews, we found that ChatGPT was adept at identifying main topics but sometimes missed detailed insights or altered the original reviews when providing examples. This indicates that while ChatGPT can quickly highlight important areas for product managers, it should be used in conjunction with human analysis to achieve a comprehensive understanding. Nonetheless, the results demonstrate that when considering group creativity, ChatGPT can be a valuable member.

Keywords: artificial intelligence, managerial decision-making, product management, creative industries, ChatGPT, good practice

JEL Classification: C55, D79, L21, Z11

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Introduction

Companies aiming for success in competitive markets must focus on meeting dynamic customer needs. This involves using analytics to accurately predict consumer preferences during new product development. By understanding these preferences, businesses can effectively adapt their offerings and maximise revenue (Majava et al., 2014; Song, 2017; Dou, Li and Nan, 2018; Soni, 2023; Seitinger, 2024). Although crucial, assessing customer needs in the early stages of product innovation remains underexplored. However, it is essential for addressing managerial challenges and guiding product definition (Kärkkäinen and Elfvengren, 2002).

Online consumer reviews (OCRs) are becoming an increasingly vital tool for consumers seeking insights into product quality. Consequently, it is crucial for marketers to understand the factors that make OCRs useful and how these assessments influence consumer decisions. Furthermore, software usability and intuitive interface design are essential for ensuring user satisfaction and fostering long-term adoption (Filieri, 2015). Ensuring product quality is a paramount priority for all organisations, as it significantly contributes to customer satisfaction, which is an important goal in marketing (Lone and Bhat, 2023).

In a world where online reviews and electronic word-of-mouth hold considerable sway, negative feedback – especially when highlighted as "most helpful" – can disproportionately damage brand perception and decrease customer loyalty. This underscores the need for proactive reputation management (Chevalier and Mayzlin, 2006; Ho-Dac et al., 2013).

1. Amazon product reviews

Amazon lists hundreds of millions of products, over half of which are offered by third-party sellers, predominantly small and medium-sized businesses, participating in the "Fulfilment by Amazon" (FBA) program (Guoming et al., 2022; Toogood, 2024). This program allows them to store their merchandise in Amazon's fulfilment centres. Customers have indicated a preference for purchasing from sellers using FBA, attributing to it competitive advantages comparable to those enjoyed by products sold directly by Amazon (Guoming et al., 2022). Amazon operates in over 100 countries and regions, earning the title of the most trusted brand by U.S. consumers in 2022. In 2023, U.S.-based sellers on Amazon sold over 4.5 billion products, averaging 8,600 items per minute (Toogood, 2024).

Amazon's product management strategy primarily focuses on working backward from customer needs. This approach involves defining relevant product and business metrics, identifying issues, and discerning trends and patterns in the data. During the initial product launch, teams rely on their intuition and a thorough understanding of the customer and the problem to determine which metrics to track. However, once the product is in use, they gather insights into customer preferences and dislikes, among other factors. This method aligns the strategy with customer needs, thereby enhancing Amazon's competitiveness in the market (Amazon Web Services, 2024; Xi et al., 2024; Rajaram and Tinguely, 2024). According to Rajaram and Tinguely (2024), research indicates that implementing technology in product management within small and medium-sized enterprises (SMEs) has a positive impact on the company. Technologies such as big data, language models like ChatGPT, the Internet of Things (IoT), and blockchain are particularly transformative in this regard (Chuma and de Oliveira, 2023; İşgüzar, Fendoğlu and Şimşek, 2024; Aguinis et al., 2024; Rajaram and Tinguely, 2024).

2. Artificial intelligence (AI) business use cases

Language models like ChatGPT are trained on diverse data sources, including curated and non-curated publicly available internet information, data obtained through third-party partnerships, and user-generated content contributed by trainers and researchers (Brown et al., 2020; Gao et al., 2021; Wang, Chang and Chen, 2024; OpenAI, 2024a). Domain-specific datasets are crucial to ensuring the accuracy and versatility of language models' outputs (Wang, Chang and Chen, 2024). The combination of 45TB of data and a domain-specific dataset has shown in the current study that ChatGPT can be useful to quickly analyse datasets. ChatGPT focused on the items, which includes the most votes when choosing its first product to review.

AI has made significant progress in achieving human-level scores on various tests, highlighting the advanced capabilities of large language models. GPT-4, which can handle both text and images, performs at a human level on various professional exams and demonstrates better accuracy and scalability. In the field of coding, models such as GPT-4, trained on GitHub code, correctly solve about 28.8% of new coding problems and can reach 70.2% accuracy by attempting multiple times. ChatGPT-4 is effective at solving easy and medium-level programming tasks in C++ and Java but has difficulty with more complex problems.

Although the code generated by ChatGPT works, it is often less efficient in terms of speed and memory compared to code written by humans (Chen et al, 2021; Bucaioni, 2024; OpenAI, 2024a). Even more recent than GPT-4 is their newly released o1 model or their o3 model, which has not yet been released to the public. The o1 and o3 models can beat the majority of coders on competitive coding websites such as Codeforces (OpenAI, 2024b,c). Particularly, o3 would score 175 out of 169074 places, while o1 would score considerably worse, although still high, as it would be in 5348 place on the leaderboard, both models were released this year (OpenAI, 2024a,b,c; Codeforces, 2024). For this reason, the study looked at how ChatGPT could be used to gain insight into publicly available data, particularly Amazon product reviews. This was done by comparing ChatGPT analysis of customer feedback with manual analysis of customer feedback.

AI has already found multiple applications in business, enabling data-driven decision-making, automation of routine tasks, and the creation of novel products and services. From leveraging AI for socio-economic progress and advanced data strategies to harnessing generative models for human-like interactions, organisations are continuously discovering new ways to benefit from these technologies. Moreover, AI-driven analytics are aiding in streamlining operations, enhancing customer experiences, and fostering innovation across various industries—underlining the pivotal role of AI in shaping today's business landscape (Knight, 2017; Weber and Schütte, 2019; Aldoseri, Al-Khalifa and Hamouda, 2023; Chuma and de Oliveira, 2023; Hassani and Silva, 2023; Rane, 2023; Wamba et al., 2023; Dinu, 2024).

3. Creative and cultural industries

According to the 1998 classification by the Department for Culture, Media and Sport (DCMS), the DCMS developed a list of activities that fall under the category of creative industry. This includes content, design, architecture, advertising and software. Design can encompass arts and crafts, design and fashion, and graphic design, among other things

(Peltoniemi, 2014; Muller, Rammer and Truby, 2024). In the current study, we focused on arts and crafts, particularly how Amazon reviews can help with product management of arts and crafts products.

Cunningham (2002) distinguishes "cultural industries" as traditional, nationally supported art forms (such as film, radio, and theatre) rooted in public funding and policy initiatives. Tied to flagship institutions (e.g., national galleries or broadcasters), these industries emphasise social and cultural significance. In contrast, "creative industries" refer to a broader, future-oriented cluster of entrepreneurial, tech-driven enterprises (e.g., software design, interactive media, fashion). Rather than relying on subsidies, they leverage innovation, intellectual property, and the commercial potential of creativity, indicating a shift toward knowledge-based, service-driven economic models.

Building on these distinctions, Moore (2014) traces how both cultural and creative industries evolved historically. She highlights that the Industrial Revolution's mass production, urbanisation, and technological advances spurred new modes of cultural creation and consumption. From the Frankfurt School's 1930s critiques of the "culture industry" to the late 20th-century rise of urban renewal initiatives, Moore shows how the concept of culture itself became both a commodity and a tool for economic development.

By the 1990s, the notion of creative industries—first prominent in Australian policy (Creative Nation) and then in the UK—broadened conventional understandings of cultural production to include digital platforms, design, and knowledge-based services. Interpreting today's creative industries requires recognising these industrial, technological, and cultural layers, especially as digitalisation reshapes how creativity propels both economic growth and social transformation (Moore, 2014).

4. Research methodology

The dataset, last updated in 2023, was retrieved from the UC San Diego Jacobs School of Engineering website (McAuley, 2023). It is part of their work on BLaIR, a pre-trained sentence embedding model for recommendation systems designed to link item metadata with natural language context for improved item retrieval and recommendations. BLaIR utilises the new Amazon Reviews 2023 dataset and is evaluated on tasks such as complex product search. Results demonstrate BLaIR's strong performance in both traditional and complex retrieval tasks (Hou et al., 2024). The Arts_Crafts_and_Sewing dataset were downloaded from their repository, including the review and metadata datasets. These datasets were initially uploaded to Google Cloud Storage and then transferred to BigQuery for further processing (Amazon Reviews, 2023; McAuley, 2023).

The methodology for this study involves several systematic steps to prepare the Amazon "Arts, Crafts & Sewing" product dataset for further analysis. Each step utilises Structured Query Language (SQL) to manipulate and refine the dataset, ensuring that the final data is clean, relevant, and structured for meaningful analysis. Below is a detailed explanation of each methodological step.

Step 1 – Dataset merging:

To establish a unified dataset that combines both product-level metadata and associated customer reviews, we utilised SQL operations to join two distinct tables:

- meta_Amazon: This table contains product metadata such as the title, main category, average rating, number of ratings, features, descriptions, images, and a unique identifier called parent_asin. The parent_asin serves as a unique product grouping identifier, effectively grouping related product variations (e.g., different colours or sizes) under a single parent product entry.

- review_Amazon: This table comprises consumer-generated review data, including the rating, review text, timestamp, helpful vote counts, and a boolean indicating whether the purchase was verified (verified_purchase).

The merging process was executed by performing a join operation on the parent_asin column, ensuring that each product's metadata is accurately associated with its corresponding set of reviews. This joint operation resulted in a comprehensive table named merged_Amazon, which encapsulates both structural attributes (such as categories, descriptions, prices, and features) and consumer-generated data (including ratings, review texts, timestamps, and verification statuses).

Step 2 - Data Cleaning and Filtering:

Post-merging, the dataset underwent a meticulous cleaning process to enhance its quality and relevance. The cleaned dataset was stored in the clean_ArtsAndCrafts_Amazon table.

- Column Pruning: Unnecessary columns that did not contribute to the analysis were removed. For instance, columns like bought_together, subtitle, author, and images were excluded, as they did not bring anything to the analysis.

- Row filtering: Quality constraints were enforced to ensure the retention of only meaningful records. Specifically, rows were filtered to exclude entries with null values in critical fields such as categories, features, and descriptions. price and store. Importantly, only reviews marked as verified_purchase = TRUE were included to increase the authenticity and reliability of the consumer feedback.

Step 3 - Domain-specific filtering (Arts, Crafts & Sewing):

To focus the analysis on a specific product domain, we applied a category-based filter. Using SQL, we selected only those records where the main_category field contained the phrase "arts, crafts & sewing". This was achieved by employing a pattern match to ensure case-insensitive and flexible filtering.

The resulting dataset exclusively comprises of products and reviews within the "Arts, Crafts & Sewing" category. This targeted filtering ensures that subsequent analyses are domain-specific, thereby enhancing the relevance and precision of the results.

Step 4 - Categorisation of Helpful Votes:

To analyse the distribution and impact of helpful votes on reviews, we categorised the helpful_vote counts into predefined ranges. This stratification facilitates a deeper understanding of user engagement and the perceived usefulness of reviews. The categorisation process involved the following steps:

- Defining Vote Ranges: We established a series of intervals to classify the number of helpful votes a review received. The ranges were defined as 0-10, 10-50, 50-199, 200-299, 300-399, 400-499, 500-599, 600-699, 700-799, 800-899, 900-999, 1000-1999, 2000-2999,

3000-3999, 4000-4999, 5000-5999, 6000-6999, 7000-7999, 8000-8999, 9000-9999, 10000-10999, 11000+

- Assigning Vote Ranges: Each review's helpful_vote count was evaluated and assigned to the appropriate vote_range based on the defined intervals. For example, a review with 25 helpful votes was categorised into the '10-50' range.

- Counting Reviews per Range: After categorisation, we computed the number of reviews falling into each vote_range. This aggregation provided insights into how reviews are distributed across different levels of helpful votes.

- Ordering for Analysis: The counts of reviews within each vote_range were ordered in descending order to identify which vote ranges were most prevalent.

This categorisation resulted in a structured overview of the distribution of helpful votes, enabling further analysis of trends and patterns related to user engagement and review usefulness.

Step 5 - Final step:

Through these systematic SQL-driven steps—merging metadata and review data, cleaning and filtering records, applying domain-specific constraints, categorising helpful votes, and reducing unnecessary columns—we have curated a final dataset tailored for analysis. This dataset encompasses verified reviews of products within the "Arts, Crafts & Sewing" category, enriched with comprehensive metadata and user-generated content.

To evaluate ChatGPT's effectiveness in analysing user-generated reviews for product managers in the arts and crafts sector, we first created a targeted dataset using a specific SQL query. This query selected all records from the ArtsAndCrafts_Amazon table where the helpful_vote exceeded 500, ensuring that only highly regarded and influential reviews were included. The resulting dataset, stored in the helpful_votes_Amazon table, was then uploaded to ChatGPT for analysis with the aim of extracting meaningful insights such as emerging trends, key quality attributes, and common user concerns relevant to product management.

To assess the accuracy and utility of ChatGPT's analysis, we conducted a comparative study against manual analysis. By juxtaposing the insights generated by ChatGPT with those identified through manual review, we attempted to determine the model's ability to replicate, enhance, and streamline the extraction of valuable information. This was done to gauge ChatGPT's potential in providing actionable intelligence for product managers, to determine its strengths and to identify areas for improvement in handling complex, domain-specific datasets.

5. Results and discussion

The results of BigQuery SQL results show that the table that contains metadata on Amazon products has 801,156 rows and 16 columns. While on the other hand, the number of rows in the review dataset was 8,966,758 and had 10 columns. Highest number of votes (11,030) for a product was for the Cricut Explore Air 2, which is a DIY Cutting Machine for all Crafts. This item, as will be discussed later, was also chosen by ChatGPT to be the first product it chose to analyse. It also has the largest number of reviews with over 500 helpful ratings per review.

Table no. 1 shows the number of occurrences of helpful vote ranges for reviews that were not used in the analysis. The two main reasons that these reviews were excluded was because of the high number of occurrences and due to the focus of this study, which was to focus on reviews that other customers found most helpful, as this was seen by the authors to be most valuable for product managers developing or trying to improve products similar or identical in function to the ones covered in this paper; however, the authors also believe that the results of this paper can also be applied to other products, not only those sold under "arts, crafts or sewing" or even on Amazon.

Table no. 1. Number of times occurrences of helpful votes (not used in the study)

Helpful vote range per review	Number of occurrences
0-10	1,131,150
10-50	20,911
100-199	2,252
200-299	157
300-399	47
400-499	33

The reviews that were used in the analysis were those that contained 500 or more helpful votes; however, they contained much fewer helpful vote ranges overall, though for the purpose of this study, the authors believe that this is not an issue. The table containing all the vote ranges is represented by Table no. 2.

Table no. 2. Number of times occurrences of helpful votes (used in the study)

Helpful vote range per review	Number of occurrences
500-599	19
600-699	14
700-799	16
800-899	3
900-999	1
1000-1999	8
2000-2999	4
3000-3999	3
4000-4999	1
6000-6999	1
7000-7999	1
11000+	1

After the final table was filtered to only include the top 72 reviews, they were feed to ChatGPT. First, the 4o model was used, because it allowed Excel files to be uploaded. The output of ChatGPT was summarised, because it is not feasible to add complete 4o outputs into this article.

The results are as follows:

ChatGPT 4o summarised: We found that the key insights from the ChatGPT analysis reveal that opinions on the Cricut Explore Air 2 vary substantially, with an overall mean of 3.0 for the reviews. Negative feedback underscores concern about software accessibility—specifically the misconception that users must purchase additional subscriptions.

Authors notes: the fact that there were concerns about software accessibility and that a subscription was needed to use the product was also found in the text. ChatGPT was not found to be hallucinating in this regard. However, when further prompted to give examples of software issues, it quoted "The machine does not come with software, and you have to pay to use their design platform". While technically that was said in two of the reviews, the quote was paraphrasing those two reviews. For example, "I bought this on Valentine's Day for my wife. It came with no useful instructions". was quoted by ChatGPT; however, while true that someone bought it for their wife for Valentine's Day, in that review they did not mention anywhere that it did not come with useful instructions. In addition, ChatGPT did not mention that while the average of the votes looked at was 3.0 for the most helpful votes, the overall rating for the item was a 4.8. Also, the actual average for the 10 most helpful reviews was 3.2.

ChatGPT 4o summarised: On the positive side, 5-star reviews praise the machine's ease of use, particularly for crafting beginners, as well as the precision and quality of its cuts. Users also value the creative potential of the device and consider it an excellent investment for arts and crafts enthusiasts.

Authors notes: The authors did not find fault in this analysis.

Then ChatGPT was asked to review a different product, and ChatGPT chose the SINGER Stylistic 7258 Sewing & Quilting Machine, as well as the SINGER 9960 Sewing Machine.

ChatGPT 4o summarised: Price and perceived value remain significant factors, as evidenced by customer discussions around cost and added features.

Authors notes: The authors found this to be true; however, when they tried to get more detail, it started hallucinating. For example, it gave an example of a review with 679 votes, a review that does exist. However, the text it gave was: "I was super excited to get this feature-rich machine, but I was let down. For the price, I expected better quality and reliability. After only a few months of use, the machine started skipping stitches and struggling with basic functions. It's disappointing to spend this much and feel like I need a replacement already." When comparing what ChatGPT gave as an example with the actual review, we can see that, while there are similarities (particularly the first sentence), there is a lot of detail missing that would be useful to someone analysing the review: "I was super excited to get this feature-rich machine, then after 20-ish days, the hand wheel became hard to turn, the machine became loud and creaky, and keeping under the plate clean didn't help. Amazon replaced the machine, and when I unpacked my new machine, I found it wasn't new AT ALL (see photos)! There was dirt and dust in the crevices on top, so I investigated further. I took the plate off to find a bunch of lint and filth. Oh wait, there's more... I prefer to use the foot pedal, so upon plugging it in, the connector port jiggled and fell out. Needless to say, the machine wouldn't run with the foot pedal... SOOOO... I tried using the start/stop button and noticed right away that the lettering on that button was worn away from heavy use, and no, it didn't work, just beeped. HOW DARE someone provide used machines to Amazon claiming that they're new? Just UGH! I'm waiting on the third machine to come in tomorrow, and we will see what happens. This third machine is as far as I'm willing to go without requesting a full refund."

ChatGPT 4o summarised: The reviews for the SINGER Stylist 7258 reveal a mix of positive and negative feedback, with reliability issues appearing prominently in the most helpful negative reviews. Customers repeatedly mention tension dial malfunctions, bobbin thread nesting, and overall machine breakdowns occurring. These complaints suggest a recurring need for stronger quality control and more robust testing procedures before shipping.

Authors notes: This is fairly accurate, although as with previous cases, it does not share much detail. Nonetheless, it did give keywords that made searching the table easier. The authors could immediately go find any mention of tension dial malfunctions, bobbin thread nesting, and overall machine breakdowns occurring, which they did, and can confirm that these flaws were mentioned.

The 4o model was chosen because the Excel files can be uploaded for analysis only with the 4o model. However, once the products were determined, the authors copy pasted the reviews into the latest o1 model and tried to analyse the reviews again. While this time, the response appeared to be of greater quality, the examples it gave (even when giving all of the reviews in the prompt that asked for examples from the reviews) still were changed versions of the review. For example, the original review is as follows: "I bought this on valentines day for my wife. Here 2 weeks later, she gets a notice that she can no longer use the software without paying $10 a month. She gets on chat with Cricut and they confirm it. So this machine is now useless to us."

While on the other hand, ChatGPT o1 gave the following response: "I bought this on Valentine's Day for my wife. Two weeks later, she was told she had to pay $10 per month to continue using the software. It's now useless to us. No one mentioned these extra fees before purchase."

However, there were exceptions such as the following safety concerns that the o1 model cited as examples: "It seems that the thread cutting guard broke (see attached pictures) exposing the razor blade. … The plastic is thin and brittle so a thicker fabric could easily get snagged and break the plastic … and you wouldn't know it. I would consider this a safety issue and a huge design flaw. … If you have this thread cutting tool, please remove it before you or someone using the machine gets hurt."

All of the above sentences can be found in the reviews, which goes to show that while sometimes it paraphrases sentences and adds or removes parts of the review, there are times when it does not change any of the original wording. Therefore, it is important to fact check ChatGPT and compare its response to the original text, even with the newest model.

Conclusions

These findings point to actionable recommendations for both manufacturers and consumers. Companies must focus on enhancing product durability, improving software descriptions, and clearly communicating total costs. In parallel, creative enthusiasts and professionals are advised to research extensively, and engage with online communities. By addressing these issues, manufacturers can foster broader acceptance and bolster innovation in the evolving landscape of arts and crafts.

This study utilized extensive Amazon product data, comprising over 800,000 metadata entries and nearly 9 million reviews, to explore how user feedback and AI-driven analysis tools—specifically various ChatGPT models—intersect in providing actionable insights for product improvement. The Cricut Explore Air 2 emerged as one of the most-discussed products, garnering the highest number of votes (11,030) and with the highest number of reviews (10 out of 72) with over 500 helpful ratings each. Analyses indicate that while this machine is highly praised for its versatility and ease of use, concerns over software fees and design limitations persist.

Subsequent examinations of the SINGER sewing machines similarly showed varied user sentiments, encompassing perceived value, reliability issues, and customer expectations regarding product quality control. Notably, ChatGPT proved adept at identifying recurrent themes such as tension dial malfunctions and bobbin thread nesting for the SINGER Stylistic 7258 Sewing & Quilting Machine. However, it occasionally paraphrased or "hallucinated" sections of reviews, underscoring the importance of verifying AI outputs against original texts.

Despite these shortcomings, ChatGPT demonstrated potential as a creative and time-saving tool for initial data exploration and thematic analysis. The authors suggest that refining prompts and carefully fact-checking outputs can enhance its effectiveness as a brainstorming instrument, particularly when used in tandem with traditional analysis methods. By integrating AI-generated insights with human expertise, product managers and researchers can achieve a more holistic understanding of user feedback and, ultimately, drive product development strategies more effectively.

Finally, it is important to note that despite its flaws, the authors concluded that ChatGPT can be useful as an additional perspective to the analysis. Group collaboration has been shown in the past to have a positive effect on creativity and other outcomes (Paulus and Nijstad, 2003; Sawyer, 2007).

An extra perspective might give insight into a topic in a way that might not have crossed the mind of the manager or other individuals involved in the decision-making. At worst, it shows promise as a tool to make it easier to get started with an analysis, since it gives a starting point and as such, in the opinion of the authors, is a good brainstorming tool, particularly due to the wealth of knowledge and verbal abilities that ChatGPT has. The authors also believe that it should be mentioned that it is possible that by developing a prompt-engineering strategy and spending time testing it would provide better results.

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