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The Social Glow-Up: The Role of Digital Marketing Practices in Shaping Consumer Preferences and Brand Reputation within the Skincare Sector – A Choice-Based Conjoint Analysis

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Abstract

This study investigates the role of digital marketing practices in shaping consumer preferences and brand reputation within the skincare sector. Combining Random Utility Theory and Information Integration Theory, a Choice-Based Conjoint Analysis experiment was conducted to quantify the impact of selected key attributes: social media platform (Instagram vs. TikTok), influencer type (dermatologists, cosmetologists, beauty influencers), follower count, shared personal experience, and discount strategies. Data was collected through an online survey primarily distributed in Italy and the Netherlands. Preferences were analyzed using both Multinomial Logit (MNL) and Hierarchical Bayes (HB) models to capture both aggregate patterns and individual-level heterogeneity.

The results show that credibility-based cues, such as endorsements by expert figures, personal experience, and pricing consistency, were more influential than reach-based signals like follower count or platform novelty. Instagram was generally preferred over TikTok, while expert influencers, particularly cosmetologists and dermatologists, increased brand selection, furtherly amplified by positive personal experience disclosure. However, while moderate price reduction enhanced purchase intention, excessive discounting undermined brand credibility, whereas consistent pricing strategies contributed to strengthening long-term brand trust.

This research contributes to the literature by integrating digital branding variables into an experimental design, providing empirical evidence on how trust-based cues influence consumer utility. Managerially, the findings suggest that skincare brand managers and digital marketers should focus on authenticity, expertise, and price coherence rather than relying exclusively on popularity metrics.

Keywords: Digital Marketing, Social Media, Skincare Industry, Influencer Marketing, Choice-Based Conjoint Analysis, Brand Reputation, Consumer Preferences, TikTok, Instagram, Pricing Strategies, Consumer Trust.

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1. Introduction

1.1 Problem Statement

Nowadays, digital marketing practices have profoundly reshaped the way consumers engage with brands, particularly within the skincare sector, where brand awareness, trust, and perceived credibility play a crucial role in shaping consumer preferences and choices (Keller, 1993). For instance, social media platforms have not only transformed brand-consumer interactions, indeed, they have redefined how reputation is built, maintained, and evaluated in such an increasingly competitive market (Gürhan-Canli et al., 2016).

In recent years, skincare brands have progressively embraced social media exposure, influencer collaborations, and algorithm-driven visibility as strategic means for enhancing their overall exposure and reputation (Bhandari & Bimo, 2022; Leung et al., 2022; Rust et al., 2021). For instance, as a key element in recent digital brand development, online influencer marketing (OIM) leverages influencers' ability to foster strong connections with their audiences, making brand endorsements appear more authentic and relatable compared to traditional advertising (Leung et al., 2022).

However, the dynamics through which social media exposure, influencer marketing, and promotional pricing strategies contribute to shaping skincare brand reputation and consumer preferences are yet to be fully explored. While past research has extensively covered brand equity and traditional brand perception models (Keller, 2016), less attention has been devoted to how social media dynamics, particularly Instagram and TikTok, enhance consumer awareness, trust and long-term brand credibility, subtly shaping consumers' skincare brand choice

Therefore, given their growing significance, this study seeks to address the following main research question:

To what extent do digital marketing practices shape consumer preferences and brand reputation within the skincare sector?

Specifically, it investigates how these platforms serve as primary channels for enhancing brand awareness, examining the role of influencers' features (e.g., expert-based influencers vs. popularity-based beauty influencers) in shaping consumers' trust, and ultimately influencing brand choice. Furthermore, it explores whether promotional pricing strategies, such as discount codes and perceived price fairness, affect purchase intent and long-term brand reputation.

1.2 Purpose of the Research

This research aims to explore the impact of social media platforms on skincare brand reputation, ultimately influencing consumer preferences, focusing on platform exposure, online influencer marketing features, and promotional pricing strategies. Grounded in Random Utility Theory (McFadden, 1974) and Information Integration Theory (Anderson, 1971), this study adopts an experimental Choice-Based Conjoint (CBC) approach to simulate real-world consumer decision-making, quantifying the relative importance of selected skincare brand-related attributes.

Data was collected through a structured online survey presenting multiple CBC tasks, with the intent of gaining meaningful insights into how marketing attributes influence consumer judgments, empirically testing the sub-research questions and hypotheses reported below. In addition to choice-based data, Likert-type scale measures were implemented to further explore perceptions of influencer trustworthiness, discount-driven value perception, and long-term reliability. The empirical investigation was geographically focused on respondents primarily based in Italy and the Netherlands, where the online survey was mostly distributed, targeting individuals who regularly follow a skincare routine.

1.3 Research Question

To structure the empirical investigation, this study formulates a series of research questions and hypotheses.

1.3.1 Main Research Question

MRQ: *To what extent do digital marketing practices shape consumer preferences and brand reputation within the skincare sector?*

1.3.2 Sub-Research Questions

Each sub-research question (SRQ#) targets a specific dimension of brand reputation within the digital environment:

- **SRQ1:** *To what extent are skincare brands discovered through social media platforms compared to traditional media?*
- **SRQ2**: *To what extent do social media platform type, follower count, influencer type, personal experience, and discount strategies influence consumers' skincare brand choices?*
- **SRQ3:** *To what extent does pricing consistency influence perceived brand credibility and trust over time?*

1.4 Significance of the Study

This study is highly relevant to skincare brand managers, digital marketers, and social media strategists, providing essential insights for preserving or elevating a brand's positioning in today's skincare digital marketplace.

From a managerial perspective, this research aims to provide practical insights to help skincare brands optimize their strategic marketing efforts within the digital environment. For instance, by understanding how influencer characteristics impacts consumer trust and brand choice, and how pricing strategies affect purchase intent and long-term brand credibility; skincare brand managers, alongside digital marketing and social media specialists, can better tailor promotional strategies enhancing visibility, building credibility, and fostering long-term consumer loyalty, ultimately reinforcing overall brand reputation.

From a scientific perspective, while past research has explored social media exposure, influencer marketing, and pricing strategies separately, this study uniquely integrates these factors within a Choice-Based Conjoint Analysis framework, quantifying their relative impact on skincare brand reputation, providing a more holistic understanding of the mechanisms driving consumer choices.

Overall, this research offers a novel contribution to the literature by integrating social media marketing elements into an experimental design, providing academic insights and practical guidance for digital skincare brand management.

2. Literature Review

2.1 Introduction

The following chapter presents a structured review of the existing academic literature, aimed at exploring and evaluating previous research on the role of digital marketing practices in shaping skincare brand reputation, conceptualized in this study as a multidimensional construct grounded in brand awareness, consumer trust and perceived long-term credibility.

By reviewing recent academic contributions in social media branding, online influencer marketing, and pricing strategy within the skincare industry, identified through databases such as *Google Scholar*, *Sage Journals* and *ScienceDirect*, this chapter identifies the key theoretical foundations of the study, defining the core variables involved in the experiment, highlighting gaps in the existing literature.

The following literature review is organized around three main constructs (**Figure 1**) that have emerged as relevant to the main research question and sub-questions: (1) social media exposure and its role in shaping skincare brand awareness, visibility and recall, (2) online influencer marketing as a driver of consumer trust and brand choice, with a particular focus on Instagram and TikTok, and (3) pricing strategies, specifically focusing on the use of influencer discount codes, and their implications for perceived brand credibility and long-term brand reputation.

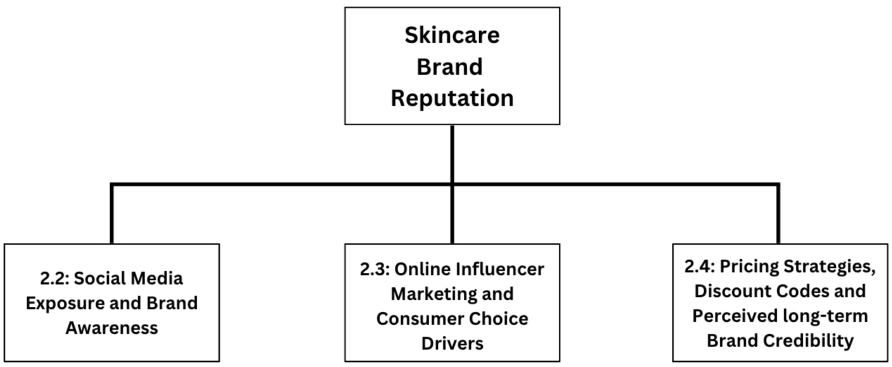


Figure 1: Skincare Brand Reputation Drivers Overview

2.2 Social Media Exposure and Brand Awareness in the Skincare Sector

Social media platforms are interactive digital tools that enable users to create, share, and exchange information, ideas, and multimedia content within virtual communities and networks (Aichner et al., 2021), progressively redefining how brands engage with consumers, particularly in industries where visual and experiential cues are central, such as the skincare market (Rodríguez et al., 2025).

As a major subset of the cosmetics industry, the skincare sector includes products and practices aimed at maintaining or improving skin's health and appearance (Choi et al., 2019), recently evolving beyond basic personal care, reflecting consumers' broader lifestyle values and priorities (Seelig et al., 2021).

In nowadays digitally mediated context, social media has become a key channel through which skincare brands can build awareness, influencing consumers' perception (Rust et al., 2021) as frequent exposure to brand-related content allows consumers to familiarize themselves with the brand, reinforcing cognitive associations; ultimately enhancing brand awareness, conceived as the extent to which consumers retain and recall information and knowledge about a brand's products, services, and features (Jamali & Khan, 2018).

Therefore, by enabling both brand-generated and consumer-shared content, social media platforms boost perceived authenticity, strengthening brand recall, ultimately influencing consumers' product quality perception (Dedeoğlu et al., 2019).

This section examines the role of social media in generating brand awareness, with a particular focus on how different platforms contribute to brand visibility and recall in the context of skincare marketing.

2.2.1 Role of Social Media in Brand Visibility

Brand visibility refers to the extent to which a brand can be easily noticed or recognized by consumers within a crowded and competitive media environment (Shao et al., 2019). Therefore, increased visibility enhances the likelihood of a brand being considered during purchase decisions, particularly when consumers are faced with numerous alternatives for the same product category (Barroso & Llobet, 2012), such as choosing between various skincare brands all offering hydrating face creams. While closely related, brand awareness goes beyond brand visibility, involving both recognition and recall, whose development is shaped by frequency and quality exposure across consumer touchpoints (Keller, 1993).

If leveraged properly, these dynamics facilitate skincare brands to secure top-of-mind positioning in saturated markets, where many products compete for attention (Rust et al., 2021). In this case, social media plays a central role in this process by offering real-time, strategically placed exposure, enabling platform-specific tactics, such as cohesive aesthetic grids, that enhance visibility, memorability, and brand recognition (Rust et al., 2021). Moreover, they allow brands to monitor consumer sentiment, fostering engagement and loyalty through continuous, personalized interactions (Jamali & Khan, 2018).

Among these platforms, Instagram and TikTok have recently emerged as particularly influential within the skincare domain, given their high user engagement and flexible content formats that strongly support visual storytelling, facilitating brand discovery (Brown, 2024; Herzallah et al., 2022), therefore representing the primary digital focus of this study.

2.2.2 Role of Social Media Usage Frequency as a Moderator

As Rapp et al. (2013) highlight, consumer engagement on social media is mainly driven by how actively brands foster interaction, supporting the idea that frequent and meaningful contact enhances brand familiarity, strengthening customer loyalty, potentially exerting a moderating effect. In statistical terms, a moderating variable influences the strength or direction of the relationship between two other variables (Memon et al., 2019), in this case, helping explain when and for whom social media exposure might be more effective.

Research has shown that frequent social media usage positively influences brand awareness, enhancing brand recognition, recall, and dominance through regular interaction and content exposure (Alnsour & Tayeh, 2019), suggesting that within dynamic environments, such as the skincare sector, consistent platform engagement may contribute to stronger brand positioning over time.

Building on the discussed theoretical insights, the following hypothesis is proposed to examine the role of social media in shaping skincare brand awareness, moderated by users' social media frequency usage.

- **H1**: *Skincare brands are more frequently discovered through social media platforms (particularly Instagram and TikTok) than through traditional media channels (e.g., TV, magazines, or in-store discovery).*
    - *This effect is expected to be stronger among individuals who frequently engage with skincare-related content on social media. To assess this, respondents will be classified as High Social Media Users if they report using social media daily or multiple times per day or as Low Social Media Users otherwise.*

2.2.3 Platform-Specific Branding Strategies: Instagram vs. TikTok

Nowadays, brands aim to reinforce their identity and narrative over time through timely, targeted, and creative social media communication strategies, fostering emotional connections and enhancing ongoing consumer-brand interactions (Gürhan-Canli et al., 2016).

While both Instagram and TikTok contribute to brand visibility, engagement levels vary significantly across platforms; for instance, TikTok's short-video format shows higher effectiveness in driving user interaction, suggesting that brands should tailor their strategies according to each platform's specific features and engagement patterns (Shen, 2023).

TikTok, a short-form video platform that uses algorithm-driven content curation to enable personalized social interaction, primarily through its signature "For You" page (Bhandari & Bimo, 2022), is particularly effective in influencer and content marketing, as well as in stimulating electronic word-of-mouth (e-WOM) for skincare products (Larasati et al., 2024). Moreover, its short-form video format has proven to be especially impactful in driving engagement and visibility among Gen Z audiences (Leung et al., 2022).

Conversely, Instagram, a mobile photo and video capturing and sharing application that allows users to instantly take pictures or videos (Hu et al., 2014), is structured around a follow-based logic, where most content comes from accounts (namely friends, influencers, or brands) that users purposely choose to follow. This design rewards visual consistency, refined branding, and long-term relationship building (Herzallah et al., 2022).

Overall, TikTok turns out to be particularly effective at capturing initial attention and generating buzz, while Instagram supports sustained engagement and loyalty-building through more refined content strategies (Libai et al., 2025), addressing different stages of the consumer journey.

2.2.4 Platform Exposure and Brand Recall

Beyond visibility, brand recall, defined as the consumer's ability to retrieve the brand from memory in response to a stimulus, stands as equally important for building strong brand equity (Aaker, 1991). Additionally, brand recall depends not only on how frequently a consumer is exposed to a brand but also on the quality, variation, and emotional resonance of the exposure itself (Keller, 2001).

As such, according to Gürhan-Canli et al. (2016), platforms such as Instagram and TikTok promote repeated interactions with branded content, which reinforces mental associations, sustaining long-term consumer-brand relationships. For instance, TikTok's rapid interface facilitates passive yet frequent engagement with content, potentially increasing the spontaneous recall likelihood by exposing users to multiple branded impressions within short periods (Jiang & Ma, 2024). On the other hand, Instagram offers a strategic environment where consumers engage with cohesive brand aesthetics, with its visual nature reinforcing pattern recognition and subtly shaping users' brand perception (Engeler & Barasz, 2021).

Therefore, while both Instagram and TikTok contribute to brand recall, the latter might hold a stronger persuasive power in shaping consumer decisions due to its highly personalized ‘For You’ feed and seamless short-form video browsing experience, fostering spontaneous and emotional engagement (Bhandari & Bimo, 2022; Leung et al., 2022; Larasati et al., 2024), especially among younger users, potentially increasing skincare brands’ appeal featured on TikTok compared to those on Instagram. (Shen, 2023).

Based on these insights, the following hypothesis is proposed:

- **H2:** *Consumers are more likely to choose skincare brands promoted on TikTok rather than Instagram.*

2.3 Online Influencer Marketing, Brand Trust and Consumer Choice

In recent years, online influencer marketing (OIM) has become a dominant force in social media branding, particularly in sectors like skincare, enhancing consumer engagement (Leung et al., 2022). Unlike traditional advertising, it leverages personal and interactive communication, fostering consumer trust through credibility, relatability, and perceived expertise (Leung et al., 2022).

This section explores how online influencer marketing builds consumers’ trust in skincare brands and how this, in turn, potentially guides their brand choice selection. It examines how different influencers’ characteristics, such as popularity, expertise and transparency, shape consumers' trust, ultimately hypothesized to act as a key driver of brand choice within the skincare domain.

2.3.1 Rise of Online Influencer Marketing (OIM) in Skincare

Online influencer marketing, defined as the strategic use of influential individuals, perceived as credible within their content domain, on digital platforms to promote products or brands, has become particularly relevant within the skincare sector (Libai et al., 2025). Nowadays, personal experience, visual proof, and trust-based recommendations are essential, as influencers build brand trust by leveraging personal narratives, community engagement, and perceived authenticity; traits often lacking in traditional advertising (Libai et al., 2025).

Therefore, social media enables brands to engage with consumers improving their brand perception, strengthening the consumer-brand relationship (Binwani & Ho, 2019). In this context, authenticity and transparent communication, especially when strategically managed by relatable influencers, are crucial for enhancing users engagement, enhancing brand credibility (Tan, 2025).

2.3.2 Credibility Drivers in Online Influencer Marketing

Credibility is a key driver of consumer trust in online influencer marketing, stemming from several drivers such as social popularity, audience reach, domain-specific expertise, and perceived authenticity (Tan, 2025).

To reflect this multidimensional nature, this section explores two distinct yet often overlapping influencer credibility factors: perceived popularity, which relies on social validation indicators such as follower count, and domain-specific expertise, related to influencers' authority and knowledge within a particular field.

2.3.2.1 Perceived Popularity and the Bandwagon Effect

While popularity, often measured by follower count, is associated with greater influence and social appeal, it may lead consumers to perceive the influencer as more trustworthy (Leung et al., 2022), in line with the bandwagon effect, a psychological tendency whereby individuals align with a specific behavior based on its current popularity or social validation (Zhang & Wang, 2019).

According to Saleh et al. (2023), influencers can be categorized based on their follower count into several categories, such as micro-influencers (10K-50K), mid-tier influencers (50K-200K), and macro-influencers (200K-900K).

Yet, credibility extends beyond popularity, relying on perceived authenticity, expertise and the strength of the influencer-follower relationship (Leung et al., 2022). Therefore, in high-involvement categories like skincare, consumers tend to be more sensitive to content relevance and source reliability, which may cause highly popular influencers, such as macro influencers, to appear overly commercial or less sincere (Leung et al., 2022). Conversely, micro-influencers, despite being perceived as highly authentic and relatable, often suffer from limited reach, reducing their effectiveness in large-scale branding campaigns (Saleh et al., 2023).

Therefore, while popularity may capture users' attention, amplifying reach, it does not necessarily guarantee trust. These insights suggest that mid-tier influencers, offering a reasonable balance between reach and authenticity, may be more effective at fostering brand trust and influencing customers' purchase intentions within the skincare domain.

Based on this premise, the following hypothesis is proposed:

- **H3:** Mid-tier influencers (e.g., 195K followers) are associated with higher brand choice probability than micro-influencers (e.g., 38K followers) or macro-tier influencers (e.g., 900K followers).

2.3.2.2 Expert Influencers vs. Popular Beauty Influencers

In the context of skincare, the distinction between popular beauty influencers and expert influencers is particularly salient. The former, counting hundreds of thousands or millions of followers, are typically approached by brands for their reach and ability to create buzz around a product (Libai et al., 2025). However, their perceived commercial orientation may limit their perceived trustworthiness in product categories where expertise and informed guidance are crucial (Libai et al., 2025).

Therefore, expert influencers, such as dermatologists or cosmetic scientists, are often perceived as credible sources due to their domain-specific knowledge (Moorman et al., 2023).

However, recent evidence suggests that beauty influencers, those with a sizeable but not celebrity-level following, may be particularly effective in enhancing consumer engagement and brand equity when there is strong brand-endorser harmony; as their credibility positively influences the brand's image, which, in turn, affects consumer trust and engagement, being way less expansive (Borges-Tiago et al., 2023).

Building on the strategic dilemma posed by the trade-off between reach and credibility, where popular beauty influencers may enhance visibility, while expert influencers (dermatologists and cosmetologists) may better support long-term brand trust and reputation, the following hypotheses are tested:

- **H4a:** Skincare brands endorsed by dermatologists are more likely to be chosen than those endorsed by beauty influencers.
- **H4b:** Skincare brands endorsed by cosmetologists are more likely to be chosen than those endorsed by beauty influencers.
- **H4c:** Skincare brands endorsed by dermatologists are more likely to be chosen than those endorsed by cosmetologists.

2.3.3 Disclosure, Storytelling & Perceived Transparency

Beyond popularity and expertise, an influencer's communication style and transparency significantly affect how trustworthy a message appears (Chen et al., 2022). Therefore, clear and honest disclosures tend to increase perceived authenticity, especially when paired with genuine experiences, while personal, emotionally consistent storytelling enhances sincerity and engagement (Pan et al., 2025).

Together, these elements function as credibility cues that significantly influence online influencer marketing effectiveness, especially in trust-sensitive industries like skincare, where brand reputation is closely tied to consumer perceptions of authenticity, safety, and trust (Pan et al., 2025).

Therefore, based on the idea that an influencer's personal experience can shape consumer trust and persuasion, the following hypothesis examines how positive versus negative experiences may impact consumers' skincare brand choice.

- **H5:** Skincare brands promoted through a positive personal experience shared by the influencer are more likely to be chosen than those lacking any experiential narrative.

2.4 Pricing Strategies and Perceived Brand Value

In the skincare industry, pricing strategies extend beyond a product's monetary value, functioning as powerful signals of quality, brand positioning, and credibility (Jyothi & Venkateswarlu, 2020). Unlike utilitarian categories, skincare products are often evaluated through emotional and symbolic lenses, where price serves as a heuristic for perceived efficacy, safety, and prestige (Jyothi & Venkateswarlu, 2020).
As a result, promotional and long-term pricing strategies have the potential to shape not only purchase intent but also broader perceptions of brand reputation and value (Yao et al., 2020).

This section examines how pricing strategies affect consumer psychology, focusing on the role of influencer discount codes, consumers' perception of price fairness, and possible long-term implications of pricing on brand equity and credibility.

2.4.1 Psychological Effects of Pricing in Skincare

In high-involvement categories like skincare, consumers often perceive higher-priced products as an indicator of superior quality and performance, particularly when evaluating product claims or unfamiliar brands (Jyothi & Venkateswarlu, 2020). Conversely, steep discounts or unusually low prices can provoke skepticism, as consumers may question the product's legitimacy, safety, or brand seriousness (Choi et al., 2019).

2.4.2 Role of Influencer Discount Codes

Influencer discount codes, commonly shared through stories, posts or video captions, might serve as a double-edged sword as when framed as exclusive or time-limited, they boost urgency, yet their overuse can undermine brand credibility, disrupt price fairness perception, which relies on consistency and alignment with value delivered (Libai et al., 2025).

To sustain brand equity, discounting strategies must align with long-term brand positioning, as excessive reliance may lead consumers to expect ongoing deals, weakening willingness to pay full price. Therefore, strategic coherence between pricing and brand communication is essential for preserving brand reputation and trust (Libai et al., 2025).

Given the dual role of influencer discount codes as both promotional tools and signals of exclusivity and value, the following hypothesis is proposed to examine their effect on consumers' purchase decisions.

- **H6:** Skincare brands offering a higher discount code are more likely to be chosen than those with lower or no discounts.

2.4.3 Pricing as a Strategic Driver of Brand Perception

Pricing significantly influences how consumers perceive skincare brands, not just in terms of affordability, but as a signal of quality, market positioning, and brand intent (Khraim, 2011). To examine this relationship, the discussion focuses on two central aspects of pricing: perceived fairness and its strategic use over time.

2.4.3.1 Perceived Price Fairness and Brand Reputation

Perceived price fairness is the extent to which consumers consider a price reasonable or justified, often based on comparisons with past prices, competitors, or market standards; shaping how consumers perceive a product's value and reinforcing overall consumer satisfaction and brand trust (Bolton et al., 2003).

In the skincare sector, where products are often perceived as expensive yet essential, consumers are more willing to pay premium prices when they perceive the product as effective and of high quality (Jyothi & Venkateswarlu, 2020). In this context, price acts as a signal of value and necessity, shaping brand perceptions and supporting premium positioning when aligned with consumer expectations (Jyothi & Venkateswarlu, 2020).

2.4.3.2 Pricing Strategies and Long-Term Brand Equity

While promotional pricing strategies (such as discount codes) can deliver short-term gains, they must be embedded within a broader approach able to sustain brand equity over time, as overusing discounts may weaken brand positioning (Aaker, 1991).

Therefore, effective pricing strategies must align with the brand's identity, whether premium, accessible, ethical, or expert-driven, fostering engagement without compromising long-term positioning or undermining consumer trust, thereby preserving price integrity (Swaminathan et al., 2022).

In contrast to short-term discounts, consistent and predictable pricing strategies may foster long-term trust by signaling fairness and brand reliability, the following hypothesis is proposed to examine how strategic pricing consistency influences long-term brand trust within the skincare sector.

- **H7:** *Skincare brands that maintain stable and predictable pricing (i.e., without frequent discounting) are perceived as more credible and reliable over time compared to those that frequently change their prices or lean heavily on discount promotions.*

2.5 Integration of Constructs and Expected Relationships

In this study, brand reputation is viewed as a multidimensional outcome influenced by three intermediate drivers: brand awareness, consumer choice drivers, and perceived brand value. The expected relationships among these constructs are described below.

First, social media exposure is expected to increase brand awareness by amplifying both visibility and recall, particularly on highly interactive platforms, namely Instagram and TikTok, fostering repeated brand interactions through emotionally engaging content (Brown, 2024; Herzallah et al., 2022), aligning with **H1**. This effect is hypothesized to be stronger among individuals who frequently engage with skincare-related content on these platforms (Alnsour & Tayeh, 2019), supporting the proposed **moderation effect**. Additionally, consumers are hypothesized to be more likely to choose skincare brands promoted on TikTok rather than on Instagram due to its algorithm-driven format and short-form video engagement (Bhandari & Bimo, 2022; Shen, 2023), resonating with **H2**.

Second, online influencer marketing is expected to influence consumers' brand choice, shaping their perceived trust. For instance, skincare brands endorsed by mid-tier influencers, those providing a balance between reach and authenticity, are more likely to be chosen compared to those promoted by micro or macro influencers (Saleh et al., 2023), endorsing **H3**. Moreover, brands recommended by expert influencers, namely dermatologists and cosmetologists, are predicted to be preferred over those endorsed by beauty influencers, given higher trust arising from their stronger domain-specific authority (Moorman et al., 2023; Libai et al., 2025), in line with **H4a** and **H4b**. Moreover, among expert types, dermatologists are expected to generate the highest brand choice likelihood, as their medical credibility is expected to surpass cosmetologists' expertise, supporting **H4c**. Additionally, influencer-shared positive personal experiences are predicted to further increase consumers' likelihood of choosing the endorsed skincare brand, enhancing authenticity and persuasion (Pan et al., 2025), as hypothesized in **H5**.

Third, pricing strategies, particularly the use of influencer discount codes, are expected to influence consumers' perceived brand value and purchase decisions. For instance, offering a higher discount is hypothesized to increase the likelihood of brand choice when compared to offering a lower or no discount at all, as supported by **H6** (Libai et al., 2025). Beyond these short-term effects, consistent and stable pricing is presumed to play a more decisive role in shaping long-term brand credibility and trust, associating predictable pricing with fairness and reliability, reinforcing perceived brand integrity over time (Jyothi & Venkateswarlu, 2020; Swaminathan et al., 2022), resonating with **H7**.

2.6 Gap in the Literature

While previous academic research has examined social media branding in isolation, this study bridges a gap in the literature by integrating platform comparisons within an experimental choice-based approach, offering a deeper understanding of consumer decision-making within the skincare sector's digital environment.

2.6.1 Lack of Comparative Platform Analysis

Previous academic research has explored the role of social media platforms (e.g. Instagram and TikTok) in shaping brand visibility, engagement, and consumer behavior in isolation. For instance, Leung et al. (2022) and Libai et al. (2025) emphasize TikTok's ability to amplify influencer-driven and viral short-form content, whereas Instagram is acknowledged for its visual consistency and capacity to sustain long-term brand relationships (Herzallah et al., 2022; Rust et al., 2021).

Recent studies, such as those by Larasati et al. (2024) and Shen (2023), highlight platform-specific strategies and engagement mechanisms, yet they do not compare their effects within an integrated framework. Therefore, despite growing interest in social media branding, comparative research remains limited in examining how platform-specific elements, such as influencer type and pricing strategies, affect brand reputation, particularly in high-involvement categories like skincare.

2.6.2 Applying Choice-Based Conjoint to Social Media Skincare Branding

Although literature has already extensively addressed influencer marketing, digital trust, and price fairness, these branding elements are often investigated separately, with limited adoption of Choice-Based Conjoint (CBC) analysis, although it would be particularly well-suited to simulate realistic trade-offs, disclosing attribute-level preferences (Gustafsson et al., 2007). Therefore, by integrating CBC with a dual-theoretical framework based on Random Utility Theory (RUT) and Information Integration Theory (IIT), this study adopts a rigorous methodological approach and provides a deeper understanding of how different combinations of platform, influencer features, and pricing cues shape consumer preferences and skincare brand reputation.

2.7 Conceptual Model and Hypotheses Overview

The conceptual model presented below visually integrates the main constructs and hypothesized relationships of the study.

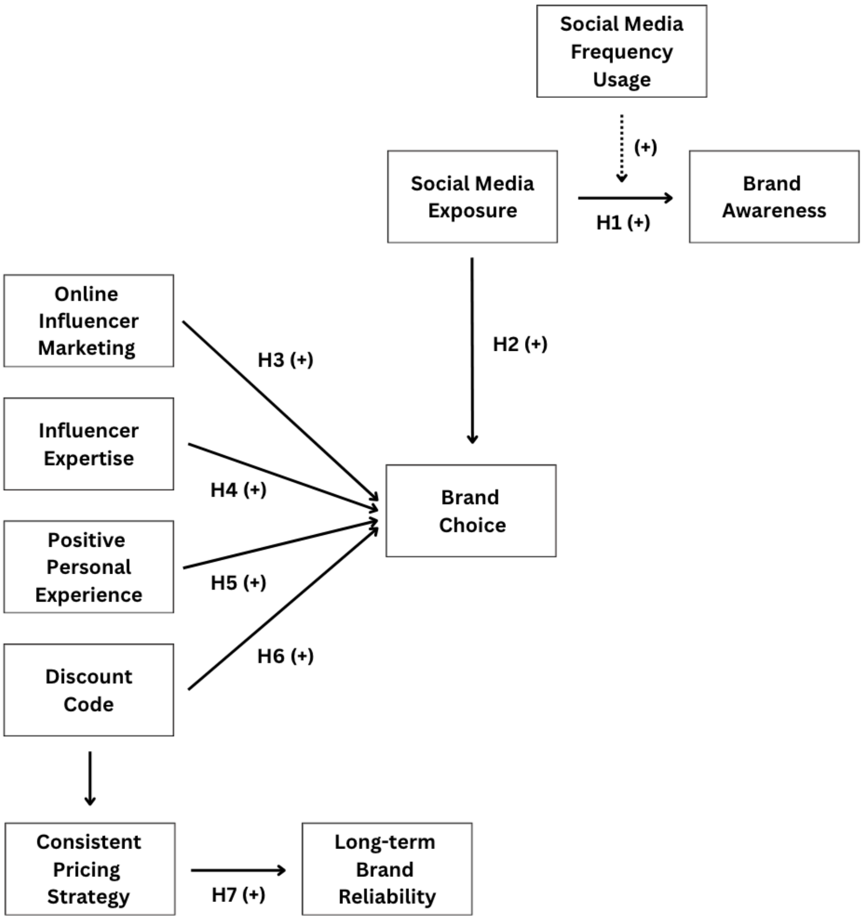


Figure 2: Conceptual Model and Hypotheses Overview

3. Methodology

3.1 Theoretical Framework

To understand the reasoning behind consumers' brand-related preferences and choices in digital contexts, this study draws on two complementary theoretical foundations: Random Utility Theory (RUT) and Information Integration Theory (IIT), which, together, support the use of Choice-Based Conjoint (CBC) analysis. Indeed, while RUT explains consumers' choice structure, IIT explains attributes' cognitive weighting, jointly providing a complementary quantitative and psychological perspective on consumer decision-making, applicable to the skincare sector.

3.1.1 Random Utility Theory and Discrete Choice Models

Random Utility Theory (RUT), introduced by McFadden (1974), states that individuals' choices are driven by the tendency to choose the alternative that yields the highest utility, formed by an observable deterministic component, influenced by product attributes, and a stochastic component, which accounts for individual variability and unobserved influences.

According to the Random Utility Model (RUM), the **Total Utility** U_{ij} is defined as:

$$U_{ij} = V_{ij}(s_i, x_j) + \varepsilon_{ij} \quad (1)$$

Where:

- U_{ij}: Represents the total utility of alternative *j*, for individual *i*. Individuals compare these utilities across all available alternatives (e.g. Brand A or Brand B) and choose the one that yields the highest value.
- $V_{ij}(s_i, x_j)$: Deterministic utility, a function of the observable attributes x_j of alternative *j* and the individual characteristics s_i of respondent *i*.
- ε_{ij}: Random error term capturing unobserved preferences, noise, or emotional bias.

This framework directly provides the foundation for the Choice-Based Conjoint experiment conducted in this study, where each skincare brand profile (Brand A vs. Brand B) was defined by a set of experimentally manipulated varying attributes (e.g., influencer type, social media platform, discount level), and consumers were asked to choose the alternative they preferred the most.

Note: While McFadden (1974) originally presents the utility function as $U = V(s, x) + \varepsilon(s, x)$, this study adopts an indexed notation (U_{ij} , V_{ij} , ε_{ij}) to explicitly account for individual-level utility for each alternative j and respondent i, in line with applied Choice-Based Conjoint literature.

Building on this theoretical foundation, choice probabilities are estimated using the **Multinomial Logit Model (MNL)**, which translates utility differences into predicted individual choices:

$$P_{ij} = \frac{e^{V_{ij}(s_i, x_j)}}{\sum_{k \varepsilon \beta} e^{V_{ik}(s_i, x_k)}} \quad (2)$$

Where:

- P_{ij}: Represents the probability that individual *i* chooses alternative *j* from the available choice set β based on the perceived utilities of all alternatives available.
- β: Choice set (in the context of this study two brand profiles per CBC task).
- $e^{V_{ij}(s_i, x_j)}$: The exponentiated deterministic component of utility for alternative *j*. It captures the utility derived from the observable attributes x_j of alternative *j*, and from individual characteristics s_i of respondent *i*.
- $\sum_{k \varepsilon \beta} e^{V_{ik}(s_i, x_k)}$: The sum of the exponentiated utilities for all alternatives *k* in the choice set β. It acts as a normalizing factor, ensuring that the probabilities across all alternatives add up to one.

Note: While McFadden (1974) denotes the choice probability more generally as $P(x_i | s, \beta)$, this study adopts the indexed notation P_{ij} to explicitly account for the probability that individual *i* selects alternative *j*, in line with standard practice in applied Choice-Based Conjoint literature.

Therefore, Equation (1) defines the total utility as the sum of a deterministic component and a stochastic error term, in line with the Random Utility Theory. Assuming that the error term follows a Gumbel distribution, the resulting choice probabilities can be modeled using the Multinomial Logit formulation (Equation 2), where only the deterministic part of utility $V_{ij}(s, x)$ is needed for the estimation.

3.1.2 Information Integration Theory and Attribute Weighting

While Random Utility Theory (RUT) provides the theoretical ground for modeling choice behavior, **Information Integration Theory (IIT)** offers a complementary perspective, illustrating the latent cognitive mechanisms behind individual preference formation. Originally developed by Norman H. Anderson, IIT states that individuals do not evaluate information in isolation but, instead, they integrate multiple cues by assigning them differential cognitive weights, based on perceived relevance and personal values.

The following formulations follow directly from Anderson's cognitive algebra framework (Anderson, 1971), which formalizes how individuals integrate weighted information from multiple sources to form a final judgment or decision.

At the core of IIT, the **Summative Integration Rule** assumes that the overall evaluation of an attribute is a **Cumulative Utility Function** of its values, each weighted by their perceived importance:

$$R = C + \sum_{j=1} w_j s_j \quad (3)$$

Where:

- R: Represents the integrated evaluation (or response) of a product or service for a given individual. It reflects how appealing or preferable the option is based on the weighted contribution of each information cue.
- C: A constant representing an initial baseline judgment prior to receiving any stimuli.
- w_j: Denotes the cognitive weight assigned to information cue j (the attribute), which captures its psychological importance or perceived relevance in the decision-making process.
- s_j: Refers to the subjective value or perceived strength of information cue j, which may vary across respondents or contexts depending on how a specific attribute's level is interpreted.

Note: The index j represents the correspondence between each attribute (cue) and the specific level presented. While w_j reflects the psychological importance of attribute j, s_j indicates the perceived value of the level of that same attribute. In this version, the summation begins at $j = 1$, excluding any prior baseline component.

This model reflects how consumers integrate multiple brand-related cues into a global preference judgment. For instance, within this study's experimental context, a skincare brand profile combining a cosmetologist, sponsoring on Instagram and offering 10% discount may receive a higher overall utility compared to a profile featuring a popular beauty influencer on TikTok providing a 20% discount.

Therefore, while the attributes are held constant across profiles, the resulting brand choices depend on the synergy between the relative importance respondents assign to each attribute and their subjective assessment of the specific levels presented.

3.1.2.1 Attribute Importance in Choice-Based Conjoint Analysis

Although Information Integration Theory (IIT) does not formally define attribute importance, Conjoint Analysis provides a practical method to quantify how much each attribute influences consumer preferences. This is particularly useful when interpreting the part-worth utilities estimated through Choice-Based Conjoint models.

Following the standard approach proposed by Orme (2006), the importance of each attribute is calculated by measuring the range of its part-worth utilities across all levels, then normalizing it against the total range across all attributes as follows:

$$Importance_j = \frac{max(u_j) - min(u_j)}{\sum_{k=1}^{n} (max(u_k) - min(u_k))} \quad (4)$$

Where:

- $Importance_j$: the relative importance of attribute j in the decision-making process.
- $max(u_j)$: the highest part-worth utility for attribute j.
- $min(u_j)$: he lowest part-worth utility for attribute j.
- $\sum_{k=1}^{n} (max(u_k) - min(u_k))$: sums the utility ranges of all k attributes, allowing for comparability across different attributes.

Note: Although Orme (2006) does not present this importance index as a formal equation, he clearly describes the procedure in words, by taking the range of part-worth utilities within each attribute and dividing it by the total range across all attributes.

Therefore, this calculation reveals, for instance, whether influencer expertise has a greater influence on consumer brand choice compared to discount level; offering meaningful insights for skincare marketers and managers deciding between trust-based and price-driven promotional strategies.

3.1.3 Application to the Present Study

Applied to the present study, Random Utility Theory (RUT) enables the estimation of part-worth utilities for each attribute level (Louviere et al., 2000), such as platform (Instagram vs. TikTok), influencer type (dermatologist vs. beauty influencer), and discount level; allowing to quantify how each element contributes to overall consumer preference for a specific brand unveiling valuable insights, especially in context-sensitive choices in high-involvement domains like the skincare sector.

Complementing this, Information Integration Theory (IIT) helps explain how consumers cognitively combine cues such as influencer credibility, platform type, and price incentives, with each being assigned a different weight when forming judgments.

Therefore, together, RUT and IIT provide a unified theoretical foundation that supports this study's Choice-Based Conjoint experiment, capturing both the underlying logic and the psychological weighting consumers apply when making decisions.

3.2 Research Design

This study adopts a cross-sectional experimental survey-based research design, aimed at investigating how different digital marketing elements, specifically social media platforms, influencer features, and promotional strategies, affect consumer preferences and skincare brand perceptions. In pursuit of this goal, a Choice-Based Conjoint (CBC) analysis was implemented to examine how variations in marketing attributes influence consumers' comparative evaluations of skincare brands.

3.2.1 Choice-Based Conjoint (CBC) Approach

This experimental context replicates realistic brand evaluation tasks (Rao, 2014) by asking respondents to choose between two fictional brand profiles, each defined by randomized levels of selected marketing attributes, minimizing brand familiarity bias, defined as the tendency to infer prior attention based on brand knowledge rather than on actual cognitive processing during exposure (Aribarg et al., 2010).

Grounded in Random Utility Theory, CBC assumes that each brand profile holds a certain utility for the respondent, who will choose the alternative yielding the highest perceived utility (Rao, 2014), in this case, treated by the researcher as a proxy for perceived trust, initially attributed to the influencer and subsequently extended to the brand endorsed. This method not only reveals which attributes are most influential in consumer decision-making but also estimates part-worth utilities that quantify the impact of each attribute level on overall brand preference (Rao, 2014), making CBC a powerful method for evaluating how digital marketing strategies shape consumer preferences and overall brand reputation within competitive market environments, such as skincare.

3.2.2 Attribute Selection and Level Design

Based on the literature reviewed, five attributes were ultimately chosen (**Table 1**), each defined through realistic levels, aimed at capturing how consumers weigh competing brand signals in the context of digital skincare marketing.

Table 1. Attributes and Levels Used in the Conjoint Experiment

Attribute	Levels
Influencer Type	Beauty Influencer, Cosmetologist or Dermatologist
Social Media Platform	Instagram or TikTok
Follower Count	38K, 195K or 900K
Shared Personal Experience	Positive or No Shared Experience
Discount Code	None, 10% or 20%

Note. The table summarizes the attributes and levels included in the choice-based conjoint design.

For instance, following Saleh et al. (2023), *Follower Count* levels (38K, 195K, and 900K) were selected to reflect representative examples of the mentioned influencer categories: micro-influencers (10K-50K), mid-tier influencers (50K-200K), and macro-influencers (200K-900K).

Discount Code levels (0%, 10%, 20%) were instead selected based on the researcher's personal observation of the most frequently encountered discounts, provided by influencers on TikTok and Instagram.

The attribute *Shared Personal Experience* included only two levels, Positive and No Experience, based on the assumption that a negative experience would logically discourage purchase and, therefore, would not be representative of real promotional content typically shared by paid influencers.

3.2.2.1 Methodological Note (Dermatologist Level)

Considering the researcher's academic and personal network, the survey was primarily distributed across Italy, alongside the Netherlands. As a result, particular attention must be given to the legal and ethical constraints regulating medical professionals' conduct in Italy. Indeed, Law No. 145/2018, article 1, commi 525 and 536, explicitly prohibits healthcare practitioners from engaging in promotional or suggestive advertising (Gazzetta Ufficiale, 2018). Furthermore, FNOMCeO guidelines (2020) stress the importance of preserving neutrality and avoiding marketing-oriented language.

Despite these limitations, the inclusion of dermatologists in this conjoint experiment serves a hypothetical purpose, isolating the perceived effect of medical expertise on consumer brand choice. Therefore, while this manipulation does not represent a legally feasible marketing practice in Italy, it simulates a scenario that aligns with the regulatory flexibility observed elsewhere.

3.2.3 Experimental Setup

The survey was developed and implemented using Qualtrics. Each participant completed 10 choice tasks in which they were asked to choose between two fictitious skincare brands, to avoid brand familiarity bias (Morgan et al., 2021). To enhance realism, each brand profile was sided by a visual representation designed using Canva. The order of brand alternatives within each task was randomized to control for order effects (Serenko & Bontis, 2013). Participants were first provided with an introductory prompt explaining how to complete the tasks, each profile displayed five attributes with randomly assigned levels, creating variation while maintaining a consistent structure.

3.3 Questionnaire and Data Collection

3.3.1 Sampling Strategy

The questionnaire targeted individuals who actively follow a skincare routine. A non-probability sampling strategy was adopted, combining convenience sampling, involving individuals easily accessible to the researcher (Mazodier & Merunka, 2012), and snowball sampling, allowing the sample to grow through referrals. Participants were primarily recruited through social media channels (Instagram and WhatsApp) and directly at the Erasmus University Rotterdam campus.

3.3.2 Survey Design and Implementation

The survey (**Appendix A**) included four sections with 23 questions aligned with the objectives of the analysis.

3.3.2.1 Survey Sections

Section 1: Skincare Product Discovery and Social Media Usage
To ensure relevance, a filter question was placed immediately at the beginning of the survey, automatically excluding participants who reported following no regular skincare routine.

The section explored how participants typically discover new skincare products and how frequently they use social media for skincare-related content. Participants revealed where they first heard about frequently used products (e.g., TikTok, Instagram, in-store, traditional media) and rated how often they discover new skincare brands through different channels. Additionally, they reported how often they use Instagram and TikTok specifically for skincare content, using a five-point frequency scale ranging from "less than once a month" to "multiple times per day." These frequency measures were then used to construct a moderator variable.

Section 2: Choice-Based Conjoint Tasks

In this section, participants completed 10 choice tasks, each presenting two fictional skincare brands (Brand A vs. Brand B), described using randomized combinations of five attributes: *influencer type, social media platform, follower count, shared personal experience and discount code* (**Appendix B**). In each task, participants were asked to select one of the two brands, based solely on the presented randomized combination of five predefined attributes. Two choice tasks exhibits are available in **Appendix C**.

Section 3: Post-Task Perceptions

After completing the 10-choice tasks, participants responded to four Likert-type scale questions (**Appendix D**) assessing their perceptions of influencer trustworthiness, follower count credibility, price-related value, and discount framing. An additional forced-bipolar-choice question (on a 7-point scale) between two brands' pricing strategies (Brand A and Brand B) to evaluate perceived brand reliability.

To avoid priming effects, namely psychological responses which occur when prior exposure to specific information influences unconsciously how participants process subsequent stimuli (Nagar, 2021), these questions were placed after the choice tasks. Furthermore, their order was randomized to prevent a natural response progression (e.g. spanning from trust to follower count, discount, and overall brand reputation), which could have potentially biased participants' evaluations.

Section 4: Screening and Demographics

This section included questions about gender, age group, nationality, and occupation, in order to gather relevant demographic information for sample description and relevant subgroup analyses.

3.3.2.2 Moderator Variable (Social Media Frequency Usage)

To assess the moderating effect of social media frequency usage, respondents were classified based on how frequently they engaged skincare-related content on social media. Participants reporting daily or multiple times per day were classified as high-frequency users, while others were categorized as low-frequency users.

3.3.3 Pre-testing and Validation

Before launching the final survey, a pre-test with 30 participants was conducted to identify potential issues related to clarity, comprehension, and technical flow. Responses from the pre-test were excluded. To ensure content validity, attribute and level selection were based on extensive literature review. Randomization and the initial screener question improved internal validity, also supported by randomizing attribute levels and question order to minimize systematic bias (Hamilton et al., 2017). Reliability was enhanced through Hierarchical Bayes estimation, which accounted for preference heterogeneity, improving model stability.

3.4 Measures

A five-point Likert-type response format assessed brand discovery frequency and post-task perceptions. In Section 1, a multi-item Likert-type scale measured how frequently participants discover skincare brands across channels. Section 3 included questions on influencer trustworthiness, follower count credibility, perceived discount value, and price consistency. Long-term brand credibility was approximated using perceived price fairness and brand reliability, while questions on influencer trustworthiness and discount value captured short-term attitudes. Although these measures reflect perceptions rather than behavior, their theoretical design makes them valid proxies for evaluating brand reputation (Diamantopoulos & Winklhofer, 2001).

3.5 Variables

The analysis focuses on four main groups of variables.

- Demographic variables capture respondents' background characteristics such as age, gender, nationality, and employment status.
- Behavioral variables reflect skincare-related habits and discovery patterns across social media and traditional channels.
- Conjoint task variables refer to the experimentally manipulated attributes shown in the choice tasks, including influencer type, follower count, platform, discount level, and shared experience.
- Attitudinal variables record respondents' perceptions of influencer trustworthiness, follower count, price-related value, and long-term brand credibility through Likert-type questions and evaluative items.

3.6 Data Analysis

3.6.1 Conjoint Estimation Techniques

To estimate consumer preferences and quantify the impact of each attribute level on brand choice, two discrete choice models were applied.

3.6.1.1 Multinomial Logit Model (MNL)

The primary estimation method used was the Multinomial Logit Model (MNL), a simple yet widely used choice model that estimates the probability of selecting a specific brand profile based on the sum of its attribute utilities (Vermeulen et al., 2008). It assumes that respondents choose the option, in this case the brand, providing the highest overall utility, which depends on the observed attribute levels and a random error component (Dellaert et al., 1996). While MNL facilitates interpretation and serves well for aggregate-level analysis, it relies on the Independence of Irrelevant Alternatives (IIA) assumption, namely the relative odds between any two choices remain unaffected by the presence of other alternatives, treating all respondents as having homogeneous preferences. (Vermeulen et al., 2008).

3.6.1.2 Hierarchical Bayes (HB)

Despite MNL serving as a baseline model for understanding general trends in attribute importance, a Hierarchical Bayes (HB) estimation, a more advanced and robust method, was also conducted to account for heterogeneity in consumer preferences with the aim of obtaining individual-level estimates, employing a Bayesian framework to estimate part-worth utilities for each respondent (Andrews et al., 2002).

Therefore, the dual application of MNL and HB provides both a macro and micro-level understanding of consumers' trade-offs, offering a robust perspective on how social media exposure, influencer type, and discount strategies affect skincare brand perception.

3.6.2 Moderation Analysis

To examine whether social media engagement frequency moderated the relationship between discovery channel and discovery frequency, respondents were classified into high or low social media users groups based on how frequently they reported to engage with skincare-related content on social media. Additional regressions per platform and interaction models were conducted to explore the hypothesized potential moderating effects of engagement on participants' discovery behaviors.

3.6.3 Hypotheses Testing Techniques

To systematically evaluate the theoretical framework proposed in Chapter 2, this section outlines the empirical approach adopted to test each of the seven proposed hypotheses (H1–H7) throughout the study. The strategy aimed at combining insights from primarily the Choice-Based Conjoint (CBC) tasks, some behavioral and post-task Likert-type questions.

Each hypothesis and its corresponding analytical method are outlined in the following overview.

- **H1: Social Media Discovery vs. Traditional Media**

The first hypothesis was tested using behavioral variables capturing the respondents' frequency of skincare brand discovery across different channels, such as Instagram, TikTok, traditional media, and in-store experiences. A moderation analysis was then conducted based on respondents' usage frequency of social media platforms to determine whether high-frequency users were more likely to discover skincare brands through digital channels.

Note: To test hypotheses H2 to H6, the conjoint data was analyzed using both a Multinomial Logit (MNL) model and a Hierarchical Bayes (HB) estimation.

- **H2: Platform Influence on Brand Choice**

Evaluated using the part-worth utilities associated with the levels of the social media platform attribute presented in the CBC experiment. A comparative analysis of estimated utilities determined whether TikTok promotion could yield higher brand choice probabilities compared to Instagram.

- **H3: Follower Count**

Assessed by examining the estimated part-worth utilities of three follower count levels (38K, 195K, and 900K) in the CBC tasks, with the aim of identifying the level most associated with higher brand selection.

- **H4a, H4b, H4c: Influencer Type**

These hypotheses were tested through the utility values assigned to different influencer types. By comparing estimated part-worth utilities, the analysis revealed whether expert-based endorsers (dermatologists and/or cosmetologists) were associated with higher brand preference relative to popular beauty influencers.

- **H5: Impact of Personal Experience Shared by the Influencer**

Investigated by comparing the effect of an influencers' positive vs. no personal shared experience, as presented in the conjoint attribute, testing whether a positive testimonial would lead to a higher choice probability.

- **H6: Discount Level**

Tested by estimating the relative impact of different discount levels (none, 10%, and 20%) on brand choice. Higher utility scores for the highest discount offer would confirm the hypothesized incremental effect of promotional pricing strategies on consumers' propensity to choose the promoted brand.

- **H7: Price Consistency and Brand Credibility**

This hypothesis was examined through post-task Likert-type responses and a forced-bipolar-choice question. The responses served as proxies for perceived brand credibility. To reinforce the robustness of the findings, beyond descriptive statistics, additional analyses were conducted, including a one-sample t-test to test deviation from neutrality, a Spearman correlation, a linear regression to assess the association between credibility beliefs and brand preference, and, lastly, an ordinal logistic regression controlling for demographic factors.

3.7 Ethical Considerations

Participation in the study was entirely voluntary, and all respondents were informed about the purpose, scope, and confidentiality of the research prior to taking part in the survey.

An informed statement was included at the beginning of the questionnaire, clearly stating that participation was anonymous and that respondents could withdraw from the survey at any point without any consequences. No personally identifiable information (PII) was collected at any stage of the study, ensuring full anonymity of the data. The data collected was stored securely and used exclusively for academic purposes related to the Master's Thesis. No third-party access to the raw dataset was granted, and the results were reported in aggregate form only. For additional transparency, the contact details of the researcher were provided at the start of the survey, allowing participants to ask questions or raise concerns at any time.

Given these precautions, the study was considered low-risk and fully compliant with ethical research standards.

4. Results

This chapter presents the empirical results grounded in the research hypotheses formulated in Chapter 2 and estimated through the methodological framework outlined in Chapter 3.

4.1 Sample Description

4.1.1 Demographic Overview

Initially, a total of 576 individuals took part in the survey. After filtering out 48 respondents who reported not following a skincare routine, the final analytical sample included 528 valid participants (**Appendix E, Table 1**) .

As expected, the sample resulted largely *female* dominated (93.6%), with only 4.7% of the respondents being *male*, 0.9% identifying as *non-binary or other*, and 0.8% preferring *not to disclose* their gender.

Age-wise, the findings reveal a relatively young sample, having the largest group of respondents falling within the *25-34* age range (40.3%), followed by the *18-24* (24.2%) and *35-44* (22.2%) ranges. Older age groups (*45–54, 55–64, 65+*) collectively add up to approximately 12.7% of the sample, while only 0.6% of respondents are *under 18*.

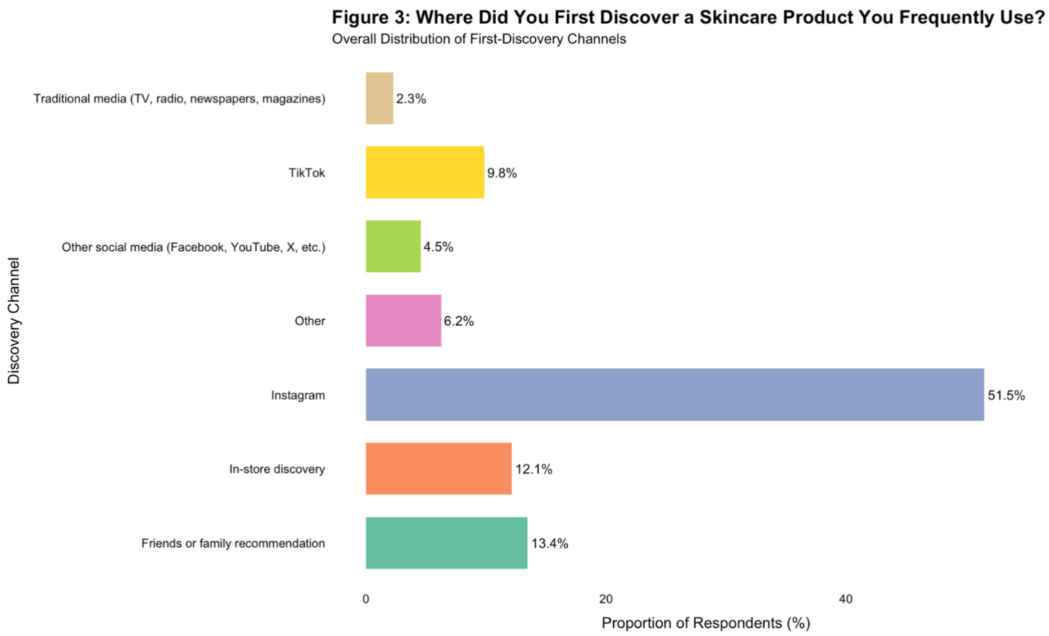
As expected, given the researcher's academic and personal network, 93.8% of the participants declared to be *Italian*, while the remaining 6.2% consisted of 19 other nationalities, including Turkish, Dutch, Greek, and Swiss.

When it comes to employment status, 47.3% of the respondents reported to be *employed full-time*, followed by 28.6% who are *students*. Less represented categories included *self-employed* (8.7%), *part-time workers* (6.3%), *unemployed* (4.9%), and *other occupations* (4.2%).

In summary, the sample is primarily composed of young Italian women, with a strong representation of working professionals and students with presumably sufficient economic engagement and digital exposure.

4.1.2 First-Discovery Channels for Skincare Products

Overall, *Instagram* dominates as the primary discovery channel, cited by 51.5% of the total respondent sample; followed by *friends or family recommendations* (13.4%), *in-store discovery* (12.1%), and *TikTok* (9.8%). *Traditional media* (TV, radio, newspapers and magazines) and *other social platforms* (Facebook, YouTube, X, etc.) and *others* contribute minimally (**Figure 3**).

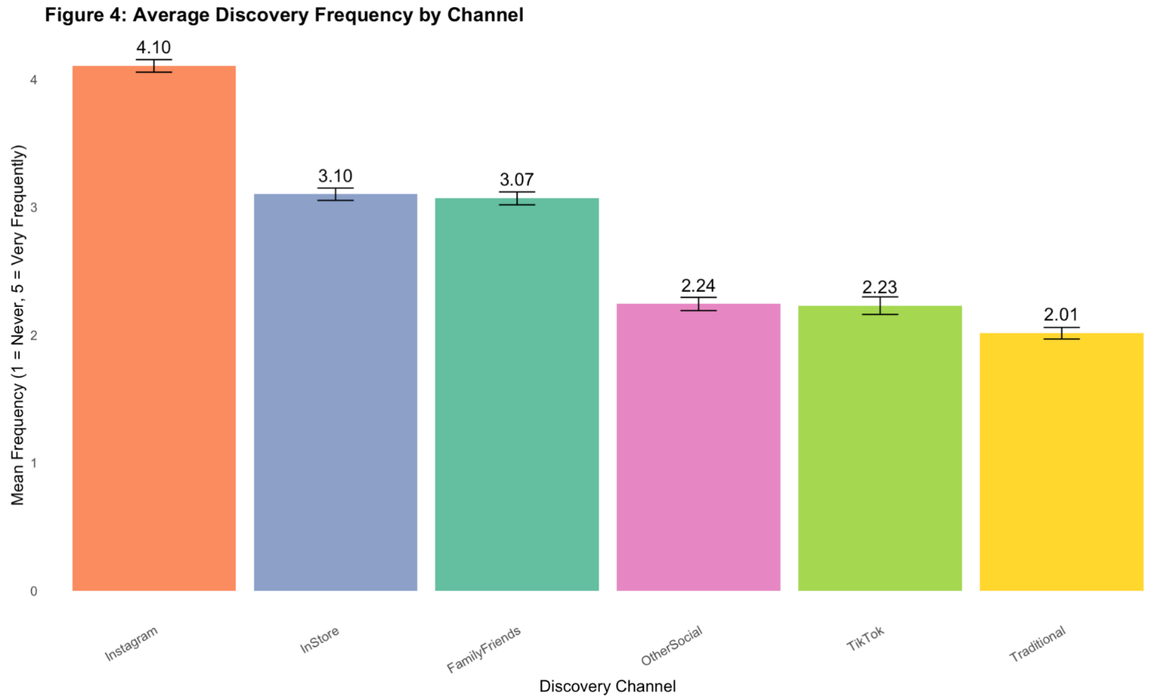


To explore possible variation across groups, discovery patterns were visualized by gender, age, and occupation. The findings confirm Instagram as the dominant channel for skincare discovery across all age groups and women, with TikTok also being an influential driver, especially among younger respondents and students. On the other hand, men claim to favor friends or family recommendations. Overall, social media dominates as the primary source of product discovery, though preferences vary across demographics.

4.1.3 Overall Skincare Engagement across Platforms

This section moves beyond initial skincare product discovery, examining how frequently respondents encounter skincare brand content through various channels over time, regardless of whether it led to a first-time discovery. Specifically, participants were asked to rank their exposure to each listed channel on a 5-point Likert-type scale measuring frequency exposure, ranging from 1 = Never to 5 = Very Frequently.

On average, in line with previous findings, Instagram stands out as the most frequent discovery source, achieving a very high mean frequency score (**4.10**) on the five-point Likert-type scale. In-store discovery (**3.10**) and recommendations from family and friends (**3.07**) also report moderate levels of repeated exposure. However, other social media platforms such as Facebook, X, and YouTube (**2.24**), TikTok (**2.23**), and traditional media (**2.01**) show considerably lower average engagement levels, suggesting a more restricted role in sustaining ongoing brand awareness (**Figure 4**).



Note: The horizontal bars on top of each column represent the standard error (SE) of the mean, reflecting the variability in average discovery frequency per channel. The shorter the bar the greater precision in the estimate.

Women report the highest average discovery rate for Instagram followed by family or friends recommendations and in-store experiences. Men display slightly lower averages across most channels, with in-store discovery being their most frequently reported source overall, however Instagram and TikTok still play a relevant role.

As expected, especially younger participants (18–34) show higher exposure to Instagram and TikTok, although the former still dominates among older groups, as well as for occupation, which, in contrast, show lower average engagement with the latter and slightly more balanced reliance on other channels.

4.2 Hypothesis 1 – Social Media vs Traditional Media Discovery

The first hypothesis (H1) claimed skincare brands to be more frequently discovered through social media platforms, particularly Instagram and TikTok, than through traditional media channels (e.g., television, magazines, in-store discovery). Additionally, it was hypothesized that this effect would be moderated by respondents' general engagement with social media, such that high social media users would report higher discovery frequencies overall.

4.2.1 Descriptive Exploration of Social Media Engagement (Moderator)

A preliminary examination of social media engagement was conducted to contextualize the sample before testing moderation effects. Overall, 220 participants (41.7%) were classified as High Social Media Users, and 308 respondents (58.3%) as Low Social Media Users (**Appendix E, Table 2**). Gender-wise, female respondents were almost equally distributed between the two categories, also given their greater representation in the sample, whereas male and non-binary participants were predominantly classified as low users. As expected, respondents aged 25-34 showed a greater tendency toward high engagement levels, whereas older cohorts were more frequently categorized as low social media users. Students and unemployed respondents mostly displayed higher social media activity across occupational categories.

4.2.2 Overall Discovery Frequency Comparison

Mean comparison analyses showed that social media channels were reported as significantly more frequent sources of skincare brand discovery than traditional media. Specifically, social media (cumulatively comprising Instagram and TikTok) mean discovery frequency was $M = 2.86$, while traditional media channels averaged $M = 2.54$ (**Appendix E, Table 3**). Moreover, a paired sample t-test confirmed that this difference was statistically significant ($p < .001$), with a mean difference of 0.32 and a 95% confidence interval (**Appendix E, Table 4**). Although the gap was less pronounced than initially expected, the findings still confirmed the social media significant involvement in the discovery process.

4.2.3 Platform-Specific Regressions

To further explore platform-specific associations between social media engagement and discovery frequency (**Appendix E, Table 5**), an extensive regression model, including all platforms and their interactions, was estimated. Compared to Instagram (the reference category), all other platforms had significantly lower baseline discovery frequencies. Moreover, the main effect of high social media engagement was positive and highly significant overall ($\beta = + 0.86$, $p < .001$), showing that respondents with higher engagement reported more frequent discovery through social media.

Significant interaction terms revealed that the effect of high social media engagement on product discovery differs across platforms. While high engagement is positively associated with discovery likelihood on Instagram (reference category), this effect is significantly weaker on TikTok, other social media platforms, and traditional media, as shown by the negative interaction coefficients. Thus, the predictive strength of high engagement is attenuated when the discovery platform is not Instagram.

Taken together, these findings provide strong support for Hypothesis 1. Skincare brands are more frequently discovered through social media platforms, particularly Instagram, compared to traditional media. Moreover, the effect of platform type on discovery is significantly moderated by users' social media engagement: the positive association between high engagement and discovery likelihood is strongest on Instagram and weaker on other platforms such as TikTok, other social media, and traditional channels.

4.3 Conjoint Analysis Results (Hypotheses 2 – 6)

4.3.1 Data Preparation and Reshaping

To test Hypotheses 2 through 6, the choice-based conjoint (CBC) dataset was prepared and reshaped into a long format, containing, for each individual, their recorded choices (Q5 - Q14) along with the specific levels of the five experimental attributes associated with each brand alternative (Brand A or B) (**Appendix B**). After data cleaning, the final dataset included 10,560 rows, corresponding to 528 respondents completing 10 choices each, with two alternatives per task.

4.3.2 Multicollinearity Diagnostics

Variance inflation factors (VIFs) were computed using a linear model regressing the choice variable on all five attributes. All VIF values were below commonly accepted thresholds (VIF < 5), more specifically between 1.17 and 2.35), revealing no substantial multicollinearity among predictors.

4.3.3 Multinomial Logit Models (H2 - H6): Individual Attributes

To individually test the impact of influencer and promotional attributes on brand choices, separate multinomial logit models were estimated for each hypothesis (**Appendix E, Table 6**).

All categorical predictors were dummy-coded with the reference category set as the lowest or alphabetically first level unless otherwise specified. Therefore, coefficients represent log-odds relative to these reference categories.

- **H2 - Platform:** Brands endorsed on TikTok were significantly less likely to be chosen compared to those on Instagram ($p < .001$), contrary to expectations.
- **H3 - Follower Count:** A follower count of 38,000 significantly increased brand choice utility, while, as expected, having 900,000 followers significantly decreased it (both $p < .001$). This pattern partially contradicted the hypothesis that mid-tier influencers (195,000 followers, being the reference category) would yield the highest brand utility compared to both micro-influencers (e.g., 38,000 followers) and macro-influencers (e.g., 900,000 followers).

- **H4 - Influencer Type:** Dermatologist and cosmetologist endorsements were both associated with a greater likelihood of brand selection ($p < .001$) compared to a beauty influencer, in line with both H4a and H4b. However, cosmetologists had a stronger effect on brand choice, contradicting the hypothesis that dermatologists would be preferred (H4c).
- **H5 - Shared Personal Experience:** Sharing a positive experience surprisingly negatively affected brand utility ($\beta = -0.167$, $p = .006$), suggesting such narratives may be perceived as less credible and sincere.
- **H6 - Discount:** Offering a 20% discount strongly increased brand selection ($p < .001$), supporting the hypothesis. However, the absence of a discount also had a significant positive effect ($p < .001$) relative to the reference category (10%).

4.3.4 Full Multinomial Logit Model

To comprehensively assess the impact of all influencer and promotional attributes on brand choice, a full multinomial logit model was estimated including platform, follower count, shared experience, discount level, and influencer type (**Table 2**).

Table 2. Full Multinomial Logit Model Predicting Brand Choice

Predictor	Estimate	Std. Error	z value	p-value
(Intercept)	−6.445	0.326	−19.800	<0.001 ***
Platform: TikTok (H2)	−6.421	0.260	−24.680	<0.001 ***
Follower Count: 38K (H3)	3.575	0.221	16.150	<0.001 ***
Follower Count: 900K (H3)	0.520	0.245	2.120	0.034 *
Influencer: Cosmetologist (H4)	1.011	0.081	12.550	<0.001 ***
Influencer: Dermatologist (H4)	1.968	0.143	13.750	<0.001 ***
Shared Personal Experience: Positive (H5)	10.109	0.421	24.000	<0.001 ***
Discount: 20% (H6)	−1.717	0.278	−6.170	<0.001 ***
Discount: No Discount (H6)	3.743	0.145	25.820	<0.001 ***

Note. *** $p < .001$, ** $p < .01$, * $p < .05$. Estimates are log-odds relative to the reference categories (Instagram, 185K followers, no experience shared, baseline discount, beauty influencer). McFadden R^2: 0.38365.

- **H2 - Platform**: Controlling for all other factors, brands promoted on TikTok were significantly less likely to be chosen compared to those promoted on Instagram ($\beta = -6.421$, $p < .001$).
- **H3 - Follower Count**: When holding other attributes constant, both smaller (38K) and larger (900K) audiences increased choice probability (in particular smaller creators) compared to the 185K reference category, clarifying that high follower counts were not detrimental when controlling for other factors, although smaller creators seems to be preferred.

- **H4 - Influencer Type**: Ceteris paribus, influencer type remained a crucial aspect: dermatologist endorsements had the strongest positive impact ($\beta = + 1.968$, $p < .001$), surpassing cosmetologists, according to the expectations.
- **H5 - Shared Personal Experience**: Holding other variables constant, shared personal experience emerged as the strongest positive predictor ($\beta = + 10.109$, $p < .001$), reversing the negative effect seen in simpler models, being in line with what was hypothesized.
- **H6 - Discount**: After adjusting for all other variables, discount effects also changed direction: offering a 20% discount reduced selection likelihood ($\beta = -1.717$, $p < .001$), while no discount increased it ($\beta = +3.743$, $p < .001$) with respect to offering a 10% discount, implying that discounts may signal lower brand value in the presence of competing cues.

Overall, controlling for all factors revealed several reversed or attenuated effects compared to separate models, highlighting consumer preferences' complexity.

4.3.5 Relative Importance of Attributes (Full MNL)

Furthermore, the relative importance of each attribute was calculated (**Appendix E, Table 7**) based on the range of utility estimates across all levels, normalized to sum to 100%. Shared Personal Experience emerged as the most influential attribute (36.7%), followed by Platform (23.3%) and Discount (19.8%). Follower Count accounted for 13.0% of the explained variance in choice, while Influencer Type was the least important factor overall (7.2%).

4.3.6 Multinomial Logit Models Comparisons - Goodness of Fit

To assess whether including additional predictors significantly improved model performance, Likelihood Ratio Tests were conducted comparing five single-attribute multinomial logit (MNL) models to the full specification, including all five attributes (platform, follower count, influencer type, shared personal experience, and discount).

Results (**Appendix E, Table 8**) showed that, across all pairwise comparisons, the full model always achieved substantially better fit. All likelihood ratio chi-squared statistics were large and highly significant (all $p < .001$), confirming that each attribute added important explanatory value compared to models analyzing each factor's impact individually.

Model selection criteria further confirmed these findings. The full model reported the lowest Akaike Information Criterion (AIC) (**Appendix E, Table 9**), highlighting its optimal balance between goodness of fit and model complexity.

Finally, the Independence of Irrelevant Alternatives (IIA) assumption was tested using the Hausman-McFadden procedure (**Appendix E, Table 10**). All tests yielded non-significant results (p = 1), with negative chi-squared statistics, showing no evidence of IIA violations, suggesting that the relative odds of selecting any alternative were stable across different subsets of the choice set, supporting multinomial logit specification appropriateness.

Overall, these model comparison diagnostics confirmed that the full MNL model provided the best and most reliable representation of respondents' brand choices, justifying its use as the primary basis for inference in this study.

4.4 Hierarchical Bayes Estimation of Individual-Level Preferences

4.4.1 Model Estimation and Convergence

Building upon the previous aggregate Multinomial Logit estimation, Hierarchical Bayes (HB) modeling was applied to capture heterogeneity in consumer preferences, obtaining individual-level part-worth utilities for each attribute level. A total of 10,000 MCMC draws were generated, retaining every 10th draw for posterior inference, which confirmed stable posterior distributions across all parameters.

4.4.2 Estimated Part-Worth Utilities

The estimated part-worth utilities (posterior means) for each attribute level are visualized in **Table 3** and **Appendix F, Figure 1** and **Figure 2**. Higher utility values revealed greater relative preference, while negative values implied lower attractiveness compared to the (omitted) baseline level. **Figure 1** shows that the strongest positive utilities were associated with the absence of a discount and the presence of a shared positive personal experience by the endorser, implying that excessive discounting might potentially harm perceived brand value. **Figure 2** illustrates the distribution of individual-level part-worth utilities, whose effects were broadly consistent across respondents, displaying relatively narrow dispersion for the strongest positive and negative utilities.

Specifically, the results (**Table 3**) show that TikTok was strongly associated with negative utility estimates, suggesting that brands promoted through this channel were perceived less favorably compared to those endorsed on Instagram, contradicting **H2**. When it comes to follower count, macro influencers (900K followers) were associated with the highest negative utility overall, while mid-tier influencers (195K followers) were closer to zero utility, therefore preferred over macro influencers but not over micro influencers overall, providing partial support for **H3**. Focusing on influencer type, cosmetologists were viewed more favorably compared to the reference category (beauty influencers) (**H4b**), while, surprisingly, endorsement by dermatologists resulted in a negative utility estimate, partially contradicting **H4a** and **H4b**, hypothesizing that dermatologists would register the highest preference. In contrast, the presence of a positive personal experience strongly increased utility, providing clear support for **H5**. Finally, the analysis revealed that offering 10% discount was the alternative leading to a substantial positive utility estimate, unlike offering 20% discount, contradicting what was expected in **H6**.

Table 3. HB Estimated Part-Worth Utilities (Baseline Levels Marked)

Attribute	Level	Utility (log-odds)	Baseline
Platform	Instagram	0.00	TRUE
Platform	TikTok	−6.81	FALSE
Follower Count	38K	0.00	TRUE
Follower Count	Count_195K	−0.24	FALSE
Follower Count	Count_900K	−12.27	FALSE
Influencer Type	Beauty Influencer	0.00	TRUE
Influencer Type	Type_Cosmetologist	2.56	FALSE
Influencer Type	Type_Dermatologist	−1.96	FALSE
Shared Experience	None	0.00	TRUE
Shared Experience	pers_exp_Positive	8.08	FALSE
Discount	No Discount	0.00	TRUE
Discount	10%	8.69	FALSE
Discount	20%	−4.30	FALSE

Note. Baseline = TRUE indicates the reference category for each attribute; utility fixed to 0. These part-worth utilities quantify the relative impact of each attribute level on the likelihood of brand choice, expressed in log-odds units. Therefore, positive or negative values show how each factor increases or decreases the probability of selection compared to the baseline, rather than representing absolute probabilities or direct measures of perception.

4.4.3 Relative Importance of Attributes (HB)

To complement these results, the relative importance of each attribute was calculated (**Appendix E, Table 11**) based on the range of part-worth utilities across all levels (including baseline levels with utility set to zero). *Discount* emerged as the most influential attribute (29.1%), closely followed by *Follower Count* (27.5%). *Shared Personal Experience* accounted for 18.1% of the explained variance in choice, while *Platform* contributed 15.2% while *Influencer Type* was the least important factor (10.1%).

Overall, these results suggest that financial incentives and social reach indicators were the primary drivers of respondents' preferences, whereas social media platform and influencer type played comparatively smaller roles in shaping respondents' decisions.

4.4.4 Preference Segmentation and Clustering

To further explore preference heterogeneity, a k-means cluster analysis was conducted on the individual-level part-worth utilities. For interpretability, a three-cluster solution was selected.

- **Cluster 1 (15.3%) - The Trustkeepers:** consumers who place high value on authenticity and credibility. They positively respond to personal influencer experiences and show a clear preference for stable pricing over discounts, suggesting a trust-based decision-making approach.
- **Cluster 2 (36.9%) - The Steadies:** consumers with moderate preferences towards influencer expertise and positive personal experiences, showing less negative attitudes towards TikTok compared to other clusters.
- **Cluster 3 (47.8%) - The Sceptics:** consumers who show mild resistance to discounts and promotional platforms like TikTok, they also do not strongly favor high-credibility cues such as personal experience or expert endorsers.

The cluster structure is visualized in **Appendix F, Figure 3**. These findings enhance the importance of tailoring digital marketing strategies to audience segments' preferences, each characterised by unique decision-making patterns. In particular, the distributions show how attributes, such as discount levels and shared experience, can be perceived differently across consumers. Moreover, this cluster analysis further displays Hierarchical Bayesian (HB) approach ability, unlike the Multinomial Logit model, to capture nuanced individual preferences, critical for designing targeted digital marketing interventions.

Therefore, by modeling respondent-level heterogeneity, HB estimation uncovers attribute patterns that standard models are unable to detect, allowing for a more refined customer segmentation and, from a managerial perspective, clarifying which attributes are most effective to prioritize, so that resources can be directed toward the factors most likely to drive engagement and conversion.

4.5 Multinomial Logit Model and Hierarchical Bayesian Modeling Comparison

This section compares the predictive performance of the two models employed in this study, Multinomial Logit (MNL) and Hierarchical Bayesian (HB), using out-of-sample holdout validation as the evaluation criterion (**Appendix E, Table 12**). To ensure robustness, the MNL model was estimated and tested across five different random 70/30 splits of the dataset, ensuring results were not dependent on a single sampling draw, providing a more reliable estimate of average predictive performance. Conversely, the HB model was fitted only once due to the considerably higher computational burden associated with MCMC estimation, which can take several hours per run.

The predictive accuracy was evaluated using the hit rate, namely the proportion of correctly predicted choices in the holdout samples (Chapman & Feit, 2015). The MNL model achieved an average hit rate of approximately 50.1%, which is close to random prediction in a binary choice context, and close to random guessing. This relatively low performance is a well-documented limitation of aggregate logit models, as they do not account for individual-level preference heterogeneity. In contrast, the HB model obtained a substantially higher hit rate, exceeding 84%, enhancing its ability to better capture variations in preferences across respondents. This substantial improvement once again rooted for the implementation of Hierarchical Bayesian estimation, as it enables more accurate predictions, offering deeper insights into consumer decision-making patterns.

4.5.1 Estimated Utilities Comparison

Figure 4, (Appendix F) shows the estimated part-worth utilities from the MNL and HB models. While both approaches identify similar patterns, such as positive utilities for cosmetologist endorsements and positive personal experience sharing, differences emerge in the magnitude and even direction of some estimates. For instance, dermatologist endorsements receive a positive utility under MNL but a negative one under HB, while 20% Discount is penalized more heavily in HB. These differences highlight HB's sensitivity to individual-level variation, producing more nuanced preference estimates, whereas MNL summarizes preferences at the aggregate level. However, the general consistency in ranking and sign of key effects supports the robustness of the findings across estimation methods.

4.6 Hypothesis 7 - Stable Pricing & Brand Credibility

Hypothesis 7 states that skincare brands maintaining stable and predictable pricing, without frequent discounting, are perceived as more credible and reliable over time. As shown in **Table 13** (**Appendix E**), most respondents agreed (40.3%) with the statement while 12.3% strongly agreed and only 13.6% expressed disagreement.

Looking at pricing preference, **Figure 5** (**Appendix F**) illustrates that 22.7% claimed a strong preference for Brand A, maintaining consistent pricing while 35.8% cumulatively selected more moderate preference levels (2 or 3). In contrast, only 5.1% reported a strong preference for the discount-driven Brand B, while around one-quarter of respondents remained neutral (rating 4 on the scale).

To statistically assess support for Hypothesis 7, multiple tests were conducted (**Appendix E, Table 14**). A one-sample t-test showed that the mean agreement score was significantly above the neutral midpoint of 3 (M = 3.49, $p < .001$), suggesting that participants tend to perceive stable pricing as an indicator of brand credibility.

A paired-sample t-test further revealed a significant difference between brand reliability agreement and pricing preference (Mean Difference = 0.39, $p < .001$), suggesting that perceptions of stable pricing positively influence preference for the consistently priced brand.

Additionally, a Spearman's rank-order correlation showed a moderate, statistically significant negative association (p = - 0.42*)* between credibility agreement (Q18) and preference for the discount-oriented brand (Q19), $p < .001$, implying that those who value pricing stability tend to reject brands that frequently use discounts.

Moreover, a simple linear regression (**Appendix E, Table 15**) showed that brand preference (Q19) significantly predicted credibility agreement (Q18), with a negative coefficient ($\beta = -0.22$, $p < .001$). This confirms that stronger preference for Brand A (lower Q19 scores) is associated with greater agreement that stable pricing signals credibility (higher Q18 scores).

Lastly, an ordinal logistic regression was conducted (**Appendix E, Table 16**), verifying a strong and statistically significant effect of brand preference (Q19) on credibility perception ($\beta = -0.55$, $p < .001$), confirming that those favoring stable-pricing brands were more likely to associate pricing consistency with credibility. While demographic variables such as gender, occupation, and nationality were not significant predictors, interestingly, only older respondents (65+) were found to be significantly less likely to agree that pricing stability signals brand reliability ($\beta = -2.13$, $p = .008$).

Taken together, these findings provide robust empirical support for Hypothesis 7, suggesting that, in the skincare industry, maintaining stable and predictable pricing contributes to increase brand trustworthiness, while frequent discounting may erode brand credibility.

4.7 Post-Task Perceptions Results

To complement the experimental choice data, respondents were asked to rate a series of statements on 5-point Likert-type scales, providing additional insights into their attitudes toward influencer credibility, follower count impact, and discount-related value perception; reinforcing and contextualizing the experimental findings. These items were positioned after the choice-based conjoint tasks, randomizing their order, to avoid priming effects that could have biased respondents' trade-offs during the experimental tasks.

4.7.1 Trust in Skincare Recommendations

On average, respondents expressed a relatively low level of trust in recommendations from general beauty influencers, compared to higher trust in expert figures such as cosmetologists and dermatologists (**Appendix E, Table 17**), being in line with the choice modeling results showing a clear preference for expert endorsements over popularity-based influencers, supporting the idea that perceived expertise exerts a significant role in shaping consumer trust.

4.7.2 Perceived Impact of Follower Count on Trust

When asked how much an influencer's follower count affects their trust in skincare recommendations, respondents, on average, reported a modest influence (M = 2.24). In fact, most participants chose lower or mid-range scores, suggesting that follower count is not seen as a strong determinant of credibility.

These results suggest that, despite the prominence of follower counts in influencer marketing, most consumers do not perceive this metric as a crucial signal of credibility.

4.7.3 Perception of Discount-Driven Value

Lastly, respondents rated how discount codes affect their perception of a product's value. The mean score was close to neutral (M = 2.8), implying that, on average, discounts may be seen as a modest incentive, however, they are generally not perceived as significantly affecting the perceived value of the product.

5. Conclusions

5.1 Summary of Findings

This study examined to what extent digital marketing practices shape consumer perceptions and brand reputation in the skincare market, using a choice-based conjoint experiment combined with Multinomial Logit (MNL) and Hierarchical Bayes (HB) models. **H1** was supported, confirming that social media channels, particularly Instagram, are the dominant source of brand discovery, with higher engagement frequency reinforcing awareness (**SRQ1**). Contrary to initial expectations (**H2**), TikTok promotions were less effective in driving brand choice compared to Instagram. Follower count (**H3**) showed inconsistent effects as micro-influencers (38K) were preferred over mid-tier (195K) and macro-influencer (900K), whose large follower count always discouraged brand choice. **H4** results revealed that endorsements by expert figures increased brand choice and perceived credibility compared to beauty influencers (H4a and H4b). However, contrary to expectations (H4c), cosmetologists were preferred over dermatologists, highlighting that perceived expertise is crucial but not uniform across professional profiles. **H5** was supported as influencers sharing their positive personal experiences increased consumer preference, enhancing storytelling's role in shaping favorable perceptions (**SRQ2**). Moreover, while moderate discounts could enhance purchase intention, excessive discounting diminished perceived brand value (**H6**). Finally, **H7** showed that stable and predictable pricing strategies improved perceptions of brand credibility and reliability over time (**SRQ3**). Overall, (**MRQ**) the findings support the idea that all the analyzed digital marketing practices, to varying degrees, significantly jointly shape consumer perceptions and contribute to building strong, credible brand reputations within the skincare sector.

5.2 Theoretical Contributions

The findings contribute to the extension of Random Utility Theory, as outlined in Chapter 3, by empirically validating that trust-based cues, particularly authentic experience-sharing and consistent pricing, exert a strong influence on consumer utility formation in the skincare context. In both MNL and HB models, attributes such as *Shared Experience* and *Discount* consistently emerged among the most influential drivers of consumer choice, outweighed popularity signals like Follower Count and, to a lesser extent, Platform, suggesting that consumers in the skincare sector tend to prioritize authenticity and price consistency over reach-oriented signals such as platform type or influencer popularity.

Second, the results support and refine Information Integration Theory, confirming that consumers uniquely assign different weights to cues. Indeed, the observed heterogeneity across preference segments proves that information integration is highly individual and context-dependent. These insights underline, once again, that consumers preferences, in relation to brand reputation, emerge from complex combinations of signals rather than any single attribute in isolation.

5.3 Managerial Contributions

This study offers several actionable insights for skincare brand managers and digital marketing practitioners aiming to strengthen brand reputation and target consumer preferences more efficiently.

While certain attributes may appear more important overall in terms of relative utility, their perceived relevance can vary significantly across consumer segments or clusters. Therefore, the following managerial insights should not be interpreted as universally prescriptive, but, rather, as general strategic guidelines that should be tailored to specific brand contexts and target consumers.

First, the results highlight that credibility-based strategies are more effective than purely popularity-driven tactics. In fact, overall, endorsements by expert figures, such as dermatologists or cosmetologists, were consistently associated with higher brand choice and perceived trust, suggesting that skincare brands should prioritize engaging with professionals whose expertise, as observed, reinforces product claims. Therefore, managers should consider investing in partnerships with credible experts rather than focusing exclusively on beauty influencers.

Second, the findings demonstrate that platform familiarity plays a key role in shaping brand choice. While TikTok is often viewed as the most dynamic platform for brand discovery, this study found that Instagram's established visual ecosystem and consistent user experience were more effective in driving brand preference. This signals that skincare brands should not assume newer platforms will automatically outperform established ones and, therefore, should align channel selection with their target audience's digital habits.

Third, authentic storytelling and moderate promotions emerged as important drivers of consumer preferences. Indeed, Influencers who shared positive personal experiences were more effective in driving consumer preference, highlighting the persuasive power of relatable content. However, the results highlight the potential risks of excessive discounting in fact, although promotions can attract attention, large discounts can indeed undermine brand credibility when overused. Managers should therefore design discount strategies that support, rather than erode, perceptions of premium value.

Finally, pricing consistency was shown to reinforce long-term brand trust. In fact, brands maintaining stable and predictable pricing were perceived as more reliable over time, emphasizing that consistency in price communication can be a strategic and valuable asset in sustaining brand reputation. This suggests that managers should balance short-term sales incentives with longer-term goals aimed at securing brand credibility and consumer trust.

5.4 Limitations and Directions for Future Research

While this study provides valuable insights into how digital marketing practices shape consumer perceptions and brand reputation in the skincare sector, several limitations should be noted.

First, from a methodological perspective, the choice-based conjoint experiment relied on respondents evaluating and choosing between two hypothetical skincare brand profiles rather than real-life brands. While this approach is widely used for estimating trade-offs and the relative importance of attributes, it does not fully replicate real-world purchase contexts, where the ultimate objective for skincare brands is to drive actual sales. For instance, the design did not include explicit price levels, which could have provided a clearer understanding of how consumers balance monetary considerations with credibility and authenticity cues, however this would have been out of the scope of this study.

Second, there are generalizability issues related to the sample composition. Participants were primarily recruited through the researcher's academic and professional networks, resulting in a relatively homogeneous group in terms of demographics and nationality. This implies that the sample lacks broad international representativeness, reflecting a consistent cultural context suitable for studying brand reputation and consumers' perception within the Italian skincare market. Caution is therefore warranted when extending the findings to other countries or consumer segments.

In conclusion, future research could build on these findings by addressing the outlined limitations in both design and sampling. First, the attribute set could be expanded including additional levels such as explicit price levels, packaging elements, and sustainability claims to better capture the full range of factors influencing consumer decision-making, affecting in turn skincare brand reputation. Additionally, exploring consumers' willingness to pay in relation to trust-based cues could offer deeper insight into value perception.

Second, future studies should aim for a more diverse and representative sample across different cultural and geographic contexts. Moreover, a cross-cultural approach would help determine whether the observed effects are consistent across markets or influenced by local norms and preferences. Finally, longitudinal research could be conducted to examine whether the impact of credibility-driven strategies persists over time, particularly within such a fast-paced and complex digital environment.

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Appendices

Appendix A: Survey Structure

The Impact of Social Media on Skincare Brand Reputation: A Consumer Survey

Dear Participant,

Welcome and thank you for taking the time to participate in this survey, which is part of my Master's Thesis in Data Science and Marketing Analytics at the Erasmus School of Economics, Rotterdam.

This study examines the impact of various aspects of **social media and influencer marketing on consumers' perceptions of skincare brands.**

The survey will take just **a few minutes of your time**, and there are no right or wrong answers!

Your responses will remain anonymous and will be used exclusively for academic research purposes. Participation is voluntary, and you may exit the survey at any time.

If you have any questions, feel free to contact the researcher at **739106mp@student.eur.nl**.

Thank you for your valuable input!

Best,
Marina Papasidero

Questions

1. Do you follow a Skincare Routine?
○ Yes
○ No (The Survey Ends)

2. Thinking about **a skincare product** you **use regularly**, where did you **first** hear about it?
○ TikTok
○ Instagram
○ Other social media (Facebook, YouTube, X, etc.)
○ Traditional media (TV, radio, newspapers, magazines)
○ Friends or family recommendation
○ In-store discovery
○ Other

Hypothesis 1

3. How frequently do you discover **new** skincare brands through the following channels?
(Please rate ***EACH*** channel from 1 = Never to 5 = Very Frequently)

○ TikTok
○ Instagram
○ Other social media (Facebook, YouTube, X, etc.)
○ Traditional media (TV, radio, newspapers, magazines)
○ Friends or family recommendation
○ In-store discovery

4. How **often** do you **engage** with skincare-related content (e.g., product reviews, routines, tutorials, influencer recommendations) **on social media**?
○ Never
○ Less than once a month
○ 1-2 times per month
○ 1-2 times per week
○ Daily or more

Hypotheses 2 - 6

In the next section, you will be shown **10** scenarios where **two skincare brands** (Brand A and Brand B) are **promoted**.

Each brand will **differ in five aspects** that describe **<u>how its skincare product is marketed</u>**:

• The **type of influencer** endorsing the brand,
• The social media **platform** used,
• The influencer's **follower count**,
• Whether they **shared a positive personal experience** with the product **(or none)**,
• The **discount** offered, if any.

Your task is to **choose** which of the two brands you would be **more likely to choose** based solely on this marketing information.

There are **no right or wrong answers!**
Just go with your personal preference.

5/6/7/8/9/10/11/12/13/14. Based on the information below, which skincare brand would you be more likely to choose?

○ Brand A
○ Brand B

Questions 15-19 were <u>randomized</u>.

15. How much do you **trust** skincare **recommendations** from each of the following **types** of influencers?
(Please rate ***EACH*** influencer from 1 = Not at all to 5 = Completely)

○ Beauty Influencer
○ Cosmetologist
○ Dermatologist

16. How much does an influencer's **follower count** impact your **trust** in their skincare **recommendations?**
1 = Not at all
2 = Slightly
3 = Moderately
4 = Very
5 = Completely

17. When an influencer offers a **discount code** for a skincare product, how does it **impact your perception** of **its value**?

1 = It makes me see the product as much less valuable
2 = It makes me see the product as slightly less valuable
3 = It does not change my perception of the product's value
4 = It makes me see the product as a good deal
5 = It makes me see the product as a great deal

Hypothesis *7*

18. To what extent do you agree with the following statement:
*"Brands that maintain **stable** and **predictable** prices are **more credible** and **reliable** than those that **frequently change their prices** or **heavily rely on discount promotions**."*

1 = Strongly Disagree
2 = Disagree
3 = Neither Agree nor Disagree
4 = Agree
5 = Strongly Agree

19. Suppose you are **comparing** two skincare **brands** with **different pricing strategies**:

- **Brand A** always maintains **stable** and **predictable** prices.
- **Brand B frequently changes** its prices and offers **regular discounts.**

Please **RATE** your **personal preference** between the two brands **on the following 7-point scale**:

1 = **Strong** Preference for Brand **A**
7 = **Strong** Preference for Brand **B**

Brand A ***Brand B***

1 *2* *3* *4* *5* *6* *7*

20. What is your Gender?
○ Male
○ Female
○ Non-binary / Other
○ Prefer not to say

21. What is your Age Group?
○ Under 18
○ 18 – 24
○ 25 – 34
○ 35 – 44
○ 45 – 54
○ 55 – 64
○ 65 or older

22. What is your Nationality?
○ Select your Nationality

23. What is your Current Occupation?
○ Student
○ Employed full-time
○ Employed part-time
○ Self-employed
○ Unemployed
○ Other

That is the end of the survey.

Thank you for your time and for supporting my academic research with your response!

Appendix B: CBC Combinations

Table 1. Overview of Choice-Based Conjoint Combinations

Question	Brand	Influencer_Type	Platform	Follower_Count	Shared_pers_ex	Discount
Q5	Brand A	Cosmetologist	Instagram	195K	No	No
Q5	Brand B	Beauty Influence	Instagram	195K	Positive	10%
Q6	Brand A	Cosmetologist	TikTok	38K	No	10%
Q6	Brand B	Dermatologist	Instagram	38K	No	10%
Q7	Brand A	Cosmetologist	Instagram	195K	No	No
Q7	Brand B	Dermatologist	TikTok	195K	Positive	No
Q8	Brand A	Dermatologist	TikTok	195K	Positive	10%
Q8	Brand B	Beauty Influence	Instagram	900K	Positive	10%
Q9	Brand A	Beauty Influence	TikTok	900K	No	10%
Q9	Brand B	Cosmetologist	Instagram	38K	No	20%
Q10	Brand A	Beauty Influence	TikTok	38K	No	No
Q10	Brand B	Dermatologist	Instagram	38K	No	10%
Q11	Brand A	Beauty Influence	TikTok	195K	No	10%
Q11	Brand B	Cosmetologist	Instagram	38K	No	20%
Q12	Brand A	Dermatologist	TikTok	195K	No	10%
Q12	Brand B	Beauty Influence	Instagram	900K	No	10%
Q13	Brand A	Cosmetologist	Instagram	195K	Positive	20%
Q13	Brand B	Dermatologist	Instagram	38K	Positive	20%
Q14	Brand A	Beauty Influence	Instagram	195K	No	20%
Q14	Brand B	Cosmetologist	TikTok	38K	Positive	20%

Note. All percentages are computed as a proportion of the final sample (N = 528).

Appendix C: CBC Task Examples

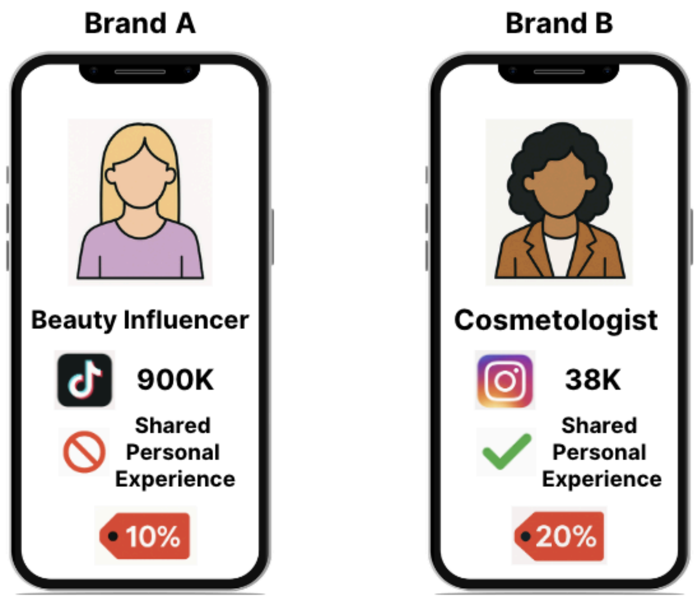

Exhibit A

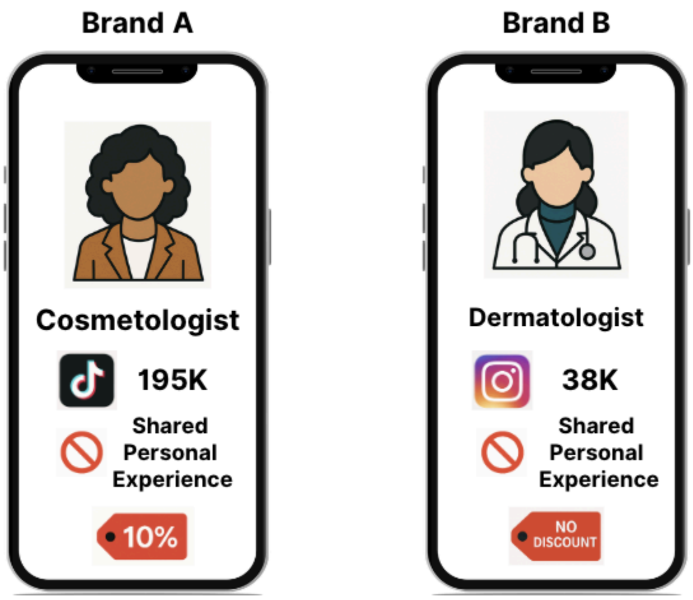

Exhibit B

Appendix D: Ordinal Rating Scales

Frequency Scale

1 = Never

2 = Less than once a month

3 = 1-2 times per month

4 = 1-2 times per week

5 = Daily or more

Trust Scale

1 = Not at all

2 = Slightly

3 = Moderately

4 = Very

5 = Completely

Perceived Value from Discount Scale (Personalised)

1 = It makes me see the product as much less valuable
2 = It makes me see the product as slightly less valuable
3 = It does not change my perception of the product's value
4 = It makes me see the product as a good deal
5 = It makes me see the product as a great deal

Agreement Scale

1 = Strongly Disagree
2 = Disagree
3 = Neither Agree nor Disagree
4 = Agree
5 = Strongly Agree

Appendix E: Tables

Table 1. Sample Characteristics of the Survey Respondents

Characteristic	Value
Initial number of participants	576.0
Excluded respondents	48.0
Final valid respondents	528.0
Gender: Female (%)	93.6
Gender: Male (%)	4.7
Gender: Non-binary/Other (%)	0.9
Gender: Prefer not to disclose (%)	0.8
Age: Under 18 (%)	0.6
Age: 18–24 (%)	24.2
Age: 25–34 (%)	40.3
Age: 35–44 (%)	22.2
Age: 45+ (%)	12.7
Nationality: Italian (%)	93.8
Nationality: Other (%)	6.2
Employment: Full-time (%)	47.3
Employment: Students (%)	28.6
Employment: Self-employed (%)	8.7
Employment: Part-time (%)	6.3
Employment: Unemployed (%)	4.9
Employment: Other (%)	4.2

Note: Percentages reflect the distribution within the final sample (N = 528).

Table 2. Social Media Engagement Level of Respondents

Engagement Level	Number of Respondents	Percentage (%)
High	220.0	41.7
Low	308.0	58.3

Note. High engagement refers to respondents who reported using social media daily or more, while low engagement includes all other usage frequencies.

Table 3. Mean Discovery Frequency by Channel

Channel Type	Mean Discovery Frequency
Social Media	2.86
Traditional Media	2.54

Note. Values represent the average frequency of skincare brand discovery across channels (1 = Never, 5 = Very Frequently).

Table 4. Paired t-Test Comparing Social Media and Traditional Discovery Frequencies

Statistic	Value
t-value	6.714
Degrees of Freedom	527
p-value	<0.001 ***
Mean Difference	0.318
95% CI Lower	0.225
95% CI Upper	0.411

Note. * p < .05, ** p < .01, *** p < .001. The t-test compares mean discovery frequency across social media and traditional channels.

Table 5. Regression Model Predicting Discovery Frequency by Platform (H1)

Predictor	Estimate	Std. Error	t-value	p-value
(Intercept)	3.747	0.068	55.088	<0.001 ***
SM Engagement (High)	0.858	0.105	8.141	<0.001 ***
TikTok	−1.623	0.096	−16.877	<0.001 ***
Other Social Media	−1.510	0.096	−15.696	<0.001 ***
Traditional Media	−1.170	0.096	−12.169	<0.001 ***
Engagement × TikTok	−0.604	0.149	−4.053	<0.001 ***
Engagement × Other Social	−0.845	0.149	−5.669	<0.001 ***
Engagement × Traditional	−0.943	0.149	−6.330	<0.001 ***

Note. The model includes main effects and interaction terms. *** p < .001. The Reference Category for Engagement is High

Table 6. Multinomial Logit Model Results for H2–H6

Hypothesis	Predictor	Estimate	Std. Error	z value	p-value
H2: Platform	PlatformTikTok	−0.189	0.035	−5.390	<0.001 ***
H3: Follower Count	Follower_Count38K	1.404	0.070	19.920	<0.001 ***
H3: Follower Count	Follower_Count900K	−0.999	0.078	−12.790	<0.001 ***
H4: Influencer Type	Influencer_TypeCosmetologist	1.540	0.045	34.020	<0.001 ***
H4: Influencer Type	Influencer_TypeDermatologist	0.645	0.046	14.110	<0.001 ***
H5: Shared Experience	Shared_pers_expPositive	−0.167	0.061	−2.750	0.006 **
H6: Discount	Discount20%	3.087	0.125	24.770	<0.001 ***
H6: Discount	DiscountNo	0.876	0.086	10.220	<0.001 ***

Note. *** $p < .001$, ** $p < .01$, * $p < .05$. Positive coefficients indicate higher log-odds of selecting the brand relative to the reference category.

Table 7. Relative Importance of Attributes (MNL Model)

Attribute	Utility Range	Relative Importance (%)
Shared Experience	10.11	36.72
Platform	6.42	23.32
Discount	5.46	19.83
Follower Count	3.58	12.99
Influencer Type	1.97	7.15

Note. Relative importance computed as the range of utility estimates per attribute, normalized to sum to 100%.

Table 8. Likelihood Ratio Tests Comparing Simpler Models to the Full Model

Model Comparison	Chi-squared	Degrees of Freedom	p-value
Platform vs Full Model	2,756.3	7	<0.001 ***
Follower Count vs Full Model	1,579.7	6	<0.001 ***
Influencer Type vs Full Model	1,365.5	6	<0.001 ***
Experience vs Full Model	2,778.0	7	<0.001 ***
Discount vs Full Model	1,296.1	6	<0.001 ***

Note. *** $p < .001$.

Table 9. AIC Comparison Across Models		
Model	**df**	**AIC Value**
Full Model	9	4,493.3
H6: Discount	3	5,777.4
H4: Influencer Type	3	5,846.9
H3: Follower Count	3	6,061.0
H2: Platform	2	7,235.6
H5: Experience	2	7,257.4

Note. Lower AIC values indicate better model fit.

Table 10. Hausman-McFadden Tests for IIA Assumption

Comparison	Chi-squared	Degrees of Freedom	p-value	Interpretation
Full vs Platform-only	−637.72	2	1.000	IIA not violated
Full vs Follower Count-only	−753.37	3	1.000	IIA not violated
Full vs Influencer Type-only	−492.56	3	1.000	IIA not violated
Full vs Experience-only	−739.73	2	1.000	IIA not violated
Full vs Discount-only	−809.51	3	1.000	IIA not violated

Note. High p-values indicate no evidence of IIA violation.

Table 11. Relative Importance of Attributes (HB)

Attribute	Utility Range	Relative Importance (%)
Discount	13.0	29.1
Follower Count	12.3	27.5
Shared Experience	8.1	18.1
Platform	6.8	15.2
Influencer Type	4.5	10.1

Note. Relative importance was computed as the range of estimated utilities for each attribute.

Table 12. Predictive Accuracy Comparison Between MNL and HB

Metric	MNL	Hierarchical Bayes
Holdout Hit Rate (%)	50.06	84.61

Note. Holdout hit rate measures the percentage of correctly predicted choices on out-of-sample data.

Table 13. Stable Pricing Perceived Credibility

Response	Number of Respondents	Percentage (%)
1 = Strongly Disagree	10	1.9
2 = Disagree	62	11.7
3 = Neutral	178	33.7
4 = Agree	213	40.3
5 = Strongly Agree	65	12.3

Note. Respondents rated their agreement with the statement 'Stable pricing increases brand credibility.'

Table 14. Statistical Tests Supporting H7

Test	Variables Involved	Statistical Results	p-value	Interpretation
One-sample t-test	Q18 vs. midpoint (3)	M = 3.49, t(527) = 12.35	< .001	Agreement significantly above midpoint
Paired-sample t-test	Q18 vs. Q19	Mean Diff. = 0.39	< .001	Credibility > Discount preference
Spearman Correlation	Q18 & Q19	ρ = – 0.42 (moderate, negative)	< .001	Higher credibility agreement predicts lower discount brand preference

Note. All tests support the hypothesis that stable pricing enhances perceived brand credibility.

Table 15. Simple Linear Regression Results for H7

Predictor	Estimate	Std. Error	t value	p-value
Intercept	4.167	0.078	53.218	<0.001 ***
Brand Preference (Q19)	−0.217	0.022	−9.744	<0.001 ***

Note. *** p < .001. The model indicates that stronger preference for the discount-oriented brand is associated with lower credibility agreement.

Table 16. Ordinal Logistic Regression Results for H7				
Predictor	**Estimate**	**Std. Error**	**z value**	**p-value**
Brand Preference (Q19)	−0.545	0.057	−9.655	<0.001 ***
Gender: Male	0.189	0.400	0.472	0.637
Gender: Non-Binary / Other	0.218	0.812	0.268	0.789
Gender: Prefer not to say	−1.033	0.913	−1.133	0.257
Age 25–34	−0.136	0.214	−0.634	0.526
Age 35–44	−0.255	0.327	−0.778	0.437
Age 45–54	−0.641	0.398	−1.610	0.107
Age 55–64	−0.625	0.631	−0.990	0.322
Age 65 or Older	−2.131	0.798	−2.671	0.008 **
Age Under 18	0.038	1.286	0.030	0.976
Occupation: Employed part-time	0.530	0.372	1.422	0.155
Occupation: Other	0.500	0.447	1.118	0.264
Occupation: Self-employed	0.184	0.291	0.632	0.527
Occupation: Student	0.128	0.275	0.464	0.643
Occupation: Unemployed	−0.236	0.382	−0.618	0.536
Nationality: Non-Italian	0.093	0.362	0.257	0.798

Note. *** p < .001, ** p < .01. Q18 was modeled as an ordinal outcome. Only brand preference (Q19) and the 65+ age group were statistically significant predictors.

Table 17. Trust in Skincare Recommendations by Influencer Type			
Influencer Type	**Mean Trust**	**Standard Deviation**	**N**
Beauty Influencer	2.37	0.85	528
Cosmetologist	4.05	0.76	528
Dermatologist	4.31	0.71	528

Note. Ratings were provided on a scale from 1 (Not at all) to 5 (Completely) in response to the question: 'How much do you trust skincare recommendations from each of the following types of influencers?'

Appendix F: Figures

Figure 1: HB Estimated Part-Worth Utilities

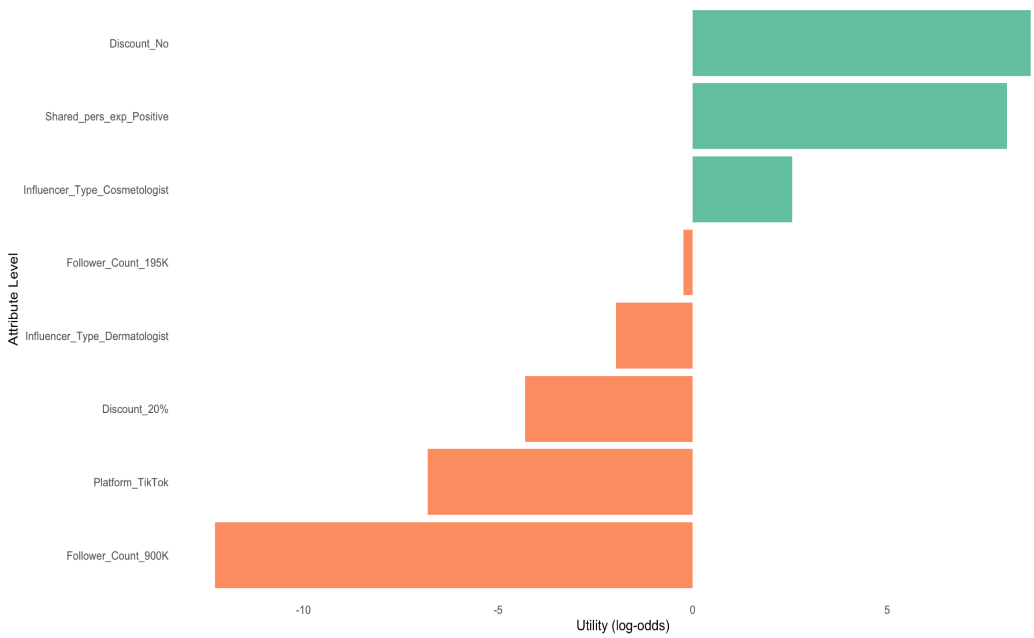

Figure 2: Distribution of Individual-Level Part-Worth Utilities

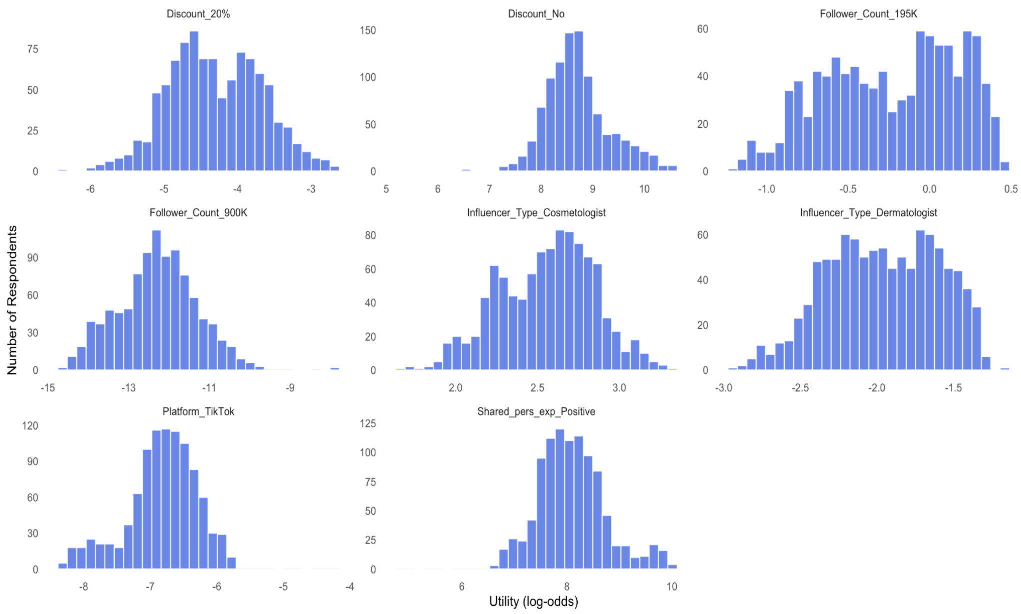

Figure 3: Distribution of Part-Worth Utilities by Cluster

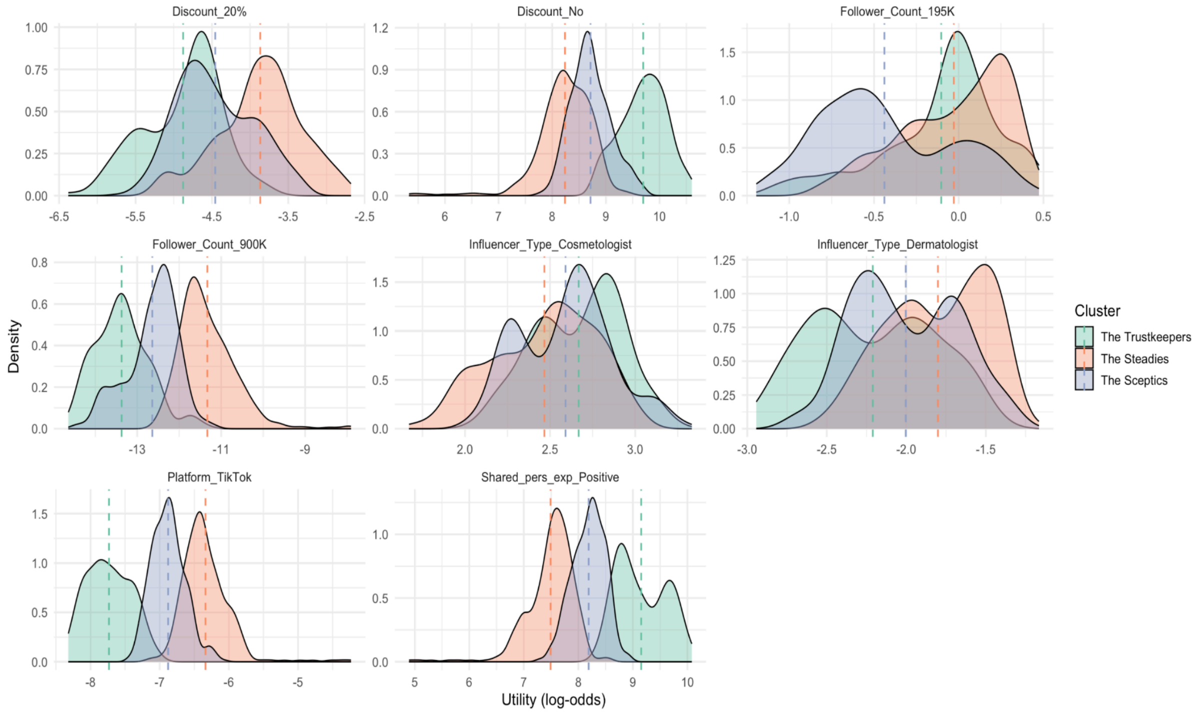

Figure 4: Estimated Part-Worth Utilities Comparison

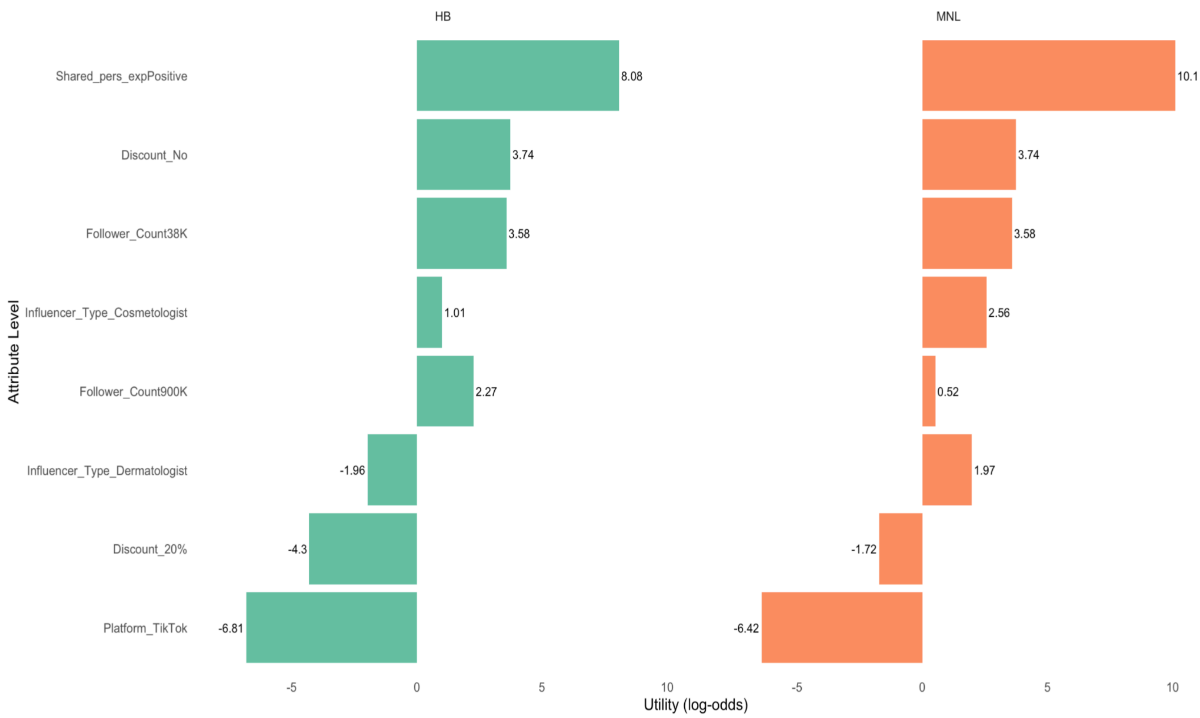

Figure 5: Brand Preference (Stable vs Discount Pricing) (Q19)

1 = Strong Preference for Brand A (Stable), 7 = Brand B (Discount)