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Product Design Enhancement for Fashion Retailing

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Abstract. As the fashion industry increasingly embraces artificial intelligence (AI), we investigate how a fast-fashion retailer should choose between using a manual design strategy or an AI-assisted design strategy to enhance existing products. A manual design is a traditional and basic approach that involves human designers only, whereas an AI-assisted design is a more innovative approach that involves both human designers and AI technologies. In this paper, the overall product enhancement is measured by two key attributes: product quality and product trendiness. *Product quality* can be measured by the product's longevity as reflected by the quality of the materials and types of fabric and stitching used, where the product's improvement level can be determined by the retailer in a continuous range. Consequently, the retailer may choose different levels of product quality under different design strategies. The two design approaches also lead to different natures of *product trendiness*, which is reflected by features such as styles, new materials, and colors, to name just a few. Specifically, we assume that the traditional manual design can predict well how trendy or popular the new product is. Hence, the trendiness attribute under the manual design is deterministic. However, given the uncertain nature of the AI-assisted design technology and the needed coordination between human designers and the adopted technologies, the trendiness of the new product designed under the AI-assisted approach is assumed uncertain. Two sets of designing costs are considered in product enhancement: the fixed design cost that is irrespective of the production volume and the variable marginal cost. Our analysis of the base model highlights the importance of decomposing different costs in determining the optimal design strategy. Specifically, the manual design is preferred when the fixed cost carries more weight, whereas the AI-assisted design is preferred when the marginal cost is a more important factor. Moreover, a higher level of innovation uncertainty under the AI-assisted design gives this strategy an advantage over the manual design. In our extended models, we demonstrate that (1) these results are robust even if the retailer does not have the flexibility to offer the existing product when the AI-assisted design is unpopular, and (2) the relative position of human designers in the two design approaches has an impact on the effects of these costs.

Supplemental Material: The online appendix is available at https://doi.org/10.1287/serv.2023.0315.

Keywords: fashion retail • AI-assisted design • quality choice • decision making under uncertainty

1. Introduction

Artificial intelligence (AI) has emerged as an important frontier of technological innovation, and one of the industries profoundly impacted by AI is fashion. AI tools are being employed to reinvent merchandising, marketing, and inventory management across the entire fashion supply chain (Business of Fashion and McKinsey & Company 2018). At the same time, for large fast-fashion retailers such as H&M and Zara, the end-to-end fashion cycle is no more than six months, and product development typically takes place within a few weeks (Berg et al. 2018). Given the fast-fashion model's reliance on constantly introducing innovative designs to the market, fashion retailers are increasingly implementing AI to automate their design process. For example, Zalando, a German fashion marketplace, collaborated with Google to develop AI-powered fashion designs based on the customer's favorite colors, textures, and other style preferences (Zalando 2022). The fashion website Fab.com uses crowd voting to predict the best-selling designs for the next season (Caro et al. 2020). According to a recent report, the market size of AI-based generative design software is estimated to be $44.5 billion in 2030 (CBInsights 2018).

However, fashion is a collective yet designer-driven system. At the current stage, AI is not yet able to replace the human designer, as human creativity and agility are needed to solve complex and volatile design problems (Song et al. 2020). In practice, there are two predominant design strategies. The first option is the manual design, which does not involve AI assistance. This proven design strategy usually leads to deterministic product trendiness and market demand. The second option is the AI-assisted design, where the design work is distributed between the human team and AI. Indeed, a recent study involving 1,075 firms confirms that significant performance improvements can be achieved when humans and AI collaborate (Wilson and Daugherty 2018). Although AI has great potential to partner with human designers, studies have also shown that AI may reduce the performance of the design team for reasons such as cognitive overload and human deviations from AI prescriptions (Sun et al. 2022). Thus, AI-assisted design is often associated with innovation uncertainty, and the resulting design's market acceptance is not perfectly known beforehand. If the resulting design is popular, significant benefits can be achieved. If the resulting design fails to excite the market, it may be marked down or even abandoned by the retailer. Regardless of whether the fashion retailer adopts the manual or the AI-assisted design, it must also make good product quality and price decisions to maximize the overall profit while facing obstacles such as a short-selling season and lack of inventory replenishment opportunities.

Given the above-mentioned trade-offs, it could be quite challenging and complicated for fashion retailers to assess the costs and benefits of different product design strategies in enhancing an existing product. In this paper, we propose a stylized two-stage economic model to understand the critical trade-offs in fast-fashion product design enhancement. Specifically, we seek to answer the following questions: (1) Under what condition is the manual/AI-assisted design more likely to be chosen by the fashion retailer? (2) Given a product design strategy, what should the retailer's optimal strategy be regarding pricing, quality, and product offering? (3) How would the cost structure, designer's ability to influence design, and innovation uncertainty affect the product design strategy choice? The answers to these questions should not only provide some guidelines for fashion retailers to make strategic and operational decisions related to product design but also shed light on the choice of supply chain structure and market competition strategies.

In order to reflect the motivating example from the fast-fashion industry and address the above-mentioned questions, we model a fashion retailer that is making a one-time decision on the product design strategy for the next selling season. The retailer considers two potential strategies: (1) a manual design that leads to predictable market acceptance and (2) an AI-assisted design with associated market risk. In particular, we assume that the consumers' valuation of the enhanced product is affected by two key attributes. The first attribute is *product quality*, which can be measured by the product's longevity (e.g., quality of stitching, thread count, fabric). The level of product quality improvement can be determined by the retailer in a continuous range. As a result, the retailer may choose different levels of product quality improvement under different design strategies. The second attribute is *product trendiness*, which is reflected by how popular or acceptable the newly designed product is to consumers in the market. The acceptance can be predicted based on the design style, new materials used, or colors used, for example. The manual (or humans) only and the AI-assisted design approaches lead to different natures of product trendiness. Specifically, we assume that the traditional manual design can predict well how trendy or popular the new product is. Hence, the trendiness attribute under the manual design is deterministic. However, given the uncertain nature of the AI-assisted design technology and the needed coordination between human designers and the adopted technologies, as indicated by the preceding motivating examples, the trendiness of the new product designed under the AI-assisted approach is assumed uncertain. The issue of design enhancement for short-lived fashion products has been previously explored in the literature; see, for example, Cachon and Swinney (2011). Different from the existing fashion retail research, which usually assumes that the design enhancement would result in a deterministic increase in product quality and market acceptance, our paper explicitly models the uncertainty in product trendiness, which is a crucial determining factor in how fashion retailers enhance an existing product.

Specifically, we consider a model setting where the fashion retailer makes decisions in two stages. In the first stage, the retailer selects which design strategy to use, followed by the decision on the corresponding level of product quality improvement. If the AI-assisted approach is adopted, we assume that the level of the quality improvement decision needs to be made before observing uncertainty in the newly designed product's trendiness, given the fact that quality improvement is part of the product design that happens before the market acceptance of the new design is known. Note that if one of the two design strategies is chosen, there is a fixed design cost associated with such a strategy, irrespective of whether and at what volume the enhanced product will be produced/sold in the subsequent stage. Certainly, the retailer always has an option not to enhance the existing product if, for example, the fixed cost coefficient is too large, which leads to no enhancement being the best strategy for the retailer. If this is the case, then the retailer would sell the existing product. Note also that given the amount of labor, time, and financial requirements involved in each design strategy, we assume that the retailer will not have the capacity to develop both the manual and the AI-assisted design strategies to enhance the existing product.

In the second stage, if the manual design is adopted in the first stage, the retailer immediately sets the selling price, as there is no uncertainty involved in this setting, and every step can be fully anticipated and calculated. However, if the AI-assisted design is used, then the uncertain product trendiness is realized at the beginning of the second stage, which can be either high if the enhanced product is popular with high acceptance in the market or low if the enhanced product is unpopular with low market acceptance. Depending on the realized value of trendiness, the firm decides whether to sell the product at a full or markdown price or abandon selling the enhanced product (in which case the retailer may or may not have the flexibility to sell the existing product). After all decisions are made, customers' demand is realized. The retailer then produces the product accordingly, which incurs the marginal production cost that is dependent on the level of quality improvement chosen in the first stage. Finally, sales occur, and the firm's profit is generated. Note that under the innovative design, the assumption that the retailer can set the retail price and production quantity after observing product trendiness is applicable to the fast-fashion industry, where a critical element of quick response is the shortened production lead time; see, for example, Cachon and Swinney (2011). The shortened lead time for production is also supported by a recent McKinsey report (Business of Fashion and McKinsey & Company 2022) that indicates the trend for fast-fashion retailers/brands to implement near- or reshoring of manufacturing. Analysis of our model framework demonstrates the following main findings/insights.

First, decomposition of the fixed design cost and the variable marginal production cost leads to opposite effects of these costs on the retailer's optimal design strategy. When human designers have similar impacts on the two design strategies, which implies an equal level of expected trendiness of the enhanced products under the two strategies, the manual design is preferred more by the retailer if the fixed design cost carries more weight, whereas the AI-assisted design is preferred more if the marginal production cost carries more weight. This finding leads to the managerial insight that high-quality clothing items such as suits may be better suited for manual design, whereas lower value items such as tops or shorts may be better suited for AI-assisted design.

Second, relative to the manual design with deterministic market acceptance, the AI-assisted design with uncertain market acceptance is more preferred, as the uncertainty in product trendiness increases. This is due to the significant upside benefits when the innovative design turns out to be popular and has a high market acceptance. This finding leads to the managerial insight that AI-assisted design is better suited for fashion sectors where uncertainty in product trendiness is high, such as those targeting young people. In comparison, clothing items targeted at older people tend to have lower uncertainty in product trendiness and may be better suited for manual design.

Third, these results are robust regardless of whether the retailer has the flexibility to abandon the enhanced product and offer the existing product instead when the newly designed product under the AI-assisted approach turns out to be unpopular and has a low market acceptance. This shows that managers should add AI-assisted design for certain items even when product lead times are long. However, the role that human designers play under the two different design strategies imposes a significant impact on how the marginal production cost affects the retailer's optimal choice of the design strategy.

The rest of this paper is organized as follows. In Section 2, we review related literature. In Section 3, we describe the model and specify the objective functions under both designs. In Section 4, we carry out the analysis for each design strategy and examine the firm's preference in the base model where the human designer's impact is the same on both designs. In Section 5.1, we relax two model assumptions: unequal designer impact in Section 5.1 and no flexibility in offering the existing product if the design under the AI-assisted approach is unpopular in Section 5.2. We state conclusions, managerial insights, and future research directions in Section 6.

2. Literature Review

First, our paper is related to the literature on operations management for the fast-fashion system. Caro and Gallien (2007) model the dynamic product assortment decisions, where the fashion retailer delivers a fixed number of products in each period to learn customers' preferences. Caro and Gallien (2012) propose a price markdown optimization model whose validity has been tested using a field experiment. Boada-Collado and Martínez-de-Albéniz (2020) show that demand for fashion products is positively affected by the store inventory display. Long and Nasiry (2022) examine the environmental consequences of fast-fashion retailing by taking into account decision variables such as product quality, variety, and inventory. Cachon and Swinney (2011) develop a two-period model that combines the critical elements of quick response (i.e., shortened production lead time) and enhanced product design (i.e., a deterministic increase in product valuation) in fast-fashion retailing. They find that the joint implementation of these features leads to synergistic outcomes. Our paper contributes to the existing literature by capturing the firm's design strategy choice (i.e., manual versus AI-assisted design). We characterize conditions under which each strategy is more likely to be adopted by the retailer while taking into account key elements in fast-fashion retailing, such as markdown sales and product abandonment. We also explore the different effects of the cost structure and the designer's influence on whether to adopt the AI tools in design.

Second, our paper also contributes to the literature that studies the use of AI in retail operations. Prior research has shown that AI can deliver value in various contexts, including wholesale pricing (Cui et al. 2022), inventory management (van Donselaar et al. 2010), and product recommendations (Häubl and Trifts 2000). However, studies have also shown that decision makers may deviate from AI inferences. The literature classifies such behavioral deviations into *information deviation*, which occurs when users deliberately ignore AI prescriptions, and *complexity deviation* when users fail to understand AI prescriptions (Sun et al. 2022). In terms of product design, both deviations may cause a reduction in designer performance, resulting in flawed designs. Indeed, recent studies have found that restaurant owners deviate from the routing rules prompted by AI (Tan and Staats 2020); packing workers may choose boxes larger than the size suggested by AI, causing waste and efficiency loss (Sun et al. 2022). We add to this literature by studying the impact of AI on the fast-fashion retailer's design strategy. Our result shows that the innovation uncertainty caused by AI integration is a determining factor in how fashion retailers make their design choices.

Third, our paper contributes to the quality choice literature, which focuses on how firms choose different quality levels to segment consumers with different willingness to pay for quality. The early work can be traced back to, for example, Mussa and Rosen (1978) and Moorthy and Png (1992). Since then, many features that can potentially influence the quality choice have been explored, including the cost structure (Bhargava and Choudhary 2001, 2008), product cannibalization (Desai 2001), the structure of distribution channels (Xu 2009), and production technologies (Chen et al. 2013, 2017). A common feature of most papers in this literature stream is that they model product quality as a deterministic attribute. Few papers, however, model product quality to be influenced by an uncertain, external factor. For example, Bernstein et al. (2022) study the problem where a retailer must make quality variation decisions for sequential product deliveries, where the consumers obtain dual sources of utility from both an uncertain product quality attribute and a service quality attribute. Feldman et al. (2019) model the overall quality of an experience good as a mix of an endogenous attribute (determined by the firm) and an exogenous and uncertain attribute (determined by nature). Our paper considers a product enhancement from two key attributes: quality and trendiness, where quality is a decision variable chosen by the retailer and the nature of product trendiness is contingent on which of the two design strategies to be adopted. We explicitly evaluate the critical trade-off of risks and benefits of adopting AI technologies in the fashion industry.

Finally, the product enhancement problem is also studied in operations management through product upgrading. The extant literature usually focuses on whether the current version of the product should be made available together with the new and upgraded version (Lim and Tang 2006, Liang et al. 2014), on the firms' pricing strategies (Kornish 2001), or on the impact of product characteristics (Bala and Carr 2009) and used goods markets (Yin et al. 2010). Our model considers unique features for fashion retailing (e.g., innovation uncertainty, AI-assisted design, markdown sales, and sales abandonment) that affect whether the firm should forgo the enhancement opportunity.

3. Model Framework

A fast-fashion retailer considers enhancing a product for the next selling season. Consumer valuation of the product is affected by two main attributes-namely, *quality* and *trendiness*. The quality attribute can be reflected by the product's longevity such as material qualities, fabric, and stitching. The trendiness attribute can be reflected by product styles, new materials, and colors, for example. The firm can set quality as a decision variable, whereas the nature of the product trendiness is defined by how acceptable/popular the enhanced product is to consumers in the market, which is contingent on the design strategy that the retailer would adopt. There are two potential design strategies that the firm can consider in enhancing the existing product. One strategy is the traditional way of design that only involves human designers. We assume that the popularity of the enhanced product under this traditional manual design can be predicted relatively well. Hence, the trendiness attribute under this approach is modelled as a deterministic factor. The other strategy is nontraditional (or innovative) in the sense that it involves both human designers and AI-assisted technologies in product design. On one hand, this new design approach might create an enhanced product that turns out to be highly popular and leads the fashion trend in the market. On the other hand, it might end up with a new product that is unpopular given the uncertain nature of the new approach and the much needed coordination between human designers and technologies to ensure its success, as discussed in the introduction. In view of this, we model the product trendiness under the AI-assisted strategy as a random variable that can be either high or low, which represents the popular (with high market acceptance) and unpopular (with low market acceptance) status of the enhanced product.

To facilitate an understanding of the retailer's optimal design strategy for product enhancement and the subsequent quality and pricing decisions, we propose a stylized economic model. We first describe the sequence of events (see Figure 1) and then characterize the demand and profit functions, which will be further analyzed in the next section.

3.1. Sequence of Events

Following Figure 1, the first decision that the firm makes is to choose which design strategy to use to enhance its existing product. Depending on this strategic decision, some operational decisions will follow, including quality improvement, the selling price, and whether to mark down the retail price, for example. We describe the sequence of events separately under a chosen product design.

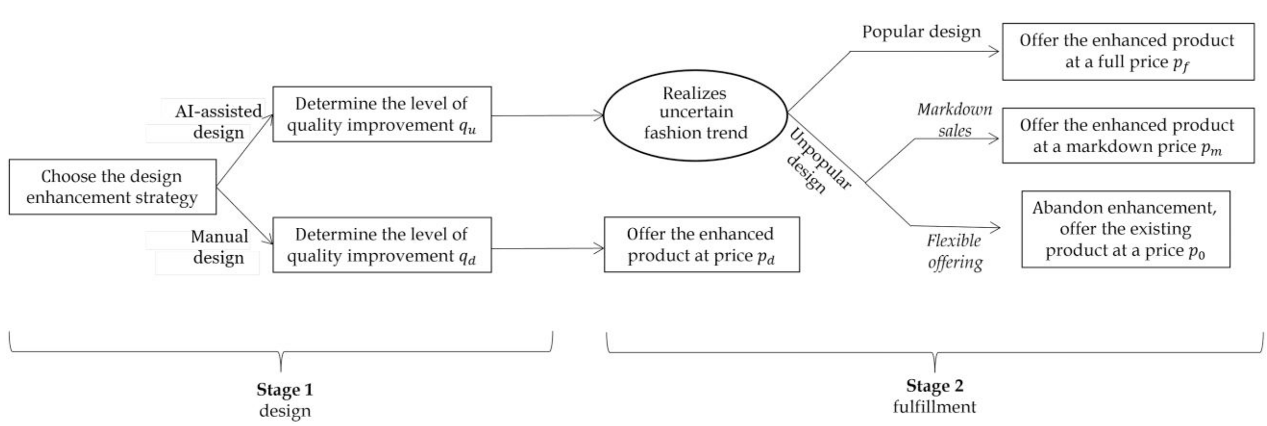
- *Manual/deterministic design*: The sequence of events, in this case, follows the bottom branch in Figure 1 and is quite straightforward. In the first stage, the firm specifies the level of quality improvement, q_d. The combination of the chosen quality improvement level and the deterministic product trendiness, measured by t_d, leads to an increase in consumer utility and also incurs a fixed design cost. In the second stage, the retailer subsequently sets a corresponding retail price, p_d, for the enhanced product sold in the market, where subscript d represents the deterministic market outcome. Accordingly, the market responds and leads to a sales quantity or demand. Because of the deterministic nature of this case, if the firm decides to set $q_d = 0$, this essentially means that the firm decides not to enhance the existing product and offer the original or existing product.
- *AI-assisted/uncertain/innovative design*: The sequence of events under this design strategy follows the top branch of Figure 1, and it is more complicated because of the uncertain nature of product trendiness, which is measured by $\tilde{t}$. For simplicity, we assume that $\tilde{t}$ follows a two-point distribution (i.e., a high or low status), measured by $t_u + \theta$ (which implies a situation of popular design) or $t_u - \theta$ (which implies a situation of unpopular design), respectively, with equal probabilities. Parameter t_u captures the human designer's impact on product trendiness, and parameter θ measures the impact of AI on product trendiness, and we assume that $\theta \in [0, t_u]$. According to the introduction as well as our model formulation, the involvement of AI is a double-edged sword to product trendiness, so θ also captures the magnitude of innovation uncertainty.

  (1) In the first stage, the firm decides to improve product quality by q_u. This decision is assumed to be made before product trendiness uncertainty is revealed, because quality improvement is considered to be part of the product design, which happens before the retailers observe the market acceptance of the new design, because of, for example, the lead time needed for the retailers to secure raw materials required. A fixed design cost is incurred when the quality choice decision is made and in expectation of uncertain product trendiness.

  (2) In the second stage, the value of product trendiness is revealed, which can be either high or low. Contingent on the chosen quality improvement level and the high or low product trendiness, the firm can decide whether to offer the enhanced or the existing product and its corresponding retail price. Specifically, under the high level of trendiness, $\tilde{t} = t_u + \theta$, the firm sets p_f when the enhanced product is sold at full price, and the subsequent model analysis indicates that the enhanced product will always be offered if the AI-assisted design is popular, as long as the marginal production cost is not too high. Under a low level of trendiness, $\tilde{t} = t_u - \theta$, the firm either sets the markdown price p_m for the enhanced product or abandons the new design completely and sells the existing product at p_0. The market then responds, and demand is realized for the product sold in the market.

We make a few assumptions under the AI-assisted design. One is that, in the second stage, the retailer can decide to offer the enhanced or the original product and the corresponding pricing and production decisions *after* the realization of the uncertain trendiness. In the fashion industry, it is very common that fashion retailers constantly do sample runs of new products to test the market acceptance and to learn the market trend and pivot their product offerings, pricing, and inventories strategies. Also, relative to decisions on design strategy and quality, pricing and production can be considered as operational decisions that can be made or adjusted rather quickly, especially in the fast-fashion industry. According to a recent McKinsey report on the state of fashion (Business of Fashion and McKinsey & Company 2022), there is a trend for fast-fashion

Figure 1. Sequence of Events



retailers/brands to implement near- or reshoring of manufacturing to shorten the production lead time, especially for retailers that implement quick response strategies (Cachon and Swinney 2011). This assumption also provides model tractability, which allows us to focus on the impact of costs and innovation volatility on the retailers' choice of design strategy. Another assumption is that the retailer has an option to sell the original product if the new design turns out to be unpopular in the second stage. Note that this assumption is different from the retailer's option of not enhancing the product at all at the beginning of the first stage. What is assumed here is that the retailer has the ability to secure the production of the original product in the last minute without a lead time. This applies to the situation where the retailer understands the uncertainty involved in the innovative design and hence prepares to adopt back the original product if needed, given the previous experience and expertise of offering the product. This assumption helps us streamline the model analysis. However, the case where the retailer does not have this flexibility is also considered and analyzed in the model extensions section (Section 5.2), where we show that the results are qualitatively consistent in models with or without this flexibility.[1]

Under both designs, recall that the firm will produce according to the market demand for the type of product offered. Following the sequence of events, one key differentiation between the two designs is worth noting. For the manual design, the initial decision on quality improvement directly indicates whether the firm will offer an enhanced product or the original product in the end. That is implied by whether $q_d > 0$ or $q_d = 0$. It is never optimal for the firm to initially set a positive quality improvement level $q_d > 0$ and later decide to offer the existing product (because this is dominated by setting $q_d = 0$ in the beginning to save the design cost). However, for the AI-assisted design, depending on the realization of product trendiness, it might benefit the firm to offer the existing product later (with no quality improvement) even if the firm previously set a positive quality improvement level, $q_u > 0$, and paid the design cost. This may happen when the realized value of product trendiness turns out to be quite low. In Section 5.2, we explore an alternative scenario where the firm is not allowed to use the existing product to replace the enhanced product under the AI-assisted design. Finally, we assume that $t_d \in [t_u - \theta, t_u + \theta]$ to avoid noninteresting cases where one design is always dominant. For ease of reference, a summary of the notation used in this paper is presented in Online Appendix A.

3.2. Demand Characterization

Before we characterize the firm's profit function, it is important to understand how consumers react to the quality improvement (if any), product trendiness, and retail price. Here, we adopt a commonly used demand model where the overall demand is determined as follows:

$$Demand = a + quality\ improvement \cdot product\ trendiness - retail\ price, \tag{1}$$

where parameter a is positive and measures the baseline market demand if the firm offers the original product at a zero price. Note that the increase of consumer utility on the original product as a result of product enhancement is measured by the multiplication of the quality improvement and trendiness attributes given their interconnected influence on the product. The multiplicative form also enables a closed-form solution in the model analysis. The actual demand function is specific to which design is adopted and the subsequent decisions made in the process:

- Under the manual design, we have the product's enhancement expressed as $q_d t_d$ and retail price as p_d. So following Equation (1), the overall demand can be rewritten as

$$Demand = a + q_d t_d - p_d. \tag{2}$$

It is clear that the existing product is sold if the firm sets $q_d = 0$.

- Under the AI-assisted design, the overall product enhancement and retail price are contingent on the realization of product trendiness and on whether the firm chooses to offer the enhanced or the existing product:

$$Demand = \begin{cases} a + q_u(t_u + \theta) - p_f \\ \quad \text{if } \tilde{t} = t_u + \theta \text{ and the enhanced product is sold,} \\ a + q_u(t_u - \theta) - p_m \\ \quad \text{if } \tilde{t} = t_u - \theta \text{ and the enhanced product is sold,} \\ a - p_0 \\ \quad \text{if the existing product is sold,} \end{cases} \tag{3}$$

where p_0 represents the base retail price when there is no quality improvement (or it is the selling price of the existing product), p_f represents the full retail price, and p_m represents the markdown sales price.

In the base model, we assume that the human designer's impact on both designs is the same (i.e., $t_d = t_u$). This further leads to the observation that the deterministic model becomes a special case of the uncertain model with $\theta = 0$. This can also be easily verified from the demand functions in (2) and (3). For clarity, in Section 4, we will still analyze the base model under the manual design in addition to the analysis of the AI-assisted design. Note that in the extended model considered in Section 5.1 where $t_d \neq t_u$, the deterministic model is no longer a special case of the uncertain model. With the demand function, we can derive the firm's profit function and its optimization problem(s) involved in the decision process.

3.3. Firm's Profit Function

Following the structure of demand characterization, we present the firm's profit function and its optimization problems separately in deterministic and uncertain cases.

Under *manual design*, the firm sets the level of quality improvement and the selling price. Because there is no further information gained or no other events occurring in between the two decisions, it is mathematically equivalent for the firm to set both q_d and p_d at the same time to maximize the following profit function, where the constraints are imposed to ensure the nonnegativity of decisions, demand, and profit margins:

$$\begin{aligned} &\underset{q_d, p_d}{\text{Maximize}} \quad \Pi_d = (\overbrace{a + q_d t_d - p_d}^{\text{market demand}}) \cdot (\overbrace{p_d - c q_d}^{\text{unit profit}}) - \overbrace{d q_d^2 t_d^2}^{\text{design cost}} \\ &\text{subject to} \quad q_d \geq 0 \text{ and } \; c q_d \leq p_d \leq a + q_d t_d. \end{aligned} \tag{4}$$

There are two sets of cost information that need to be discussed. The first cost is the marginal cost in producing one more improved product. In order to reflect the fact that producing a higher-quality product requires more resources, the marginal production cost is assumed to be proportionally increasing in the level of quality improvement. That is measured by cq_d. This also applies to the AI-assisted design's case. The effect of a quadratic marginal cost function will be discussed in Section 5.

In addition to the marginal production cost, the second type of cost is the design cost associated with the overall product enhancement, which is characterized by $dq_d^2 t_d^2$, where d is a positive design cost coefficient. This design cost is incurred during the first stage and hence not related to the number of units produced. The quadratic function implies that the benefits from higher values of quality and trendiness are increasingly costly. This function form has been widely used in literature for development-intensive products; see, for example, Krishnan and Zhu (2006). The increasing difficulty in designing a trend-setting, high-quality product has also been observed in the fashion retail industry. Indeed, much time, energy, and creativity is required when a highly fashionable design goes into product development, and a high-quality product design requires special labor and/or machines to test new product styles, materials, colors, and the like and to also determine the best fit of material quality, the fabric type, stitching methods, and similar considerations (Westling 2018). Hence, this fixed design cost is a function of the effort spent in both quality improvement and trendiness exploration. Finally, there is no design cost if the retailer offers the original product because, by definition, both attributes q_d and t_d represent levels of product enhancement, which are 0 for the original product.

Under *AI-assisted design*, according to the sequence of events presented earlier, the firm's decisions can be framed as a two-stage optimization problem where the standard backward induction approach can be used to solve for the optimal decisions. Specifically, we can consider the design strategy and quality improvement decisions made before the uncertain trendiness realization as the first-stage decision and the retail pricing (and the production volume) decision made after trendiness realization as the second-stage decision. In solving the problem, we apply backward induction. We first solve the second-stage pricing problem (knowing the level of quality improvement and the realized value of product trendiness). Then, we solve the first-stage quality improvement decision, anticipating the best-response functions (in terms of pricing) in the second stage and in expectation of the uncertainty in trendiness. The detail is presented as follows.

- In the second stage, the quality improvement q_u is known, and the value of trendiness is realized. If the resulting design is popular (i.e., $\tilde{t} = t_u + \theta$), *and* the firm decides to sell the improved product, then the firm sets a full price p_f to maximize its profit obtained only in this stage (because the profit/cost incurred in the first stage is sunk):

$$\begin{aligned} &\underset{p_f}{\text{Maximize}} \quad \Pi_f^{\text{stage 2}} = [\overbrace{a + q_u(t_u + \theta) - p_f}^{\text{market demand}}] \cdot (\overbrace{p_f - c q_u}^{\text{unit profit}}) \\ &\text{subject to} \quad c q_u \leq p_f \leq a + q_u(t_u + \theta), \end{aligned} \tag{5}$$

where the constraints are applied to guarantee nonnegative demand and profit margins. Similarly, if the design is unpopular (i.e., $\tilde{t} = t_u - \theta$), *and* the retailer decides to offer the improved product, then the retailer sets a markdown price p_m to maximize its profit obtained only in this stage:

$$\begin{aligned} &\underset{p_m}{\text{Maximize}} \quad \Pi_m^{\text{stage 2}} = [\overbrace{a + q_u(t_u - \theta) - p_m}^{\text{market demand}}] \cdot (\overbrace{p_m - c q_u}^{\text{unit profit}}) \\ &\text{subject to} \quad c q_u \leq p_m \leq a + q_u(t_u - \theta). \end{aligned} \tag{6}$$

However, if the retailer chooses to instead offer the original product, then the retailer sets p_0 to maximize $\Pi_0 = (a - p_0)p_0$, which is concave in p_0 with a global optimal $p_0^* = a/2$ and a corresponding optimal profit $\Pi_0^* = a^2/4$.

- In the first stage, anticipating the best-response pricing functions, $p_f^*(q_u)$, $p_m^*(q_u)$ and $p_0^* = a/2$, and in expectation of the uncertain trendiness, the retailer sets the level of quality improvement, q_u, to maximize its *expected* profit:

$$\underset{q_u}{\text{Maximize}} \quad E(\Pi)$$

$$= \frac{1}{2}\max\{\overbrace{[a + q_u(t_u + \theta) - p_f^*(q_u)] \cdot [p_f^*(q_u) - cq_u]}^{\text{offer the enhanced product under popular design}}, \overbrace{\frac{a^2}{4}}^{\text{offer the existing product}}\}$$

$$+ \frac{1}{2}\max\{\overbrace{[a + q_u(t_u - \theta) - p_m^*(q_u)] \cdot [p_m^*(q_u) - cq_u]}^{\text{offer the enhanced product under unpopular design}}, \overbrace{\frac{a^2}{4}}^{\text{offer the existing product}}\}$$

$$- \overbrace{dq_u^2(t_u^2 + \theta^2)}^{\text{design cost}}$$

$$\text{subject to} \quad q_u \geq 0. \tag{7}$$

In our setting, AI-assisted design is a form of distributed design, in which the design work is split across multiple parties (Caetano and Amaral 2011). Consistent with the literature (Bala et al. 2014), the design cost is modeled as $dq_u^2(t_u^2 + \theta^2)$, which reflects both the designer's impact (captured by t_u^2) and AI's impact (captured by θ^2) on the design. The quadratic functional form is consistent with that in the manual design's case. Indeed, a highly fashionable AI-assisted design requires much human creativity and significant improvements in the AI model's accuracy, which are increasingly difficult to obtain (Song et al. 2020).

By comparing the fixed design costs under the manual and AI-assisted design strategies, given in Equations (4) and (7), respectively, we note that when an innovative product and a base product possess the same level of quality and (expected) trendiness, designing an innovative product leads to a higher fixed cost relative to a base product.

4. Model Analysis

In this section, we will individually solve for the optimal decisions under the manual and AI-assisted designs, assuming both designs have an equal expected trendiness, and then compare the firm's optimal profits under the two designs to understand the firm's best product enhancement strategy. We start the analysis of the manual/deterministic case in Section 4.1.

4.1. Model Analysis Under Manual Design

Recall that the firm's problem is presented in Equation (4). Note from our model analysis that the design cost coefficient d needs to be relatively high so that the firm's optimal level of quality improvement is not unbounded (or infinite). Specifically, in this deterministic model, we assume $d > d_0$, where $d_0 = (t_d - c)^2/(4t_d^2)$ when $0 < c \leq t_d$ and $d_0 = 0$ when $c \geq t_d$, to ensure the optimal improvement on quality and the firm's optimal profit is finite. Accordingly, it is straightforward to show that the firm's profit function is jointly concave in (q_d, p_d) with a unique global optimal solution. The following proposition summarizes the optimal solution to the firm's problem under the manual design. All the technical proofs are presented in Online Appendix B.

Proposition 1 (Optimal Quality and Pricing Decisions Under Manual Design). *Under the manual design, the firm's optimal quality improvement level and retail price are as follows:*

- *The firm will serve a quality-improved product to the market if the marginal production cost of quality improvement is relatively low (i.e., when $0 \leq c \leq t_d$). The optimal level of quality improvement and price are, respectively,*

$$q_d^* = \frac{a(t_d - c)}{4dt_d^2 - (t_d - c)^2} \text{ and } p_d^* = \frac{a(-c^2 + ct_d + 2dt_d^2)}{4dt_d^2 - (t_d - c)^2}.$$

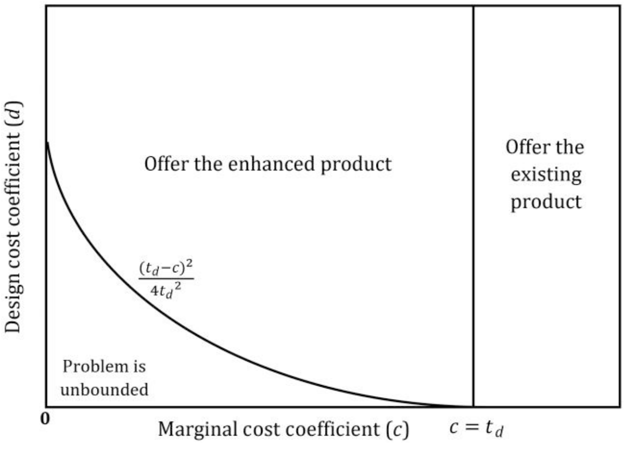
Accordingly, the firm's optimal profit is

$$\Pi_d^* = \frac{a^2 dt_d^2}{4dt_d^2 - (t_d - c)^2}.$$

- *Otherwise, when the marginal cost is high (i.e., $c \geq t_d$), the firm will serve the existing product without improving its quality. So $q_d^* = 0$, $p_d^* = p_0^* = a/2$, and $\Pi_d^* = \Pi_0^* = a^2/4$.*

A visual presentation of Proposition 1 is also given in Figure 2 on a (c, d) plane. Following this figure and also from the optimal solution, we can make a number of observations. First of all, the optimal level of quality improvement is getting smaller as either the marginal production cost coefficient c or the design cost coefficient d increases. In other words, higher costs deter quality improvement. Second, as the product trendiness t_d increases, the firm is more likely to serve the enhanced product to the market.

Figure 2. Optimal Quality/Product Decision Under Manual Design



4.2. Model Analysis Under AI-Assisted Design

Because the sequence of events in this case is more involved, the analysis is also more complicated. We start with the firm's pricing problems in the second stage and then backtrack to the first stage's quality improvement problem. In the second stage, given the level of improvement on quality, q_u, the state-contingent optimal pricing decision is summarized in Lemma 1.

Lemma 1 (Optimal Type of Product Offered and Its Pricing Under AI-Assisted Design). *Under the AI-assisted design, given the quality improvement level q_u, the optimal type of product offered and its retail price are dependent on the realized value of trendiness $\tilde{t}$ as follows:*

- *If the marginal cost coefficient is small (i.e., $0 \le c \le t_u - \theta$), the firm offers the improved product regardless of the realized state of trendiness. The corresponding price is $p_f^* = 1/2[a + q_u(c + t_u + \theta)]$ if the design is popular or is $p_m^* = 1/2[a + q_u(c + t_u - \theta)]$ if the design is unpopular.*
- *If the marginal cost coefficient is medium-sized (i.e., $t_u - \theta \le c \le t_u + \theta$), the firm offers the improved product at $p_f^* = 1/2[a + q_u(c + t_u + \theta)]$ if the design is popular and offers the existing product at $p_0^* = a/2$ if the design is unpopular.*
- *If the marginal cost coefficient is large (i.e., $c \ge t_u + \theta$), the firm offers the existing product at $p_0^* = a/2$ regardless of the realized state of trendiness.*

The insight behind Lemma 1 is as follows. Let us first understand how the firm can make a nonnegative profit by selling an improved product. First of all, both the market demand, $a + \text{quality improvement} \cdot \text{trendiness} - \text{retail price}$, and the marginal profit, $\text{price} - \text{marginal cost}$, need to be nonnegative. When the marginal cost is on the high side, there is no feasible price that generates a positive profit. So offering the improved product cannot lead to a nonnegative profit (even without taking into account the sunk design cost incurred in the first stage). Thus the only option is for the firm to continue to offer the existing product. Similarly, even if the marginal cost is only moderate but the design turns out to be unpopular, the firm faces the same dilemma in that the retail price needs to sufficiently low to generate positive sales but also needs to be high enough to cover the production cost. In that situation, the firm will again abandon the enhanced product and keep the existing product in the market. The understanding of these insights has significant influence on how the firm would set its level of quality improvement of the existing product in the first stage.

In the first stage, knowing the distribution of the uncertain trendiness and anticipating the best reactions in the second stage, the firm will now set the quality improvement level. Similar to the deterministic model, we first impose a lower bound on the coefficient in the design cost (i.e., $d > d_1$) in order to ensure the optimal level of improvement on quality, and the firm's optimal profit will be bounded (or finite).[2]

Proposition 2 (Optimal Quality Improvement Under AI-Assisted Design). *Under AI-assisted design, the firm's optimal level of quality improvement is characterized as follows (see Figure 3).*

- *Region (a) with a small marginal cost coefficient* (i.e., $0 \le c \le t_u - \theta$): *In stage 1, the firm's optimal quality improvement level is*

$$q_u^* = q_a = \frac{a(t_u - c)}{4d(t_u^2 + \theta^2) - (t_u - c)^2 - \theta^2}.$$

In stage 2, the firm offers the improved product regardless of the state of trendiness-namely, the markdown sales strategy. Its profit is

$$\Pi_{II}^* = \frac{a^2\left(\theta^2 - 4d\left(t_u^2 + \theta^2\right)\right)}{4\left(c^2 - 2ct_u - (4d - 1)\left(t_u^2 + \theta^2\right)\right)}.$$

- *Region (b) with a medium marginal cost coefficient* (i.e., $t_u - \theta \le c \le t_u + \theta$): *In stage 1, the firm's optimal quality improvement level is*

$$q_u^* = q_b = \frac{a(t_u + \theta - c)}{8d\left(t_u^2 + \theta^2\right) - (t_u + \theta - c)^2}.$$

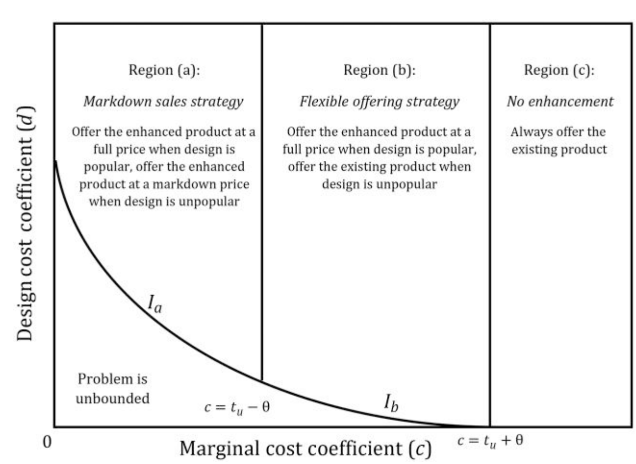
In stage 2, the firm offers the improved product if the design is popular and offers the existing product if the design is unpopular-namely, the flexible offering strategy. Its profit is

$$\Pi_{IE}^* = \frac{a^2\left(c^2 - 2c(\theta + t_u) + (1 - 16d)\theta^2 + (1 - 16d)t_u^2 + 2\theta t_u\right)}{8\left(c^2 - 2c(\theta + t_u) + (1 - 8d)\theta^2 + (1 - 8d)t_u^2 + 2\theta t_u\right)}.$$

- *Region (c) with a high marginal cost coefficient* (i.e., $c \ge t_u + \theta$): *It is too costly for the retailer to improve product quality. So $q_u^* = 0$, and the retailer offers the original product to get a profit of $a^2/4$.*

By Lemma 1 and Figure 3, we can conclude that all the three scenarios stated in Lemma 1, in terms of the

Figure 3. Optimal Quality/Product Decision Under AI-Assisted Design



product offering strategy, can be optimal depending on the model parameters. Proposition 2 further characterizes the corresponding level of quality improvement as well as the optimal profit in each scenario. There are a number of points that worth noting about this result.

First of all, by following the expression of the optimal level of quality improvement, q_u^*, it is straightforward to show that q_u^* always decreases in the marginal production cost coefficient c or in the design cost coefficient d. This observation is quite intuitive but important to understand the three regions presented in the aforementioned result.

Let us start with region (c), where the marginal cost coefficient is high, $c \geq t_u + \theta$. The outcome in this region is quite intuitive because it is too costly to produce the enhanced product. So it is natural for the firm to choose not to perform quality improvements on the existing product. As the marginal cost parameter c decreases, we move to region (b), where the firm is more willing to design a quality-improved product in the first stage. However, such investment is only intended for the scenario where the AI-assisted design turns out to be a "hit." Indeed, a high level of trendiness serves as a multiplier in front of the improved product quality (as indicated in the demand function in Equation (3)), which leads to high demand and benefit from offering the enhanced product. If the design turns out to be unpopular, then according to Lemma 1, the firm cannot find any price to guarantee positive sales profit if it sells the enhanced product. In this case, it is best for the firm to forgo the enhanced product and offer the existing product instead. This strategy is also known as the flexible offering strategy. Finally, note that the existence of region (b) requires θ to be strictly positive. That is, $\theta > 0$. If $\theta = 0$, then it is clear that this region is gone, and the model is degenerated to a deterministic model, where Figure 3 is also reduced to Figure 2 under the manual design.

Now, let us consider region (a), where the marginal production cost is low, $0 \leq c \leq t_u - \theta$. The low marginal cost enables the firm to offer the enhanced product even if the resulting design is unpopular-that is, adopt the markdown sales strategy. So the firm will always design a higher level of quality improvement in the first stage (compared with what is offered in region (b) at the same design cost coefficient d) and then offer the improved product in the second stage regardless of trendiness realizations.

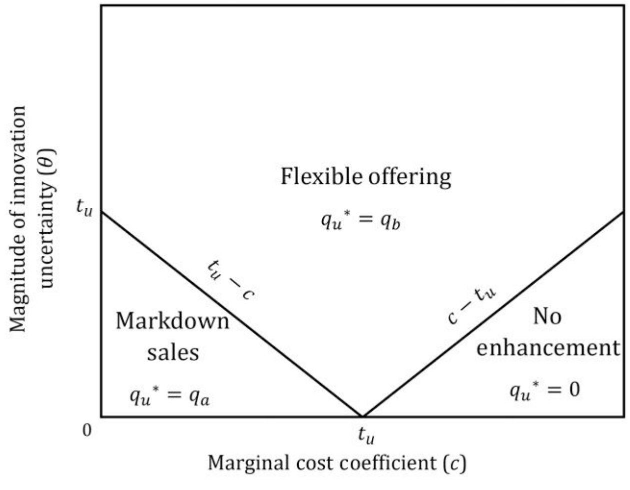
Recall that the firm ultimately needs to choose between the manual and the AI-assisted design. The main difference between the two designs is that the latter is associated with uncertainty. So in order to solve the firm's design enhancement problem, it is important to understand how innovation uncertainty affects the firm's optimal decisions and profit. According to the distribution of product trendiness (i.e., $\tilde{t} = t_u + \theta$ or $\tilde{t} = t_u - \theta$ with equal probabilities), parameter θ measures the magnitude of innovation uncertainty. Proposition 2 and Figure 3 immediately lead to the following result in terms of the effect of θ on the firm's optimal product offering strategy.

Proposition 3 (Effect of Innovation Uncertainty on the Product Offered Under AI-Assisted Design). *The firm adopts the flexible offering strategy if the magnitude of innovation uncertainty* (*i.e.,* $\theta \geq |t_u - c|$); *otherwise, the firm adopts the markdown sales strategy if marginal cost coefficient is small* (*i.e.,* $c \leq t_u$) *and does not offer product enhancement if marginal cost coefficient is large* (*i.e.,* $c \geq t_u$), *regardless of trendiness realization. See also Figure 4.*

Here is an explanation on why the flexible offering strategy is used when θ is high. Recall that the level of product enhancement is measured by $q_u(t_u + \theta)$ under the popular design and by $q_u(t_u - \theta)$ under the unpopular design, where the realized value of trendiness serves as a multiplier that can influence the benefit of the improvement on quality. When θ is sufficiently high, it motivates the firm to increase the level of quality improvement in the first stage because the firm knows that the potential benefit of quality improvement is amplified under a fashionable design in the second stage. The effect of θ on the firm's optimal product offering strategy helps us interpret its effect on the firm's optimal profit in the following result.

Proposition 4 (Effect of Innovation Uncertainty on the Firm's Optimal Profit Under AI-Assisted Design). *Under AI-assisted design, the firm's optimal profit increases in* θ, *the innovation uncertainty, except when design cost carries sufficient weight* (*i.e.,* $d \geq \underline{d} = 1/4$), *and the level of uncertainty is small* (*i.e.,* $\theta \leq t_u - c$), *in which case the firm's profit decreases in* θ.

Figure 4. Effect of Innovation Uncertainty on the Product Offered Under AI-Assisted Design



The explanation of the effect of θ on the firm's profit in Proposition 4 is based on the effect of θ on the firm's product offering strategy in Proposition 3. Let us first consider the case when $c \geq t_u$. Proposition 3 indicates that the firm offers the existing product when θ is low, for either state of trendiness, and it uses the flexible offering strategy when θ is high. Clearly, in the low θ case, the firm's profit is independent of θ. In the high θ case, the firm always benefits from an increase in θ. This is because the firm offers the improved product only if the design turns out to be popular, and the product value increases in θ as a result of $\tilde{t} = t_u + \theta$. Note that if the design turns out to be unpopular, θ does not affect the firm's profit because the existing product is offered.

Now, consider the case when $c \leq t_u$. Proposition 3 indicates that the firm offers the enhanced product when θ is low, regardless of the realization of trendiness, and it uses the flexible offering strategy when θ is high. For the high θ case, we can follow a logic similar to the one we used previously for the case when $c \geq t_u$ to conclude that the firm's profit increases in θ. For the low θ case, the firm sells the quality-improved product regardless of fashion trends' realization. In this case, an increase in θ is a double-edged sword. On one hand, if the design is popular ($\tilde{t} = t_u + \theta$), a higher θ leads to higher demand and hence benefits the firm more. On the other hand, if the design is not popular ($\tilde{t} = t_u - \theta$), it is the opposite: a higher θ leads to lower demand and hence harms the firm more. Note that in this case, a low d leads to a high improvement on quality, q_u, and moreover, $q_u^* = q_a$ increases in θ when $d \leq 1/4$. So when d is low, because product trendiness serves as a multiplier to improvement on product quality (see the demand function in Equation (2)), as θ increases, its benefit on demand as a result of the popular design outweighs its harm as a result of the unpopular design. Together with the relatively low design cost, the firm benefits from an increase in θ when d is low. However, as d increases, q_u becomes lower. Because q_u^* is also decreasing in θ (when $d \geq 1/4$), its multiplier effect is reduced. Together with high design cost, the harm of an increase in θ on the firm's profit is higher than its benefit. As a result, the firm's profit decreases in θ. In the next subsection, it will become evident that this understanding of the effect of θ on the firm's profit plays a significant role in the firm's optimal product design strategy.

4.3. The Optimal Design Strategy Under Equal Designer Impact

We are now ready to analyze the firm's different product enhancement design by comparing the optimal profits under both strategies. To make the comparison valid, we focus on regions where the optimal level of quality improvement under both designs are bounded (i.e., $d > \max(d_0, d_1)$). In the base model, because we assume the designer exerts an equal impact on both designs (i.e., $t_d = t_u$), neither design has any (dis)advantage on product trendiness in expectation. Consequently, the firm's design choice is largely influenced by the effect of innovation uncertainty θ on the firm's optimal profit, presented in Proposition 4. Recall from Propositions 1 and 2 that when the marginal cost coefficient is sufficiently large, $c \geq t_u + \theta$, the firm will not improve the product quality under either design, and the existing product will be served. In this case, the choice of product design is irrelevant. So we focus on the case where $c \leq t_u + \theta$ in the following proposition.

Proposition 5 (Firm's Design Strategy for Product Enhancement). *The firm's preference over the two designs is as follows (see also Figure 5):*

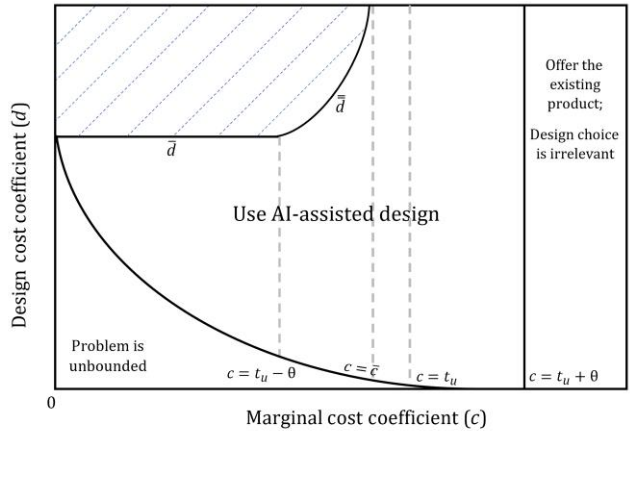
(1) *For a sufficiently small marginal cost coefficient (i.e., $0 \leq c < \bar{c}$) where $\bar{c} < t_u$ $(= t_d)$, there exists a threshold value, $\tilde{d}$, such that the retailer prefers the AI-assisted design if the design cost coefficient, d, is below this threshold (i.e., $d \leq \tilde{d}$), and the retailer prefers the manual design otherwise.*[3] *Moreover, $\tilde{d}$ is (weakly) increasing in c.*

(2) *For a sufficiently high marginal cost (i.e., $\bar{c} \leq c \leq t_u + \theta$), the retailer prefers the AI-assisted design.*

Proposition 5 directly indicates that the manual design is favorable when the design cost coefficient d is high and the marginal cost coefficient c is low. This further implies the opposite impact of the marginal production cost and the design cost on the firm's design strategy choice, where high design cost encourages the manual design and high marginal cost favors the AI-assisted design (if the design cost does not carry too much weight). The explanation for this result stems from the product offering strategy adopted in the uncertain model (presented in Figure 3) together with the effect of innovation uncertainty on the firm's profit.

Consider first the case when the marginal cost is low-that is, when $c \leq t_u - \theta$. Under the AI-assisted design,

Figure 5. The Optimal Design Strategy Under Equal Designer Impact ($t_d = t_u$)



according to Figure 3, this case falls in region (a), and the firm always provides the enhanced product regardless of trendiness realization. Under the manual design, according to Figure 2, the firm also offers the enhanced product. Indeed, the deterministic model is a special case of the uncertain model with $\theta = 0$. In the uncertain model, according to Proposition 4 and the discussion thereafter, we observe that an increase in θ may benefit or harm the firm's profit, depending on whether realized trendiness is high or low. The discussion there further indicates that, for a sufficiently low design cost coefficient d $\left(\text{i.e., } d \le \tilde{d} \;\left(=\overline{d} = 1/4\right)\right)$, the benefit of a higher θ outperforms its harm, which leads to an overall benefit to the firm. Hence, the firm favors the AI-assisted design with $\theta > 0$. On the other hand, when $d \ge \tilde{d}$, it is the opposite, and a higher θ results with a net harm to the firm, and the firm would prefer the manual design with $\theta = 0$.

Consider next the case when the marginal cost is moderate-that is, when $t_u - \theta \le c \le t_u\ (= t_d)$. Note that this case requires $\theta > 0$. Under the AI-assisted design, according to Figure 3, this case falls in region (b), and the firm adopts the flexible offering strategy, which implies that the enhanced product is offered if the resulting design is popular and the existing product is sold if the resulting design is unpopular. Under the manual design, Figure 2 indicates that the firm always offers the enhanced product. In this case, essentially, we compare an uncertain model with $\theta > 0$ that offers an (improved/existing) product and a deterministic model that offers a quality-improved product. Our analysis shows that, similar to the low marginal cost case, there exists a threshold value, $\tilde{d} = \overline{\overline{d}}$, such that the AI-assisted design is favored if $d \le \tilde{d}$ and the manual design is preferred otherwise.

This result can be explained based on the logic behind the firm's choice on the quality improvement level. In the uncertain model, the quality improvement q_u determined in the first stage has two direct impacts on the firm's profit. One is through the design cost incurred in the first stage, $dq_u^2(t_u^2 + \theta^2)$. The other is through consumer demand (or utility) in the second stage. As a result of the flexible offering strategy, its impact on the consumer's demand (or utility) is measured by $q_u(t_u + \theta)$ only when the realized trendiness is high. Note that the existing product is offered when the design turns out to be unpopular and hence q_u is not relevant. This allows the firm to be able to improve the product quality much more significantly in the uncertain model than that in the deterministic model as long as the design cost does not carry too much weight. Consequently, it leads to a much higher increase in consumer demand and in the firm's profit than that in the deterministic model. Hence, the AI-assisted design is preferred. However, as d increases to become quite high (i.e., when $d \ge \overline{\overline{d}}$), the improvement on q_u in the uncertain model is constrained because of the high design cost, which further limits the increase in consumer demand and the firm's profit. This makes the uncertain model lose its advantage, and the firm would adopt the manual design instead.

Moreover, in the case when $t_u - \theta \le c \le t_u\ (= t_d)$, our analysis shows that the threshold value for the design cost coefficient, $\overline{\overline{d}}$, exists only when $t_u - \theta \le c < \overline{c}$ $(< t_u)$. Otherwise, when $c \ge \overline{c}$, AI-assisted design always dominates the manual one regardless of the level of the design cost coefficient. Also, we show that $\overline{\overline{d}}$ increases in c in its relevant range. This implies that a higher marginal cost makes the AI-assisted design more favorable. Recall that in the scenario when $\overline{\overline{d}}$ is applicable, the flexible offering strategy is adopted under the uncertain model and an improved product is offered under the deterministic model. As the marginal cost c increases, with AI-assisted design, the firm can still be quite aggressive in terms of setting a high level of quality improvement. This is because the enhanced product is offered only when the product trendiness turns out to be high. However, with manual design, the improved product is always offered, which causes the quality improvement to be more significantly restricted as the marginal production cost increases relative to the AI-assisted design. Consequently, as marginal cost c increases, AI-assisted design is more likely to dominate.

The effect of high c on the firm's design choice continues to the case when c increases beyond t_u. That is, when $t_u \le c \le t_u + \theta$, AI-assisted design always dominates manual design. Note that in this case, the firm will not improve the product quality at all for the manual design (see Figure 2), which is clearly dominated by the AI-assisted design, because no enhancement is always an option in the uncertain model.

Finally, the effect of innovation uncertainty θ on the firm's design strategy is summarized in the following proposition. This result immediately follows Proposition 4.

Proposition 6 (Effect of Innovation Uncertainty on the Firm's Design Strategy). *As the level of innovation uncertainty θ increases, it is more likely for the firm to adopt the AI-assisted design.*

An intuitive explanation for this result is that a higher level of innovation uncertainty, combined with higher product quality, gives the firm a significant upside advantage when the resulting design is popular. An alternative approach to understanding this effect is from Proposition 4. Note from this proposition that the firm's profit under the AI-assisted design is always increasing in θ, except when $d \ge \overline{d} = 1/4$ and $c \le t_u - \theta$. Putting aside the exceptional area, because the firm's profit increases in θ under the AI-assisted design and its profit is irrelevant to θ under the manual design, it is apparent that AI-assisted design is more likely to be preferred as θ increases. Now, consider the exceptional case where the firm's profit decreases in θ. Following from Figure 5, the manual design always dominates in this region. As θ increases, this region becomes smaller, implying that manual design's dominance becomes less likely.

5. Model Extensions

In this section, we briefly discuss our extension of the base model by relaxing two assumptions. Section 5.1 considers a case where human designers may have different impacts under the two design strategies. Section 5.2 considers an alternative model where the retailer does not have the flexibility to offer the original product if the newly designed product under the innovative design is unpopular. For consideration of space, the details of these extensions are presented in Online Appendix C.

5.1. The Model with Unequal Designer Impact

So far, we have assumed that the designer has an equal impact on both designs (i.e., $t_d = t_u$), and neither design has a (dis)advantage on product trendiness in expectation. As a result, the focus is on how uncertainty and cost structure affect the firm's decisions. When we extend the model to relax the assumption of equal trendiness, which allows $t_d \neq t_u$, the firm's design strategy will also be impacted by the differences in the designer's ability to influence design.

The analysis of the extended model leads to several observations. Here, we focus on the effect of the marginal cost on the firm's design choice. When the marginal cost is high, it is consistent with the base model that a higher marginal cost makes the AI-assisted design more likely to be dominant. However, when the marginal cost is low, different from the base model, the effect of a higher marginal cost on the firm's optimal design strategy is actually contingent on the relationship between t_d and t_u. Specifically, an increase in the marginal cost works in favor of a design when such a design has a higher designer impact.

5.2. Alternative Model Without Flexible Product Offering

In the previous analysis, we have assumed that when the AI-assisted design turns out to be unpopular, the retailer has the flexibility to instead offer the original product (with no enhancement) to the market. In this section, we explore a scenario where the flexible offering strategy is unavailable. That is, when the enhanced design turns out to be a "miss," the retailer may be forced to abandon product sales.

The analysis of the extended model without the flexible offering option indicates that the main findings in the base model with the option still hold true. First of all, the manual design is only preferred when the design cost coefficient is sufficiently high. Second, the effect of the design cost on the firm's design choice decisions in the extended model is consistent with its effect in the base model. Finally, a higher level of innovation uncertainty would still give the firm more advantage when the design is popular, even when the flexible offering option is not available. As a result, the AI-assisted design is more likely to dominate.

Finally, it is worth noting that in our model setting so far, we adopt a linear marginal cost because the quadratic fixed cost structure already helps remove the risk of unbounded profit. To further check the robustness of our main results with respect to this linear marginal cost function, we numerically carry out an analysis of the base model where we replace the linear marginal cost (e.g., cq_d under the base design) with a quadratic marginal cost function (e.g., cq_d^2). Fortunately, under the wide range of parameter values that we explore, our analysis shows that the main results of the base model are qualitatively valid. For example, the threshold policy of the firm's preference over the two design strategies in Proposition 5 of the base model still holds. That is, there exists a threshold value for the fixed cost coefficient such that the retailer prefers the AI-assisted design if the design cost is below this threshold, and the retailer prefers the manual design otherwise. For another example, the effect of level of innovation uncertainty in the AI-assisted design in Proposition 6 of the base model is also valid for a quadratic marginal cost. That is, as the level of innovation uncertainty increases, it is more likely for the firm to adopt the AI-assisted design.

6. Discussions, Conclusions, and Future Research

Product design is the engine of fashion. In this fast-paced and competitive industry, retailers engage in "time-based competition" to constantly enhance their existing products for the upcoming selling season, and AI is transforming the very nature of how they design the enhanced products. Upon gathering granular consumer data, fashion manufacturers are training AI models to augment the designers' understanding about consumers' fashion needs. At the same time, existing studies have shown that designers may deviate from AI's prescriptions for reasons such as information overload and lack of confidence in AI. Consequently, the use of AI in design is often associated with significant innovation uncertainty. In this paper, we explore how a fast-fashion retailer should choose between using manual design and AI-assisted design to enhance existing products. The overall design enhancement is affected by two key attributes. The first attribute is *product quality*, which is the firm's decision variable. The second attribute is *trendiness*, which measures the market acceptance of the newly designed product. The two design strategies are differentiated by the trendiness attribute, as the integration of AI causes product trendiness to be uncertain a priori. Our analysis shows that in the base model when the human designer has the same impact on both designs, manual design is preferred when the design cost carries more weight, whereas AI-assisted design is preferred when the production cost carries more weight. We also show that when the human designer has more impact on the manual design than on the AI-assisted design, the impact of the production cost on the design strategy is no longer monotonic. Finally, a higher level of innovation uncertainty actually makes the AI-assisted design more likely to be a dominant strategy. These results imply that when fashion retailers choose the design approach, they need to be mindful of the design cost structures, uncertainty involved in adopting new AI technologies, and the coordination/potential conflicts between human designers and the AI tools. In addition, the chosen design strategy also imposes some subsequent actions. For example, if innovative design is adopted and the retailer would like to have the flexible product offering option, then the retailer needs to keep the supply chain of the original product in close contact so that this option is viable if needed.

In our main model, the key results are obtained under the assumption that when the AI-assisted design is unpopular, the firm has the flexibility to offer the existing product (with no enhancement) to the market. As a robustness check, we also explore an alternative model where this "flexible offering strategy" is disabled, and the firm may only mark down the enhanced product or abandon product sales if the AI-assisted design is unpopular. This alternative model makes sense especially because, oftentimes, there only exists a one-time inventory procurement opportunity in fast-fashion retailing as a result of short product life cycles, and quick response strategies may be too costly. The detailed analysis shows that the key results about the impact of design cost and innovation uncertainty on design strategy choice remain unchanged. We now confirm that even without the option value from the "flexible offering strategy," the AI-assisted design may dominate the manual design because of the popular design's significant upside benefits.

Our theoretical findings also shed light on how to implement AI strategies in practice. For example, given equal human designer impact, AI-assisted design is preferred when the marginal cost carries sufficient weight. This implies that formal rather than casual clothes might be more suitable for AI-assisted design. For formal clothes, the upside gains of a popular design would be significantly amplified. Indeed, it is observed that an increasing number of bridal designers are turning to AI tools to offer alternative styles or even customization for gowns (Business of Fashion and McKinsey & Company 2018). Second, our study suggests that the decision makers should be cautious about the human designer's actual impact on the design project. Existing empirical studies have found that AI assistance lowers the designer's mental demand and creates an illusion of success (Zhang et al. 2021). As a result, designers may be less motivated to get involved in the design project. According to our study, reduced human effort under the AI-assisted design would change the conditions under which the AI-assisted design is used.

There are several valuable future research directions to extend our research. First, a direct extension of our paper can be a competition model. That is, there could be multiple firms that need to either simultaneously or sequentially determine which design to adopt, given the trade-offs considered in this paper. The outcome will not only shed light on each firm's product decisions but also carry implications for social welfare because both firms' design choices jointly affect the overall level of innovation. Second, in the current paper, we assume that AI has an identical impact on trendiness in both popular/high and unpopular/low states with equal probabilities. It is worthwhile to explore the situation where we still have two states but with different levels of increase and decrease in trendiness and with different probabilities for the two states. Finally, our model assumes a make-to-order scenario, which is realistic given the quick response system widely used in the fast-fashion industry. Future works may consider inventory decisions when analyzing the optimal design strategy in different retail settings.

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Endnotes

[1] We thank an anonymous referee for suggesting that we extend the base model to a case where the retailer does not have the flexibility of selling the original product when the innovative design is unpopular in the market.

[2] If $0 \le c \le t_u - \theta, d_1 = I_a = \frac{(t_u - c)^2 + \theta^2}{4(t_u^2 + \theta^2)}$; if $t_u - \theta \le c \le t_u + \theta, d_1 = I_b = \frac{(t_u + \theta - c)^2}{8(t_u^2 + \theta^2)}$; and if $c \ge t_u + \theta, d_1 = 0$. Furthermore, $I_a = I_b$ when $c = t_u - \theta$ and $I_b = 0$ when $c = t_u + \theta$.

[3] Note that $\tilde{d} = \overline{d} = \frac{1}{4}$ when $c \le t_u - \theta$ and $\tilde{d} = \overline{\overline{d}} = \frac{(c - t_u)^2 (t_u + \theta - c)^2}{4\theta^2(4c^2 - 8ct_u + 3t_u^2) + 8\theta t_u^2 (c - t_u) + 12 t_u^2 (c - t_u)^2}$ when $t_u - \theta \le c \le \overline{c}$, where $\overline{\overline{d}}$ always increases in c in this range, and $\overline{d} = \overline{\overline{d}}$ when $c = t_u - \theta$. Note also that $\overline{c}$ is the left root of the quadratic function, $4\theta^2(4c^2 - 8ct_u + 3t_u^2) + 8\theta t_u^2(c - t_u) + 12t_u^2(c - t_u)^2$, the denominator of $\overline{\overline{d}}$.

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