Luxury Exclusivity in the Digital Age: A Conjoint Analysis

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Abstract

The rising digitization of consumer markets has led luxury brands to adapt their traditionally exclusive identities to online spaces that democratize consumer access to luxury, reshaping both the luxury playbook and the ways these brands engage with consumers. This study investigates how different digital marketing strategies shape consumer preferences for luxury brands, and how these preferences vary across consumer demographics of age, income, and gender. Using a choice-based conjoint study administered to a panel of 260 U.S. luxury consumers, we quantify consumer trade-offs among key attributes of digital marketing strategies. Specifically, we decompose the digital strategies of luxury brands into five attributes: online product availability, adoption of advanced technologies, exclusivity of digital communities, type of influencer partnership, and level of social media interaction. To analyze preferences, we estimate two hierarchical Bayesian models: a baseline pooled model without covariates, and a second model that incorporates covariates to account for demographic effects. Model comparison metrics favor the inclusion of covariates, supporting their importance in explaining preference heterogeneity. Our analysis suggests that consumers generally prefer larger online catalogs, technology-enhanced experiences, and exclusive digital communities. These preferences, however, vary across demographic segments. Specifically, higher-income, younger, and male consumers favor smaller, more limited online catalogs, whereas lower-income, older, and female consumers prefer more expansive digital access to luxury goods. The findings offer valuable insights into luxury consumer behavior and provide guidance for luxury brand managers in balancing exclusivity with the opportunities of digital expansion.

Keywords: luxury goods, exclusivity, digital marketing, conjoint analysis, hierarchical Bayes, demographic heterogeneity

1. Introduction

Luxury brands have long been symbols of exclusivity, quality, and status. The rapid digitization of consumer markets, however, has compelled these traditionally conservative industries to adapt to a more inclusive and democratized online environment—broadening luxury access to a wider, mass-market audience. This shift raises critical questions about how luxury brands can maintain their exclusive image and a sensory-rich, personalized shopping experience while engaging with a new generation of consumers accustomed to digital interactions.

Slow adopters of digital mediums, luxury brands have only relatively recently begun embracing social media and establishing online identities as they adapt to changing trends in consumers' shopping habits. Whereas other retail industries adopted e-commerce strategies in the 1990s, many luxury brands did not make a big push for online retailing until around 2010 (Clifford, 2010). The global market value of luxury e-commerce has steadily grown each year to $76 billion and makes up 20% of total personal luxury good sales worldwide in 2024, up from 9% in 2019 (Statista, 2019, 2023, 2024). Digital channels open up not only additional avenues for marketing and distribution but also access to large-scale consumer data and new platforms for creative engagement (Baker Retailing Center, 2016). Tapping into this increasingly important channel for sales, luxury brands are exploring ways to replicate the luxury experience online, whether by creating sensory-rich experiences through high-production storytelling or building curated online communities open only to an exclusive group.

Online channels present luxury brands with new opportunities for differentiation. Indeed, there are noticeable differences in the approaches brands are taking towards digital marketing. For example, some brands like Rolex do not sell their products online while other brands like Gucci offer a wide product line for sale on their website. A traditional luxurist may expect Gucci's inclusive strategy to dilute the brand's value as a symbol of prestige and exclusivity; however, Gucci has remained a top luxury brand with a growing brand value. Burberry offers another compelling approach, having embraced digital early through innovative campaigns and cross-channel initiatives that have become core to its brand positioning. Other differences manifest in how brands approach exclusivity in digital spaces, ranging from invite-only online forums to open-access events. Similarly, brands differ in their adoption of technology, with some leveraging AI and AR to create immersive, personalized experiences, while others prioritize human-driven interactions. It is not clear a priori which strategies best support luxury brand positioning, highlighting the need for a deeper understanding of how consumer perceptions of luxury brands are affected by their digital marketing. Specifically, they raise important questions about whether inclusivity and accessibility necessarily undermine exclusivity, or whether certain digital strategies can enhance a brand's prestige while broadening its reach.

At the same time, luxury brands are grappling with how to best appeal to the varied tastes and expectations of their consumer base, which is diverse in age, income, and gender. In particular, tech-savvy younger consumers who grew up in a digital age are an increasingly important segment of luxury consumers: by 2030, Gen Z is expected to account for 25–30% of luxury market purchases with millennials contributing 50–55% (D'Arpizio et al., 2024). Older generations represent a potentially contrasting segment that continues to value exclusivity, craftsmanship, and timeless design (Chandon et al., 2016). This generational divide creates a unique challenge for luxury brands: how to balance the needs of younger consumers who seek digital engagement with the expectations of older consumers who may favor traditional luxury hallmarks. Successfully navigating these dynamics requires strategies that integrate modern digital tools while preserving the heritage and exclusivity that define luxury.

Accordingly, our research aims to address the following two questions:

1. How do different approaches to digital marketing shape consumer preferences for luxury brands?

2. How do preferences for digital marketing strategies differ by consumer demographics, such as income, age, and gender?

Using a choice-based conjoint analysis, we quantify consumer preferences for various attributes of digital marketing strategies. By collecting data on survey respondents' demographic characteristics, we assess how these preferences differ among consumer groups. In exploring these questions, this study contributes to the broader literature on luxury branding and deepens our understanding of digital-driven shifts in luxury consumer behavior.

The remainder of the paper is organized as follows. Section 2 provides an overview of the literature on the consumption and digital marketing of luxury products. Section 3 discusses our conjoint survey design, data, and estimation of preferences. Findings are presented in Section 4 and discussed in Section 5 along with managerial implications and limitations. Section 6 concludes.

2. Literature Review

2.1. Luxury consumption

Luxury brands are distinguished by their ability to confer social status and personal prestige to their consumers (Han et al., 2010; Vigneron and Johnson, 1999; Bagwell and Bernheim, 1996), who perceive these products or services as exclusive, of high quality, and having a prestigious market image (Ko et al., 2019; Phau and Prendergast, 2000). This social theory of luxury traces its roots to the idea of conspicuous consumption proposed by Veblen (1899), wherein individuals consume highly visible goods to signal wealth and status to others. Through the consumption of luxury brands, individuals communicate their identity as members of certain desirable groups (Berger and Ward, 2010; Charles et al., 2009). Past work has also shown that these brands resonate emotionally with luxury consumers, satisfying psychological desires for hedonistic gratification (Hagtvedt and Patrick, 2009), social recognition (Nia and Lynne Zaichkowsky, 2000), and self-esteem (Truong and McColl, 2011). As such, these goods are not solely characterized by their functional utility—they also carry significant symbolic utility for their consumers derived from their exclusivity as markers of wealth and status (Bagwell and Bernheim, 1996; Amaldoss and Jain, 2005; Liu et al., 2022, 2024).

To reinforce exclusivity, luxury brands have traditionally adopted strategies that control product access and create scarcity (Phau and Prendergast, 2000). Limited-edition releases, long wait times, and selective distribution channels are all methods used to heighten consumer perceptions of rarity and privilege (Keller, 2017; Kapferer and Bastien, 2017), while marketing campaigns are strategically crafted to amplify this sense of exclusivity (Pollay, 1984). The sensory and experiential aspects of luxury retailing also play a crucial role, with in-store environments carefully crafted to evoke emotional responses and reinforce brand prestige (Atwal and Williams, 2009). These established methods are designed to engage consumers on a deeper, more personal level, fostering brand loyalty and enhancing perceived value.

Consumer preferences in luxury often vary by demographics, including income, age, gender, and cultural background (Husic and Cicic, 2009; Eastman et al., 2020; Stokburger-Sauer and Teichmann, 2013; Phau and Prendergast, 2000). For example, older and higher-income consumers may prioritize exclusivity and craftsmanship, while younger, tech-savvy consumers may seek digital engagement and brand storytelling (Chandon et al., 2016). This segmentation within luxury consumers highlights the importance of demographic factors in understanding shifts in the luxury market, particularly as brands adapt to engage with newer consumer segments.

2.2. Digital marketing in luxury

The digital era presents both an opportunity and a challenge for luxury brands, as online platforms inherently promote accessibility and inclusivity—dynamics that could potentially conflict with traditional luxury values (Dall'Olmo Riley and Lacroix, 2003; Chandon et al., 2016). Initially, luxury brands hesitated to adopt digital strategies due to concerns that broader accessibility might dilute exclusivity and remove consumers from sensory-rich shopping experiences (Hennigs et al., 2012). However, as consumer expectations for online engagement grew, luxury brands began experimenting with social media and digital marketing. These strategies have included social media marketing, digital storytelling, and e-commerce (Arrigo, 2018; Creevey et al., 2022; Ko et al., 2016; Üçok Hughes et al., 2016). Nevertheless, a content analysis of 92 luxury brand websites by Baker et al. (2018) reveals substantial heterogeneity in the way different firms have embraced digital marketing. For example, some brands only use their digital presence to communicate product information while others also sell products online.

Recent literature has suggested positive benefits to consumer relationships from social media marketing. Focusing on attributes such as entertainment, customization, interaction, word of mouth, and trendiness in the social media strategies of luxury brands, Kim and Ko (2010, 2012) find that each factor positively influences customer intimacy, trust, and purchase intentions. Similarly, Godey et al. (2016) report positive effects of social media marketing on consumer-based brand equity, noting that it increases brand image, willingness to pay, and brand loyalty. This body of work suggests that digital marketing not only broadens reach but also reinforces luxury values when strategically aligned with brand exclusivity and consumer expectations.

While the adoption of digital marketing by luxury brands has been an active area of research over the past ten years, relatively little empirical work addresses how online strategies affect consumer perceptions of exclusivity. In particular, no work to our knowledge has sought to quantify consumer preferences for the wide array of digital strategies luxury brands could adopt. This study aims to address these gaps using conjoint analysis, as is popular in marketing research seeking to measure consumer preferences for specific product or service attributes (Green and Srinivasan, 1978). We further contribute to the literature on demographic differences in luxury preferences by quantifying heterogeneity in preferences by income, gender, and age. By addressing these research questions, we aim to provide insights into how luxury brands can effectively balance exclusivity with digital reach, contributing to the evolving literature on digital transformation within luxury branding.

3. Materials and Methods

3.1. Conjoint analysis

We use conjoint analysis (Green and Rao, 1971) to measure consumer preferences for the digital marketing strategies of luxury firms. This method models consumer decision-making by viewing digital strategies as a bundle of attributes, each with varying levels. Consumers evaluate and compare these attribute bundles, allowing us to estimate the relative importance of different features and the trade-offs they are willing to make. By identifying relevant attributes and their corresponding levels, we can construct hypothetical bundles derived from the complete set of factorial combinations across all attributes. Consumers are then asked to complete a series of "choice tasks," where they are presented with a small number of hypothetical bundles and asked to select their most preferred bundle. From these data, we can estimate the relative utilities consumers place on each level of the attributes.

A variety of utility and consumer choice models for conjoint analysis have been proposed to formalize the estimation of preferences (Green and Srinivasan, 1978; Marshall and Bradlow, 2002). In line with current practice, we employ a choice-based conjoint (CBC) model (Louviere and Woodworth, 1983) that assumes a random utility model wherein consumer i obtains the following utility from bundle b:

$$U_{ib} = \boldsymbol{\beta}_i^{\intercal} \boldsymbol{x}_b + \varepsilon_i$$

where $\boldsymbol{\beta}_i$ is a vector containing consumer i's part-worth utilities (i.e., attribute importance scores) for different attributes, $\boldsymbol{x}_b$ is a vector describing each attribute in bundle b, and ε_i is a stochastic component. Among all bundle choices $b = 1, \ldots, B$, consumer i chooses the bundle maximizing their utility. The probability p_{ib} that consumer i chooses bundle b is thus governed by a multinomial logit model (Train, 2009):

$$p_{ib} = \frac{\exp(\boldsymbol{\beta}_i^\intercal \boldsymbol{x}_b)}{\exp(\boldsymbol{\beta}_i^\intercal \boldsymbol{x}_1) + \cdots + \exp(\boldsymbol{\beta}_i^\intercal \boldsymbol{x}_B)} = \frac{\exp(\boldsymbol{\beta}_i^\intercal \boldsymbol{x}_b)}{\sum_{j=1}^{B} \exp(\boldsymbol{\beta}_i^\intercal \boldsymbol{x}_j)}$$

Further distributional assumptions on $\boldsymbol{\beta}_i$ relevant to the estimation of part-worths are described in Section 3.3.

3.2. Survey design

We now identify and explain the attributes and levels used in our survey. To determine the attributes, we explored the websites, social media presence, and digital strategies of ten of the top luxury brands (Porsche, Louis Vuitton, Chanel, Gucci, Hermès, Christian Dior, Cartier, Rolex, Tiffany & Co., and Burberry), taking note of the experience, features, and digital offerings used by these firms. This analysis was supplemented with case studies and industry reports to gather additional information on digital marketing trends in the luxury industry. Capturing the major differences and features of approaches to digital marketing among luxury brands, we identified a list of five attributes, each with 2 or 3 levels, as outlined in Table 1. In total, there are $3 \times 3 \times 3 \times 2 \times 3 = 162$ possible strategy bundles.

Table 1: Attributes and levels.

Attribute	*Level 1*	*Level 2*	*Level 3*
(A) Online product availability	Exclusively in-person	Partial online catalog	Extensive online catalog
(B) Technology use	Minimal	Moderate	Advanced
(C) Digital communities	None	Open	Exclusive
(D) Influencer strategy	Elite	Diverse	—
(E) Social media interaction	Minimal	Moderate	High

Online product availability refers to the degree to which the brand's product line is available for online purchase and delivery through the brand's website. The three levels are "Exclusively in-person," "Partial online catalog," and "Extensive online catalog." For example, Rolex does not allow consumers to purchase their watches online (a level of "exclusively in-person"): consumers can look at and find information about watches on the website, but purchases must be completed through a physical Rolex Jeweler. Chanel embodies a "partial online catalog," offering only items like fragrance and cosmetics for online sale but not any fashion products. On the other hand, Gucci offers an "extensive online catalog"—ranging from fragrances and jewelry to ready-to-wear collections and handbags.

Technology use is concerned with the extent to which a luxury brand integrates advanced digital technologies, such as augmented reality (AR), artificial intelligence (AI), or blockchain-based assets (e.g., non-fungible tokens, or NFTs), into its online consumer experience. The three levels are "Minimal," "Moderate," and "Extensive." Hermès, for instance, exhibits a "minimal" level of technology use, relying on traditional craftsmanship storytelling rather than integrating digital innovations. Burberry, on the other hand, represents an "extensive" approach by offering virtual AR try-on features, AI-powered chatbots, and blockchain-backed digital certificates that authenticate ownership and document the provenance of individual items, while also leveraging AI to provide hyper-personalized shopping experiences based on customer data. Other brands like Louis Vuitton use a "moderate" level of technology, experimenting with virtual try-on and NFT products but maintaining a primarily traditional retail experience rather than fully embracing digital transformation.

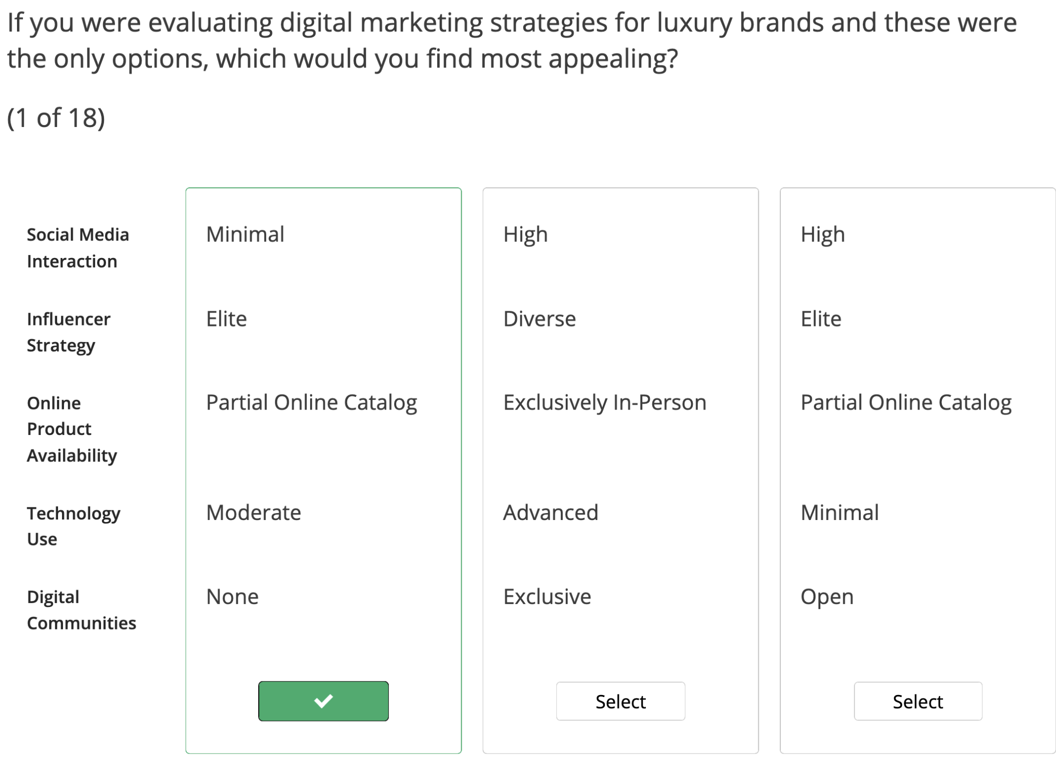
Digital communities covers how luxury brands foster online engagement through digital platforms, forums, or livestream events. The three levels are "None," "Open," and "Exclusive." Louis Vuitton, for example, has a Discord server with certain conversations and exclusive content only open to individuals who hold $41,000 NFTs obtained from the brand's VIA initiative (the "exclusive" level). Other brands are active on social media spaces like Instagram, TikTok, and YouTube, fostering vibrant communities that are open to all (the "open" level). Still other brands—notably Bottega Veneta—are absent from social networks and have minimal brand-curated online community (the "none" level).

Influencer strategy refers to how the luxury brand approaches the promotion of their products through endorsements and partnerships. The two levels are "Elite" and "Diverse." Some brands—such as Patek Philippe—partner exclusively with Hollywood celebrities and other high-profile figures (the "elite") to maintain their aura of exclusivity and align their image with aspirational lifestyles. Other brands are increasingly embracing a more inclusive strategy by partnering with a more "diverse" collection of influencers that engages micro-influencers such as niche fashion bloggers and social media creators in addition to high-profile celebrities. These new digital-era influencers often have a large reach and are well-liked by younger generations.

Social media interaction refers to the level of engagement a luxury brand maintains with its followers through digital platforms, particularly in responding to user-generated content and comments. The three levels are "Minimal," "Moderate," and "High." A brand like Rolex demonstrates "Minimal" engagement, maintaining a curated and controlled online presence with limited interaction with consumers. In contrast, Porsche follows a "Moderate" approach, occasionally engaging with users by resharing content or responding to select comments. Burberry exemplifies a "High" level of interaction, frequently engaging with followers, resharing user-generated content, and leveraging social media trends to drive brand participation.

As is common practice in modern conjoint surveys, we employ a choice-based conjoint (CBC) design (Louviere and Woodworth, 1983) to present choice sets to survey respondents. Each respondent evaluates 18 sets of three strategies, with 16 sets used for estimating preferences and two fixed holdout sets—identical across all respondents—reserved for out-of-sample validation. In each choice task, respondents are asked to select their most preferred bundle among the three. Figure 1 presents an example prompt a respondent may encounter. The 16 choice sets assigned for preference estimation are generated by the Sawtooth Software survey platform to ensure level balance and orthogonality, such that each level appears equally often and is evenly paired with levels from other attributes. The order of attributes shown to respondents is randomized to avoid any order effects.

Figure 1: Example of a conjoint survey task.



3.3. Estimation method

We estimate part-worths using a hierarchical Bayes procedure for choice-based conjoint, as first proposed by Lenk et al. (1996), further developed by Rossi and Allenby (2003), and later implemented for commercial use by Sawtooth Software, Inc. (2021). This method allows us to estimate *individual* part-worths even with relatively little choice data from each individual, thereby explicitly accounting for heterogeneity in consumer tastes.

The model has two levels. In the higher level, individual part-worths $\boldsymbol{\beta}_i$ are drawn from a multivariate normal distribution with mean $\boldsymbol{\alpha}$ and covariance matrix $\boldsymbol{D}$; that is, $\boldsymbol{\beta}_i \sim \mathcal{N}(\boldsymbol{\alpha}, \boldsymbol{D})$. In the lower level, individuals choose among alternative bundles by a multinomial logit model given their part-worths $\boldsymbol{\beta}_i$, as described in Section 3.1.

The estimation of parameters $\boldsymbol{\alpha}$, $\boldsymbol{D}$, and $\boldsymbol{\beta}_i$ are achieved through an iterative Markov chain Monte Carlo (MCMC) process. The procedure begins by initializing each parameter to a value of 0. In each iteration, given values for $\boldsymbol{D}$ and $\boldsymbol{\beta}_i$, a new value for $\boldsymbol{\alpha}$ is drawn from a normal distribution with mean equal to the average $\boldsymbol{\beta}_i$ value and a covariance matrix equal to $\boldsymbol{D}/r$, where r is the number of respondents. Then, given values of $\boldsymbol{\beta}_i$ and the drawn $\boldsymbol{\alpha}$, a new estimate of $\boldsymbol{D}$ is drawn from an inverse Wishart distribution. Finally, given the drawn values of $\boldsymbol{\alpha}$ and $\boldsymbol{D}$, the set of $\boldsymbol{\beta}_i$ is updated using the Metropolis-Hastings algorithm (Metropolis et al., 1953; Hastings, 1970). These steps are iterated several thousand times until optimal convergence is achieved such that there is a high posterior probability that the estimated $\boldsymbol{\beta}_i$'s fits respondent i's choices, given that $\boldsymbol{\beta}_i$ is drawn from the population distribution. Details can be found in the technical report provided by Sawtooth Software, Inc. (2021).

In the demographic heterogeneity analysis, we are interested in whether the covariates of age, gender, and income are predictive of different preferences. Accordingly, covariates can be incorporating into the higher level by including a vector $\boldsymbol{z}_i$ of covariates into the population distribution (Rossi and Allenby, 2003):

$$\boldsymbol{\beta}_i = \boldsymbol{\Theta}^{\intercal} \boldsymbol{z}_i + \boldsymbol{\eta}_i, \quad \boldsymbol{\eta}_i \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{D})$$

where $\boldsymbol{\Theta}$ is a matrix of regression coefficients. This approach induces Bayesian shrinkage of part-worth $\boldsymbol{\beta}_i$ draws toward areas in the population distribution where a higher density of respondents exhibit similar values for the covariates.

3.4. Sample

Our initial sample consists of 302 U.S. consumers who have either purchased or aspire to purchase luxury goods. These consumers represent a broad cross-section of major U.S. geographical regions—including urban, suburban, and rural areas—and exhibit a diverse range of educational backgrounds. The survey was conducted on January 31, 2025, through Pure-Spectrum Marketplace's network of online survey panels, and respondents were compensated for their participation. To ensure that participants read instructions, two attention check questions were included, and respondents were asked about their favorite luxury brands and product categories before the choice tasks to reinforce the saliency of luxury when completing the survey. After data cleaning in accordance with Sawtooth Software's recommended guidelines (Orme, 2019)—in particular, filtering out respondents who exhibited speeding, inattentive or arbitrary responding, or bot-like behavior—the final sample size is 260.

We collected demographic data on respondents' gender, age, and income. Women comprise 51.5% of the sample. In terms of age, most respondents fall into the 25–34 (20.4%), 35–44 (33.1%), and 45–54 (25.0%) age groups. Older (55–64) and younger (18–24) respondents account for 15.8% and 5.8% of the sample, respectively. Household income distribution is similarly varied, with low-income respondents (under $40,000) making up 20.8% of the sample and higher-income respondents (above $160,000) accounting for 11.9%. The rest fall within the $40,000–$80,000 (21.9%), $80,000–$120,000 (30.0%), and $120,000–$160,000 (15.4%) brackets.

4. Results

We estimate and discuss two models. Model 1 is a pooled analysis that does not account for individual-level demographic information. Model 2 incorporates covariates, allowing us to examine how preferences vary across age, gender, and income. 10,000 draws from the Metropolis-Hastings sampler are used for inference after discarding the initial 20,000 draws as a burn-in period to ensure convergence to the posterior distribution (Gelman et al., 1995).

4.1. Pooled analysis

Model 1 estimates consumer preferences by pooling all respondents together, where individual part-worths are drawn from a common upper-level distribution without incorporating demographic data. This model will serve as a baseline measure of preferences before incorporating covariate effects in Model 2. The results highlight general trends in consumer choice across the full sample.

The parameter estimates for Model 1 are reported in Table 2 and Figure 2. Absent covariates, the point estimate of the intercept yields the mean posterior estimates of the corresponding part-worth. We also provide 95% credible intervals—the Bayesian equivalent of confidence intervals—calculated as the range spanning the 2.5^{th} and 97.5^{th} percentiles of the posterior intercept draws. Of the five attributes, online product availability (A), technology use (B), and digital communities (C) exhibit clear preference patterns with significant differences in consumer valuations between the highest and lowest levels[1]. Specifically, consumers show a stronger preference for larger online catalogs, higher levels of technological integration, and exclusive digital communities. In contrast, influencer strategy (D) and social media interaction (E) show more muted effects, with smaller (and possibly insignificant) differences between levels. The relative importance of each attribute, as displayed in Table 2, similarly suggests that attributes A, B, and C have the greatest influence on consumer preferences in the sense that variations in these attributes have the largest effect on customers' choices.

At face value, the strong preference for extensive online catalogs may seem at odds with luxury brands' traditional reliance on exclusivity. However, these results are aggregated and mask potential heterogeneity in consumer preferences, where high-income or status-seeking consumers may still favor restricted access. We explore these nuances further in our upcoming discussion of Model 2. Still, the clear preference for greater online accessibility is notable. One possible explanation is that our surveyed consumers view luxury products more as high-quality goods than as status symbols. For these consumers, accessibility enhances convenience without diminishing the brand's perceived value. Additionally, modern consumers may be more accustomed to seamless e-commerce experiences and expect luxury brands to offer the same level of accessibility as mainstream retailers.

Our results also suggest that greater integration of new technologies and exclusivity in digital communities generate positive utility for consumers. Use of advanced technologies, such as augmented reality (AR) and artificial intelligence (AI), may complement the digital

[1]It is important to note that part-worth values may be compared *within* an attribute but never *between* attributes because utility differences are meaningful only relative to other levels within the same attribute.

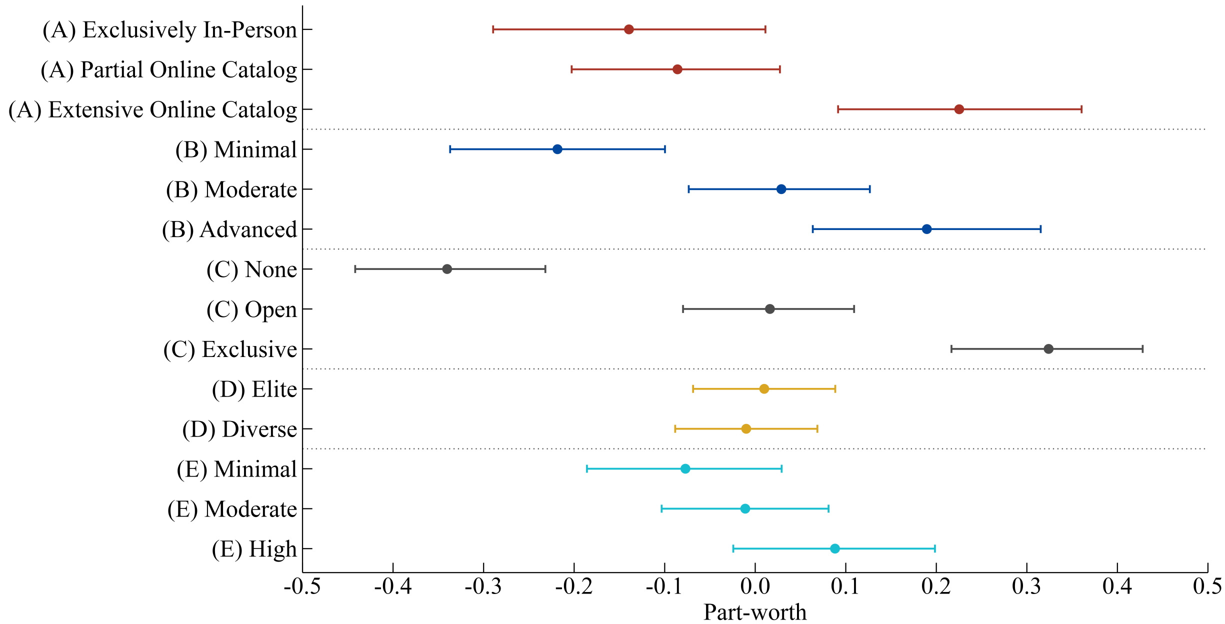
Table 2: Parameter Estimates and Attribute Importance: Model 1.

(Attribute) Level	*Intercept*	*Attribute Importance*
(A) Exclusively In-Person	-0.139	
	[-0.289, 0.011]	
(A) Partial Online Catalog	-0.086	28.828
	[-0.203, 0.027]	
(A) Extensive Online Catalog	0.225	
	[0.092, 0.360]	
(B) Minimal	-0.218	
	[-0.337, -0.100]	
(B) Moderate	0.029	22.411
	[-0.073, 0.127]	
(B) Advanced	0.190	
	[0.064, 0.315]	
(C) None	-0.340	
	[-0.442, -0.232]	
(C) Open	0.016	19.409
	[-0.080, 0.109]	
(C) Exclusive	0.324	
	[0.217, 0.428]	
(D) Elite	0.010	
	[-0.069, 0.088]	
(D) Diverse	-0.010	11.366
	[-0.088, 0.069]	
(E) Minimal	-0.077	
	[-0.186, 0.029]	
(E) Moderate	-0.011	17.986
	[-0.103, 0.081]	
(E) High	0.088	
	[-0.024, 0.199]	

Notes: Table 2 reports point estimates and 95% credible intervals (in brackets) for the part-worths, as given by the intercepts in Model 1. Attribute importances are computed by calculating the range of attribute utilities (difference between the best and worst utilities per attribute) and normalizing them to sum to 100.

luxury experience by enhancing personalization, creating immersive shopping environments, and reinforcing brand prestige through innovative consumer interactions. Moreover, preferences for exclusive digital communities highlight the continued importance of selective access, even in an online environment. These patterns suggest that although accessibility in purchasing may be desirable, elements of exclusivity in brand interactions remain highly

Figure 2: Parameter Estimates: Model 1.



Notes: Figure 2 displays point estimates and 95% credible intervals (whiskers) for the part-worths (intercepts) given by Model 1. Part-worth values may be compared within an attribute but not between attributes.

valued in digital spaces.

While social media and influencer collaborations are important marketing tools, they may be secondary considerations in consumer decision-making compared to attributes that directly shape the luxury experience, such as exclusivity and product availability. Unlike selective online availability or private digital communities, which clearly signal exclusivity, there is no strong expectation that one type of influencer strategy—whether elite endorsements or a mix of micro- and macro-influencers—conveys a more prestigious brand image. Similarly, differences in social media engagement levels may not meaningfully alter perceptions of exclusivity. Given that most luxury brands engage in some form of influencer marketing and social media activity, consumers may see these attributes as standard promotional tools rather than defining elements of a brand's luxury positioning.

4.2. Demographic heterogeneity

We now extend the analysis by incorporating demographic covariates, allowing us to better account for heterogeneity in consumer preferences. By introducing variables such as age, income, and gender, Model 2 enables us to examine how different consumer segments value various aspects of digital luxury strategies, potentially revealing systematic differences in preferences that may be masked in the pooled analysis.

We include the following covariates: gender (dummy-coded, with 1 for female), age (treated as a continuous, mean-centered variable[2]), and income (dummy-coded, with 1 indicating earnings above \$120,000). We dichotomize income at \$120,000—approximately the median household income for luxury consumers and a threshold that places individuals in the top 10% of U.S. earners (Smith and Halpin, 2016)—to distinguish higher- from lower-income respondents. Robustness checks using alternative variable definitions confirm that these choices do not change our qualitative findings (see Appendix).

First, we justify the inclusion of covariates and the modeling of individual heterogeneity through statistical comparisons of Model 2 with two baseline models: Model 1, which employs hierarchical Bayes (HB) estimation but excludes covariates, and Model 3, which is estimated using a multinomial logit (MNL) framework that assumes homogeneous preferences across all individuals (i.e., $\boldsymbol{\beta}_i = \boldsymbol{\beta}$ for all i). In particular, we compare the three models across four measures of fits: McFadden's Pseudo-R^2 (McFadden, 1974), root likelihood[3] (RLH) (Sawtooth Software, Inc., 2021), the Watanabe-Akaike information criterion (WAIC) (Watanabe and Opper, 2010), and the hit rate on holdout tasks. McFadden's Pseudo-R^2 and RLH are in-sample measures of how well the model explains observed choices. WAIC—a generalization of the Akaike Information Criterion (AIC)—is widely used in hierarchical Bayesian settings to balance model fit with effective complexity. To assess out-of-sample predictive accuracy, we use the estimated parameters to predict choices for the two holdout tasks ex-

[2]The data reports age in six categorical buckets. We assign each respondent the median value of their respective age group to construct a continuous age variable.

[3]RLH is computed as $L^{(1/n)} \in [0, 1]$ where L is the likelihood and n is the number of choice tasks completed by respondents. A random model has an RLH of $1/k$, where k is the number of alternatives in each choice task (in our case, $k = 3$), and a perfect model has an RLH of 1.

cluded from model estimation. The performance of Models 1, 2, and 3 on these four measures are presented in Table 3.

Table 3: Measures of Fit.

Model	Description	*McFadden*	*RLH*	*WAIC*	*Hit Rate*
1	HB, no covariates	0.353	0.481	7024.364	0.556
2	HB, covariates	0.362	0.496	7016.907	0.550
3	MNL	0.017	0.340	–	0.404

These fit statistics provide strong evidence that hierarchical Bayes, by accounting for individual-level heterogeneity, achieves markedly superior model fit and out-of-sample predictive accuracy relative to the multinomial logit model, which assumes homogeneous preferences. Additional gains emerge when covariates are incorporated. The modest increases in McFadden's Pseudo-R^2 and root likelihood from Model 1 to Model 2 suggest that covariates contribute meaningful explanatory power. Additionally, the lower WAIC for Model 2 ($\Delta = 7.457$) represents strong support for the improved model fit (Burnham and Anderson, 2004), supporting the inclusion of covariates without introducing unnecessary complexity. While the hit rate on holdout tasks is marginally lower in Model 2, the overall improvements in McFadden's R^2, RLH, and WAIC over Model 1 favor the use of covariates in the model.

Having established that Model 2 better represents consumer preferences by leveraging covariates in explaining individual heterogeneity, we now turn to quantifying the effects of covariates on part-worth estimates. Recall that covariates enter the higher-level population distribution through a regression-type model:

$$\boldsymbol{\beta}_i = \boldsymbol{\Theta}^\intercal \boldsymbol{z}_i + \boldsymbol{\eta}_i, \qquad \boldsymbol{\eta}_i \sim \mathcal{N}(\mathbf{0}, \boldsymbol{D})$$

where $\boldsymbol{\Theta}$ is a matrix of regression coefficients relating covariates $\boldsymbol{z}_i$ to the part-worths $\boldsymbol{\beta}_i$. These coefficients thus capture the influence of individual characteristics on consumer preferences. The posterior means and standard deviations of the coefficients in $\boldsymbol{\Theta}$ for Model 2 are reported in Table 4. To facilitate interpretation, Figure 3 visually depicts mean part-worth estimates for each attribute, distinguishing between low- and high-income earners, younger and older respondents, and male and female consumers. For each covariate, we fix the other two at their mean value to isolate the effect of the focal demographic characteristic.

Model 2 replicates several of the trends observed in Model 1—namely, that luxury con-

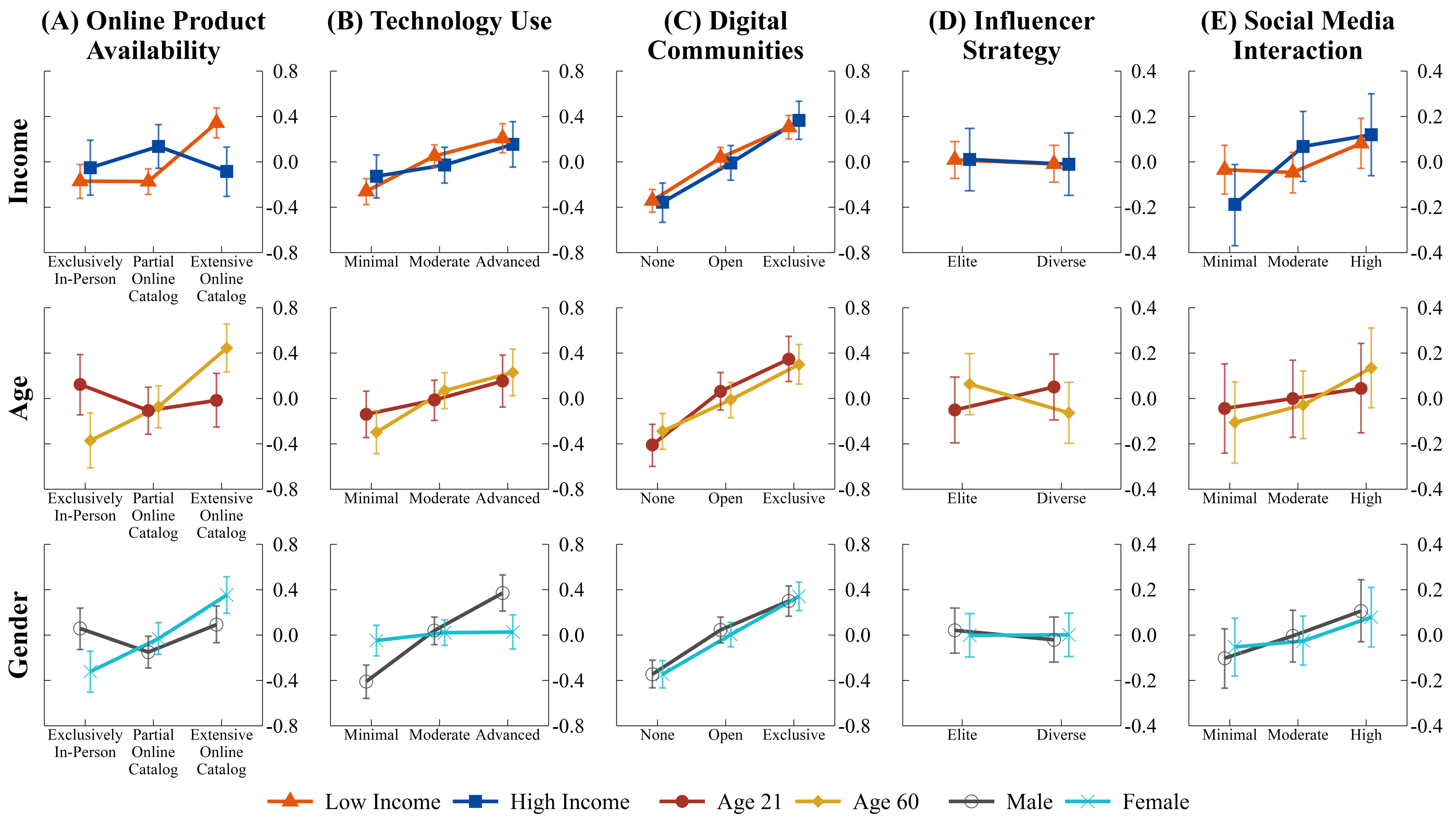
Table 4: Parameter Estimates and Covariate Effects: Model 2.

(Attribute) Level	*Intercept*	*Female*	*Age*	*IncOver120k*	*Importance*
(A) Exclusively In-Person	0.026	-0.381**	-0.013*	0.118	
	(0.127)	(0.157)	(0.007)	(0.174)	
(A) Partial Online Catalog	-0.235**	0.120	0.001	0.309**	28.990
	(0.097)	(0.123)	(0.005)	(0.135)	
(A) Extensive Online Catalog	0.209*	0.261*	0.012*	-0.428**	
	(0.113)	(0.141)	(0.006)	(0.156)	
(B) Minimal	-0.446**	0.362**	-0.004	0.133	
	(0.099)	(0.122)	(0.005)	(0.136)	
(B) Moderate	0.061	-0.019	0.002	-0.079	22.571
	(0.086)	(0.100)	(0.005)	(0.114)	
(B) Advanced	0.385**	-0.344**	0.002	-0.053	
	(0.110)	(0.135)	(0.006)	(0.144)	
(C) None	-0.342**	0.000	0.003	-0.014	
	(0.086)	(0.107)	(0.005)	(0.123)	
(C) Open	0.058	-0.041	-0.002	-0.047	19.321
	(0.078)	(0.097)	(0.004)	(0.108)	
(C) Exclusive	0.284**	0.041	-0.001	0.060	
	(0.091)	(0.115)	(0.005)	(0.119)	
(D) Elite	0.021	-0.022	0.003	0.001	
	(0.068)	(0.083)	(0.004)	(0.098)	
(D) Diverse	-0.021	0.022	-0.003	-0.001	11.269
	(0.068)	(0.083)	(0.004)	(0.098)	
(E) Minimal	-0.060	0.050	-0.002	-0.153	
	(0.091)	(0.113)	(0.005)	(0.125)	
(E) Moderate	-0.035	-0.023	-0.001	0.115	17.849
	(0.078)	(0.097)	(0.004)	(0.109)	
(E) High	0.095	-0.027	0.002	0.038	
	(0.095)	(0.116)	(0.005)	(0.129)	

Notes: Table 4 reports point estimates and standard deviations (in parentheses) for the higher-level parameters in Model 2. Statistical significance is assessed based on whether the $(1-\alpha)\%$ credible interval excludes zero. Attribute importances are computed by calculating the range of attribute utilities (difference between the best and worst utilities per attribute) and normalizing them to sum to 100.
Significance codes: * $p < 0.1$, ** $p < 0.05$.

sumers assign higher utility to greater technology use and more exclusive digital communities, while showing little to no preference for a brand's choice of influencers or level of social media interaction. The attribute importance scores remain stable as well. The most notable difference is in online product availability, where consumer preferences become more nuanced once we account for covariates. The negative coefficient on extensive online catalogs for the *IncOver120k* dummy (where 1 denotes a household income above $120,000) suggests that higher-income consumers derive less utility from having many products available for purchase online than lower-income consumers, instead preferring a partial online catalog. Figure 3 visually confirms this difference, with non-overlapping credible intervals indicating a statistically significant distinction between income groups. Similarly, younger consumers and males prefer exclusively in-person shopping experiences while older consumers and females prefer extensive online catalogs. The other notable covariate effect is in gender-based preferences for technology use, where male consumers show a clear preference for advanced technology while exhibiting lower utility for minimal use relative to females.

Figure 3: Mean Part-Worth Estimates by Covariates.



Notes: Figure 3 presents mean part-worth estimates for each attribute level, comparing groups within each covariate (income, age, and gender). Estimates are derived from Model 2, with comparisons made while holding other covariates at their mean values. Whiskers denote 90% credible intervals. Part-worth values may be compared within an attribute but not between attributes.

5. Discussion

Our models provide interesting insights into how luxury consumers assess the digital marketing strategies of luxury brands and how preferences vary across income, age, and gender. Consumers demonstrate a preference for larger online catalogs, technology-enhanced experiences, and exclusive digital communities. These findings underscore the evolving nature of exclusivity in luxury marketing, revealing that consumers seek curated online experiences—such as invite-only brand events and private digital memberships—as symbols of prestige. This suggests that while digital channels make luxury brands more accessible, controlled access and exclusivity in online spaces remain a key tool for preserving brand desirability.

The growing importance of cutting-edge technologies, such as artificial intelligence (AI) and augmented reality (AR), in shaping the luxury experience is a relatively recent discovery that has only recently gained attention in the literature (Rahman et al., 2023; Javornik et al., 2021). Our study provides empirical evidence that luxury consumers value these advanced technologies in enhancing the luxury experience. Rather than diminishing the personal touch of luxury shopping, AI has the potential to replicate it within digital spaces by enabling data-driven personalization. Furthermore, the sensory-rich experience of in-store shopping can be replicated by the immersive and interactive digital environments created by AR. These technologies reinforce luxury brands' positioning as pioneers of innovation. For these brands, integrating advanced technology into the digital shopping experience offers a way to maintain personalized, high-touch service while fostering consumer engagement in an increasingly digital marketplace.

Our analysis reveals that demographic covariates explain part of the heterogeneity in preferences. Higher-income consumers—the core customer base for luxury—prefer more limited online catalogs, suggesting that broad online availability of luxury products may dilute the perception of exclusivity for this segment. In contrast, lower-income consumers exhibit stronger preferences for extensive online catalogs. Similarly, younger and male consumers favor in-person shopping, while older and female consumers show stronger preferences for digital accessibility, highlighting generational and gender differences in luxury consumption. These empirical findings align with theoretical work which model heterogeneity in consumers' desire for exclusivity, wherein certain segments derive utility from uniqueness while others are functionality-oriented (Amaldoss and Jain, 2005; Sajeesh et al., 2020).

It is not immediately clear why younger and male consumers seem to prefer in-person shopping relative to their counterparts, though recent reports suggest a broader resurgence of mall shopping among Gen Z consumers (Repko, 2024). One possible explanation is that authenticity-seeking younger consumers value the social and experiential aspects of luxury shopping that online shopping cannot replicate. Moreover, the aesthetic appeal of physical stores may align with younger consumers' pursuit of shareable moments for social media. The gender-based findings offer a nuanced extension of prior research, which suggest that women place greater emphasis on quality, uniqueness, and the social value of luxury (Stokburger-Sauer and Teichmann, 2013). While in-person shopping may be perceived as more exclusive, this does not necessarily conflict with a preference for online channels, as brands can maintain exclusivity even with extensive online catalogs by enforcing high price points and limiting product releases. Additionally, women may be more inclined to browse and compare options over time, making online shopping a more attractive channel for assessing quality and discovering unique items. Future research could further investigate the underlying drivers of these age- and gender-based differences in shopping preferences.

Another finding is that while technology adoption and digital community exclusivity enhance perceived value, social media engagement and influencer strategy have more muted effects. It is possible that social media and influencer effects operate in more subtle and subconscious ways, shaping perceptions over time rather than driving immediate, explicit preferences. Unlike direct signals of exclusivity—such as private online communities or restricted product availability—social media exposure and influencer endorsements may blend into the background of consumer decision-making, reinforcing brand desirability in ways that are less consciously recognized.

5.1. Limitations and future work

Given the nature of online survey samples, our study likely under-represents core, high-value luxury customers, who may be the most driven by a desire for exclusivity. As such, our results may overstate the preference for extensive online catalogs. Yet, despite this limitation, our results still capture a segment of luxury consumers who are willing to forgo the functional benefits of online shopping in favor of increased exclusivity. Additionally, the depth of digital experiences is difficult to fully capture in a conjoint study. Browsing a website in real time provides a sensory and interactive dimension that differs from merely conceptualizing it in a survey setting. Furthermore, the luxury industry spans multiple sectors—such as automobiles, fashion, and hospitality—and varying levels of brand positioning—from affordable to *haute couture* luxury. Our study is agnostic to both luxury category and brand, yet it is reasonable to assume that these factors shape consumers' expectations and preferences for online shopping.

Future research could explore whether the patterns observed in this study are unique to the luxury industry by replicating the analysis in a non-luxury context. Conducting a similar conjoint study on mainstream brands would help distinguish whether consumer preferences for online accessibility, exclusivity, and technology adoption are specific to luxury consumption or reflective of broader digital shopping trends. Additionally, future studies could investigate how brand positioning—ranging from accessible luxury (e.g., Coach) to ultra-luxury (e.g., Hermès)—moderates the effects we found. Examining product category-specific dynamics, such as differences between luxury automobiles, fashion, and hospitality, could also provide deeper insights into differences in preferences across these sectors.

6. Conclusion

Building on the luxury marketing literature, this study provides an empirical analysis of how digital strategies shape consumer preferences and identifies demographic heterogeneity as a critical moderating factor. Employing a choice-based conjoint analysis, we quantify trade-offs between key digital marketing attributes—online product availability, technology adoption, digital community exclusivity, influencer strategy, and social media engagement. Our findings suggest that luxury consumers broadly prefer larger online catalogs, advanced technology integration, and exclusive digital communities. However, these preferences are not uniform across consumer groups. Notably, higher-income consumers favor more limited online catalogs, reinforcing the idea that extensive online availability may dilute exclusivity for high-valued luxury customers.

These results contribute to the ongoing discussion of how luxury brands can navigate digital transformation without compromising exclusivity, reinforcing the idea that controlled access remains a key tenet of maintaining brand desirability. From a managerial perspective, luxury brands would benefit from adopting digital marketing strategies that preserve elements of exclusivity through mechanisms such as exclusive digital events and limited product drops. Rather than prioritizing mass digital accessibility, brands should leverage high-touch, curated online experiences to maintain their exclusivity and aspirational status. Additionally, recognizing preference heterogeneity across luxury consumers is essential: younger and higher-income consumers may prioritize exclusivity while male consumers may respond more positively to greater technological offerings. Thus, luxury brands must approach digital positioning strategically: depending on their target customer base, they should optimize their digital presence to enhance appeal among their most valued or target consumers.

Overall, this study sheds light on the evolving intersection of digital accessibility and exclusivity in luxury marketing, offering both empirical contributions to the literature on luxury consumers and practical implications for luxury managers navigating the digital age.

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A. Appendix: Robustness of Covariate Specification

For the main analysis in Model 2, we treated age as a continuous variable and dichotomized income. This decision was driven by the income distribution in our sample, which was skewed toward lower brackets as only 24.8% of respondents reported being in higher-income categories. Given the limited representation of high-income earners, modeling income as a continuous variable may have introduced estimation challenges and potential instability, making a dichotomous approach more appropriate for capturing broad income effects. Nevertheless, we demonstrate that these choices for how to model covariates do not substantially change our findings.

We test two alternative specifications of age and income. First, we model income as a continuous variable in the same manner as age—that is, we assign each respondent the median value of their respective income bracket and mean-center the resulting values. The mean posterior estimates of coefficients using continuous specifications of age and income is presented in Table A1. Second, we fully dummy-code each age and income category, excluding the lowest group in each to avoid multicollinearity and establish a reference category. These results are provided in Table A2.

In both of these specifications, most coefficients remain directionally consistent with the results reported in Table 4, although statistical significance may differ. In the full dummy-coding specification, coefficients roughly increase or decrease with higher category levels in accordance with the same directional pattern observed in Model 2. Local deviations from the expected trend can be attributed to small sample sizes in certain categories as well as potential overfitting to noise in the data from the increased flexibility of the model. Importantly, our conclusions remain unchanged. In both specifications, higher-income consumers assign greater utility to partial online catalogs and lower utility to extensive online catalogs compared to lower-income consumers. Indeed, Table A2 may even suggest that the highest-income consumers ($160k+) exhibit the highest preference for exclusively in-person luxury shopping. Additionally, younger and male consumers continue to favor exclusively in-person experiences more than older and female consumers. Overall, these findings confirm that our results are stable and robust to different covariate specifications.

Table A1: Parameter Estimates with Continuous Income and Age Specification.

(Attribute) Level	*Intercept*	*Female*	*Age*	*Income*
(A) Exclusively In-Person	0.081	-0.413**	-0.013*	-0.005
	(0.111)	(0.156)	(0.007)	(0.014)
(A) Partial Online Catalog	-0.143	0.097	0.002	0.013
	(0.087)	(0.122)	(0.005)	(0.011)
(A) Extensive Online Catalog	0.063	0.316**	0.011*	-0.008
	(0.101)	(0.142)	(0.006)	(0.013)
(B) Minimal	-0.401**	0.340**	-0.004	0.001
	(0.086)	(0.123)	(0.005)	(0.011)
(B) Moderate	0.049	-0.023	0.002	-0.008
	(0.077)	(0.105)	(0.005)	(0.009)
(B) Advanced	0.352**	-0.317**	0.002	0.007
	(0.096)	(0.134)	(0.006)	(0.011)
(C) None	-0.339**	-0.011	0.003	-0.003
	(0.075)	(0.107)	(0.005)	(0.010)
(C) Open	0.038	-0.028	-0.002	0.002
	(0.070)	(0.098)	(0.004)	(0.009)
(C) Exclusive	0.300**	0.039	-0.001	0.001
	(0.078)	(0.113)	(0.005)	(0.010)
(D) Elite	0.021	-0.024	0.003	0.000
	(0.061)	(0.085)	(0.004)	(0.008)
(D) Diverse	-0.021	0.024	-0.003	-0.000
	(0.061)	(0.085)	(0.004)	(0.008)
(E) Minimal	-0.089	0.035	-0.002	-0.015
	(0.082)	(0.115)	(0.005)	(0.010)
(E) Moderate	-0.028	0.007	-0.000	0.019**
	(0.068)	(0.097)	(0.004)	(0.009)
(E) High	0.116	-0.042	0.002	-0.004
	(0.084)	(0.118)	(0.005)	(0.011)

Notes: Table A1 reports point estimates and standard deviations (in parentheses) for the higher-level parameters in a model where age and income were transformed into continuous variables. Statistical significance is assessed based on whether the $(1-\alpha)\%$ credible interval excludes zero.
Significance codes: * $p < 0.1$, ** $p < 0.05$.

Table A2: Parameter Estimates with Dummy-Coded Age and Income Categories.

(Attribute) Level	*Intercept*	*Female* $n = 134$	*Age25-34* $n = 53$	*Age35-44* $n = 86$	*Age45-54* $n = 65$	*Age55-64* $n = 41$	*Inc40-80k* $n = 57$	*Inc80-120k* $n = 78$	*Inc120-160k* $n = 40$	*Inc160k+* $n = 31$
(A) Exclusively In-Person	-0.471	-0.434**	0.721*	0.268	0.136	-0.087	0.504	0.431	0.250	0.557
	(0.415)	(0.165)	(0.387)	(0.271)	(0.246)	(0.261)	(0.389)	(0.383)	(0.371)	(0.399)
(A) Partial Online Catalog	-0.043	0.108	-0.165	0.093	0.268	0.238	-0.201	-0.344	-0.381	0.043
	(0.307)	(0.125)	(0.293)	(0.205)	(0.187)	(0.199)	(0.286)	(0.287)	(0.277)	(0.299)
(A) Extensive Online Catalog	0.515	0.325**	-0.555	-0.361	-0.404*	-0.152	-0.303	-0.087	0.131	-0.600*
	(0.361)	(0.146)	(0.337)	(0.238)	(0.222)	(0.231)	(0.338)	(0.331)	(0.324)	(0.349)
(B) Minimal	-0.633**	0.349**	0.458	-0.064	0.156	-0.054	0.278	0.130	0.078	0.205
	(0.313)	(0.125)	(0.301)	(0.205)	(0.190)	(0.201)	(0.286)	(0.284)	(0.274)	(0.297)
(B) Moderate	-0.080	-0.016	-0.024	0.091	0.125	0.243	0.062	0.028	-0.011	-0.013
	(0.260)	(0.109)	(0.247)	(0.171)	(0.162)	(0.166)	(0.241)	(0.237)	(0.227)	(0.242)
(B) Advanced	0.713**	-0.333**	-0.434	-0.027	-0.282	-0.190	-0.341	-0.158	-0.067	-0.192
	(0.339)	(0.139)	(0.332)	(0.222)	(0.206)	(0.219)	(0.316)	(0.312)	(0.305)	(0.325)
(C) None	-0.578**	-0.020	-0.121	-0.062	0.047	0.040	0.259	0.221	0.239	0.199
	(0.279)	(0.109)	(0.265)	(0.181)	(0.167)	(0.173)	(0.259)	(0.266)	(0.255)	(0.275)
(C) Open	0.119	-0.024	-0.068	-0.018	0.081	-0.148	-0.134	-0.017	-0.036	-0.142
	(0.259)	(0.105)	(0.246)	(0.171)	(0.151)	(0.160)	(0.238)	(0.244)	(0.241)	(0.254)
(C) Exclusive	0.459	0.044	0.189	0.080	-0.128	0.108	-0.124	-0.203	-0.203	-0.057
	(0.290)	(0.117)	(0.274)	(0.185)	(0.171)	(0.186)	(0.269)	(0.274)	(0.263)	(0.280)
(D) Elite	0.335	-0.048	-0.238	-0.050	-0.194	-0.149	-0.135	-0.139	-0.247	-0.292
	(0.218)	(0.089)	(0.206)	(0.142)	(0.131)	(0.137)	(0.199)	(0.203)	(0.194)	(0.206)
(D) Diverse	-0.335	0.048	0.238	0.050	0.194	0.149	0.135	0.139	0.247	0.292
	(0.218)	(0.089)	(0.206)	(0.142)	(0.131)	(0.137)	(0.199)	(0.203)	(0.194)	(0.206)
(E) Minimal	-0.521*	0.049	0.010	0.054	0.111	0.015	0.439	0.458	0.369	0.391
	(0.301)	(0.121)	(0.274)	(0.191)	(0.173)	(0.190)	(0.278)	(0.279)	(0.270)	(0.290)
(E) Moderate	0.341	-0.003	-0.170	0.016	0.014	-0.100	-0.562**	-0.363	-0.241	-0.349
	(0.244)	(0.100)	(0.232)	(0.159)	(0.146)	(0.155)	(0.235)	(0.229)	(0.224)	(0.238)
(E) High	0.179	-0.046	0.160	-0.070	-0.125	0.085	0.123	-0.095	-0.129	-0.042
	(0.304)	(0.124)	(0.286)	(0.201)	(0.187)	(0.194)	(0.282)	(0.282)	(0.274)	(0.289)

Notes: Table A2 reports point estimates and standard deviations (in parentheses) for the higher-level parameters in a model where age and income are fully dummy-coded. Sample sizes (n) for each category are reported, with a full sample of $n = 260$. The reference groups are males ($n = 126$), the 18–24 age group ($n = 15$), and the below-$40K income bracket ($n = 54$). Statistical significance is assessed based on whether the $(1 - \alpha)\%$ credible interval excludes zero. Significance codes: * $p < 0.1$, ** $p < 0.05$.