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Emerging Technologies in Beauty Industries

The impact on the consumer experience

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NOVA Information Management School

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Emerging Technologies in Beauty Industries:

The impact on the consumer experience

by

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Master Research is presented as a partial requirement for obtaining a Master's degree in DataDriven Marketing, with a specialization in Digital Marketing and Analytics.

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

[*Carolina Moreira*]

[*Lisbon, 15.07.2024]*

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ABSTRACT

This paper examines the evolving dynamics between beauty, technology, and consumer behavior, tracing a path from historical conceptions of beauty to contemporary emphasis on diversity and individuality. The incorporation of artificial intelligence (AI) and augmented reality (AR) within the beauty industry has significantly altered consumer experiences by providing personalized recommendations and instant makeup trials. As industry leaders such as L'Oréal embrace digital transformation, AI and AR technologies enhance retail engagements, reshaping consumer expectations and loyalty. This research examines consumer perceptions and behaviors towards Virtual Try-On (VTO), AR, chatbots, and AI within the beauty industry, identifying crucial factors that influence technology adoption and satisfaction using empirical data from 230 respondents. Results demonstrate the pivotal role of VTO accuracy and usability in influencing purchase decisions and trust in product recommendations, and interactions with AI-driven chatbots positively correlate with consumer satisfaction and brand loyalty, underscoring the value of personalized digital engagement. AR applications enhance consumer engagement by providing immersive experiences, and future research should explore cross-cultural nuances and longitudinal trends in technology adoption. This study contributes to a deeper understanding of the complex interplay between beauty, technology, and consumer behavior in the digital era, concluding that these technologies transform consumer expectations and loyalty, and highlights the need for further research into cross-cultural and long-term trends in technology use in the beauty sector.

KEYWORDS

Technologies; Beauty industry; Artificial intelligence; Virtual Try-On; Augmented Reality; Chatbots; Customer satisfaction; Beauty Market **Sustainable**

Development Goals (SGD):

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LIST OF ABBREVIATIONS AND ACRONYMS

AR - Augmented Reality

VR - Virtual Reality

VTO - Virtual Try-On

U.S. - United States

3D - Three Dimensional

SPSS - Statistical Package for the Social Sciences

EFA - Exploratory Factor Analysis

KMO - Kaiser-Meyer-Olkin (measure)

ANOVA - Analysis of Variance

1. INTRODUCTION

Beauty, an enduring facet of human expression, has woven its narrative through the tapestry of history, spanning millennia and embodying varied cultural ideals. According to Tzou et al., (2022), ancient Egyptians, some 7,000 years ago, elevated beauty to a symbol of holiness, employing copper carbonate to craft vibrant green eyeshades. Still according to Tzou et al., (2022), the Greek philosopher Plato philosophically intertwined beauty with the essence of philosophy, laying the groundwork for the multifaceted significance of beauty across civilizations. In ancient China, the practice of painting fingernails emerged as a pioneering expression of beauty, while tribes globally utilized cosmetics to denote affiliations, roles, and status.

Recently, ELLE magazine (Griffin, 2015) encapsulated this essence with a poignant quote by photographer Mihaela Noroc: "Beauty is everywhere... We are all beautiful because we are different." This contemporary perspective on beauty seamlessly aligns with the ongoing integration of artificial intelligence (AI) and augmented reality (AR) into the beauty industry. As technology advances, the world of high technology finds itself entwined with beauty, democratizing the beauty experience. This integration assists individuals in navigating the vast array of beauty products available, tailoring choices to their unique features (Griffin, 2015).

The roots of this technological evolution can be traced back to the early days of paint and photo editing applications. However, the real breakthrough occurred with the advent of AI and AR technology. Perfect Corp.'s AR virtual try-on and AI skin diagnostic technologies exemplify this surge, enabling consumers to use their smartphones for instant makeup trials and receive personalized beauty recommendations in less than 50 milliseconds. The optimization for limited computational power and the real-time simulation of various cosmetic combinations heralds a novel era in the intersection of technology and beauty (Tzou et al., 2022). Simultaneously, the business landscape undergoes a profound transformation with the pervasive influence of artificial intelligence. Regular engagements with AI underscore its transformative impact on diverse business activities across industries. Uzialko (2023) highlights this phenomenon, stressing the imperative for widespread adoption of AI technologies to maintain a competitive edge.

Expanding the technological horizon, Azuma (1997) positions Augmented Reality (AR) as a variant of Virtual Reality (VR), emerging after various VR projects conducted between 1960 and 1990 (Olmedo, 2013).

From a reality-Virtuality Continuum perspective AR can be considered between the real and virtual environments, leaning closer to the real world, unlike VR, which entirely immerses

users in a virtual environment. This distinction positions AR as a technology-enhancing enhancing user experience by overlaying digital content onto the real environment.

Furthermore, McElroy and colleagues (2007) delve into the impact of personality and cognitive style on the utilization of online technologies, revealing personality as a significant factor explaining the variance in internet usage. Individuals resistant to adopting new online technologies tend to favor traditional methods, illustrating the challenges in expressing their intention to use innovative technologies (Bullinger et al., 2011). Additionally, the exploration of technological paradoxes by Mick & Fournier (1998), including control/chaos, freedom/enslavement, and efficiency/inefficiency, highlights the complexities consumers face with emerging technologies. Their coping strategies further suggest a potential link between technological adoption and how consumers navigate these challenges.

In weaving together, the historical, technological, and psychological dimensions, this comprehensive exploration sets the stage for a nuanced literature review. The integration of these diverse perspectives promises a deeper understanding of the intricate interplay between beauty, technology, and consumer behavior. Grounded in the exploration of ancient beauty practices (Tzou et al., 2022) and contemporary technological advancements (Griffin, 2015; Uzialko, 2023), this research aims to address a crucial question: What is the impact of Augmented Reality (AR) like Chatbots and Virtual Try-On on the consumer experience within the beauty industry? By exploring into the implications of AR integration, particularly in relation to consumer perceptions, preferences, and behaviors, this study seeks to uncover insights that can inform both industry practices and academic discourse. Additionally, the theoretical framework draws on established models of consumer behavior (McElroy et al., 2007; Mick & Fournier, 1998) to provide a robust foundation for understanding the complexities inherent in consumer interactions with emerging technologies in the beauty sector.

This work begins with an Introduction, providing a general overview and the objectives of the research. The Literature Review follows, offering a detailed examination of the beauty market. It then explores Technology Adoption in Beauty, with a focus on Virtual Try-On Technologies (VTO), Augmented Reality (AR), and Artificial Intelligence (AI). The review also discusses Consumer Experience and Satisfaction and presents a Conceptual Model, including a Conceptual Framework that underpins the study. The Methodology section describes the Questionnaire Design and Measurement, the Data Collection process, and information about the Respondents. Results and Discussion present the findings of the research and their implications. The research concludes with Conclusions and Future Research, detailing the Theoretical Contributions and Practical Implications of the study, along with its Limitations and Further Developments. Finally, all sources are cited in the References section.

2. LITERATURE REVIEW

The literature review in this study provides a comprehensive examination of previous research covering various dimensions of the beauty industry and its technological advancements. The study focuses on three topics—Augmented Reality (AR) and Virtual Try-On (VTO) technologies, Artificial Intelligence (AI), and Technological Adoption in Beauty—each of which plays a distinct role in shaping consumer experiences and satisfaction. These topics are explored in relation to a single dependent variable: Consumer Experience and Satisfaction, which encompasses consumers' perceptions, preferences, and behaviors regarding their interactions with beauty products and technologies.

By synthesizing insights from the existing literature and constructing a conceptual model, this study aims to elucidate the interplay between these variables and formulate hypotheses that contribute to a deeper understanding of how technological innovations impact consumer behavior in the beauty industry.

2.1 BEAUTY MARKET OVERVIEW

The cosmetics industry, recognized for its resilience and buoyed by the global emphasis on self-care and wellness, has demonstrated consistent growth since 2004, with a brief interruption in 2020 due to the Covid-19 pandemic (Petruzzi, 2024). Despite this setback, projections indicate a sustained positive trend, forecasting revenues to reach nearly 129 billion U.S. dollars by 2028, according to Petruzzi, (2024). Key players such as L'Oréal, Unilever, Procter & Gamble Co., The Estee Lauder Companies, Shiseido Company, and Beiersdorf contribute to the flourishing landscape. L'Oréal, the leading global beauty manufacturer as of 2022, reported revenues surpassing 40 billion U.S. dollars, with its flagship brand, L'Oréal Paris, holding the top global position valued at almost 48 billion U.S. dollars in 2023 (Petruzzi, 2024).

Binwani & Ho (2019) suggest that this industry's robust growth is further propelled by influencers and celebrities venturing into cosmetics, establishing their brands, or engaging in collaborations. Examples include Kylie Jenner's Kylie Cosmetics, Katrina Kaif's Kay, Rihanna's Fenty Beauty, and the partnership between Too Faced and YouTube beauty influencer Nikkie Tutorials, known as Too Faced x NikkieTutorials. Technological advancements in cosmetics play a pivotal role in this dynamic landscape, providing individuals with opportunities to transform their physical appearance.

Capitalizing on the influential role of social media, beauty firms actively embrace digital platforms to boost visibility, credibility, and sales. Strategic collaborations with influencers are a common

practice, involving compensation for product promotion, tutorial creation, and the cultivation of consumer trust (Ridder, 2020). In the context of this research, this overview establishes the thriving backdrop of the cosmetics industry, highlighting key players and the evolving dynamics driven by technological advancements and influencer engagements. That is why we hypothesize that:

H1: The robust growth of the cosmetics industry, driven by technological advancements and influencer collaborations, positively impacts consumer perceptions and engagement with beauty brands.

2.2 TECHNOLOGY ADOPTION IN BEAUTY

In the evolving landscape of advertising strategies, which have transitioned from traditional approaches to online and mobile trends, technology plays a pivotal role. This transformation is exemplified by the integration of advanced tools and techniques, including 3D animations and 360-degree visualization, offering augmented interactivity and vivid experiences for consumers (Li et al., 2008).

Coinciding with this era of technological evolution, L'Oréal embarked on its digital transformation in June 2014 with the launch of the Makeup Genius augmented reality (AR) app (Paris, 2014). This app introduced virtual try-on experiences for makeup through a user-friendly interface, representing an early phase in the integration of augmented reality into the beauty industry. This innovation preceded the broader adoption of augmented reality technologies, such as Snapchat's Lenses feature, which became widely used after its launch in 2015.

The strategic significance of L'Oréal's digital transformation was underscored by the appointment of Lubomira Rochet as the first Global Chief Digital Officer, just prior to the Makeup Genius release. Rochet played a pivotal role in shaping L'Oréal's digital strategy and commitment to digital transformation at the highest organizational levels. The company's dedication to digital advancement continued with the appointment of Asmita Dubey as the new Global Chief Digital and Marketing Officer in April 2021, entrusted with leading the next phase of digital transformation. This strategic move emphasized the role of beauty services in driving the ongoing digital revolution. L'Oréal further solidified its position in the beauty tech industry by acquiring ModiFace in 2018, leveraging its digital expertise and benefiting from ModiFace's advanced AI and AR technologies. These technologies, encompassing real-time facial analysis, feature tracking, and comprehensive diagnostics for skin, hair, and makeup, provided L'Oréal with a competitive edge and established a robust foundation for growth in the beauty tech sector (Paris, 2014). This leads us to hypothesize that:

H2: The adoption of advanced technologies such as AR and AI by beauty companies like L'Oréal significantly enhances consumer engagement and satisfaction with their products and services.

2.2.1 VIRTUAL TRY-ON TECHNOLOGIES (VTO)

Virtual Try-On (VTO) technologies are website features designed to manipulate product or environment images, aiming to simulate or even exceed the actual experience with the product or setting (Fiore et al. (2005). Through the implementation of VTO, customers gain the capability to visualize the appearance of products via virtual displays before making a purchase decision. It is noteworthy that many consumers express a desire to physically touch a product before committing to a purchase (Pantano et al., 2017)

The introduction of VTO effectively addresses this consumer need and enhances the overall shopping experience. By streamlining the research process, VTO technology improves time efficiency and reduces the necessity for channel switching (Willems et al., 2017). As a result, customers can make more informed decisions, bridging the gap between online exploration and the tactile experiences traditionally associated with offline shopping. This integration contributes to a smoother and more cohesive shopping journey for consumers which allows us to suggest that:

H3: The implementation of Virtual Try-On (VTO) technologies in the beauty industry positively impacts consumer decision-making processes and enhances their overall shopping experience.

2.2.2 AUGMENTED REALITY (AR)

According to (Bona et al., 2019), Augmented Reality (AR) emerges as a promising technology within the realms of retailing and e-commerce, offering consumers the ability to virtually overlay products on their faces or surroundings, seamlessly integrating them into their real-world environments. Despite the growing interest among marketers and retailers in exploring the potential of AR, a significant barrier exists. The lack of knowledge regarding the extent to which AR can add value for both consumers and brands often leads companies to hesitate in investing in this innovative technology ((Bona et al., 2019).

In the retail context, Augmented Reality (AR) technology can engage consumers through two distinct approaches. Firstly, AR can be implemented within retail stores through the

utilization of virtual mirrors (Rauschnabel, 2018). Secondly, according to the same authors, consumers themselves can leverage AR technology on their personal devices, including smart glasses, tablets, or smartphones (Rauschnabel, 2018). Numerous companies, such as IKEA, Wayfair, BMW, Volkswagen, Lego, Sephora, Macy's, and Adidas, have embraced AR integration in their marketing campaigns (Dacko, 2017). This broad application spans various sectors, from clothing and cars to furniture and personal products, showcasing the widespread exploration of AR technology in diverse retail offerings.

In the beauty industry, there is a growing trend of brands embracing Augmented Reality (AR) technology, especially gaining momentum after the constraints imposed by the Covid-19 pandemic on in-person product try-outs. This technology enables consumers to virtually experience a variety of products before making purchase decisions (Mangtani et al., 2020).

Noteworthy examples of beauty brands incorporating virtual mirrors on their websites include Sephora (using Sephora Virtual Artist), L'Oréal group's brands (with Makeup Genius), Chanel (Chanel Beauty's try-on), and MAC. This application of AR technology enhances the consumer's ability to explore and try different beauty products in a virtual space, contributing to an enriched and interactive shopping experience. Under these circumstances, we suggest that:

H4: The use of Augmented Reality (AR) technology in the beauty industry enhances consumer interaction and satisfaction by providing immersive and interactive product experiences.

2.2.3 ARTIFICIAL INTELLIGENCE (AI)

Commonly, AI is defined as mimicking human intelligence. In 1955, AI was described as the problem of "making a machine behave in ways that would be considered intelligent if it were human" (McCarthy et al., 1955, p. 11).

Artificial Intelligence (AI) stands as a distinct branch of computer science, delving into the programming of computers to exhibit behaviors that appear intelligent. Riche (2014) encapsulates this notion by defining AI as a study focused on enabling computers to perform tasks that are typically better executed by humans (Chandra & Hareendran, 2014).

Multiple perspectives contribute to the understanding of AI, each providing nuanced definitions. Booth, (2014a, p. 30) views AI as the examination of mental faculties using computational models, while Mangtani et al., (2020) interpret it as the art of creating machines capable of intelligent functions traditionally performed by people (Booth, 2014a, p. 30). Quintana-Amate and colleagues, (2017) characterizes AI as a field seeking to explain and emulate intelligent behavior through computational processes, and Winston (1992) defines it as the study

of computations facilitating perception, reasoning, and action. (Rajasekaran & Pai, 2003) present AI as the branch of computer science concerned with automating intelligent behavior. Given the intelligence capabilities of these tools, we hypothesize that:

H5: The integration of Artificial Intelligence (AI) in the beauty industry significantly improves consumer satisfaction through personalized recommendations and enhanced customer service.

2.3 CONSUMER EXPERIENCE AND SATISFACTION

According to Solomon (2020), consumer behavior stands as one of the most extensively researched aspects within the field of marketing. Regarded as a key factor that provides profound insights into how customers think and act, a comprehensive understanding of consumer behavior is crucial for delving into subsequent topics.

Defined by Solomon (2020, pg.28) as "the processes involved when individuals select, purchase, use, or dispose of products, services, or experiences to satisfy needs and wants", consumer behavior encapsulates the intricate decision-making processes that individuals undergo in their quest to fulfil their desires and requirements.

Based on the findings of Mariani and colleagues, (2023), with the help of insights about consumers' behavior patterns, brands coming up with more personalized consumer experiences are more likely to witness a shift in customer loyalty towards their specific brand. According to Microsoft, 97% of customers say that customer service is an important factor when they choose a brand. Artificial Intelligence has further enhanced customer service through chatbots, ensuring quick responses as they can handle multiple queries simultaneously and are available 24/7. By leveraging clustering and data collected about customers, businesses can easily match their likes and dislikes, recommending specific products or services. These subtle personalized touches can effectively turn a one-time customer into a loyal and regular client (Mariani et al., 2023).

Troyer (2019) states that most companies in the beauty industry are already implementing AI strategies to stay competitive in the market. For example, Sephora experienced an 11% revenue growth in the first quarter after launching the Sephora Virtual Artist, a tool that allows customers to "try on" products. This trend is part of the broader global investment in AI, including the Fashion, Luxury, and Cosmetics sectors, which is expected to grow to $7.3 billion by 2022. The integration of AI mechanisms in the beauty market is transforming the way brands operate, providing services that are 10 times more efficient (Mangtani et al., 2020b).

2.4 CONCEPTUAL MODEL

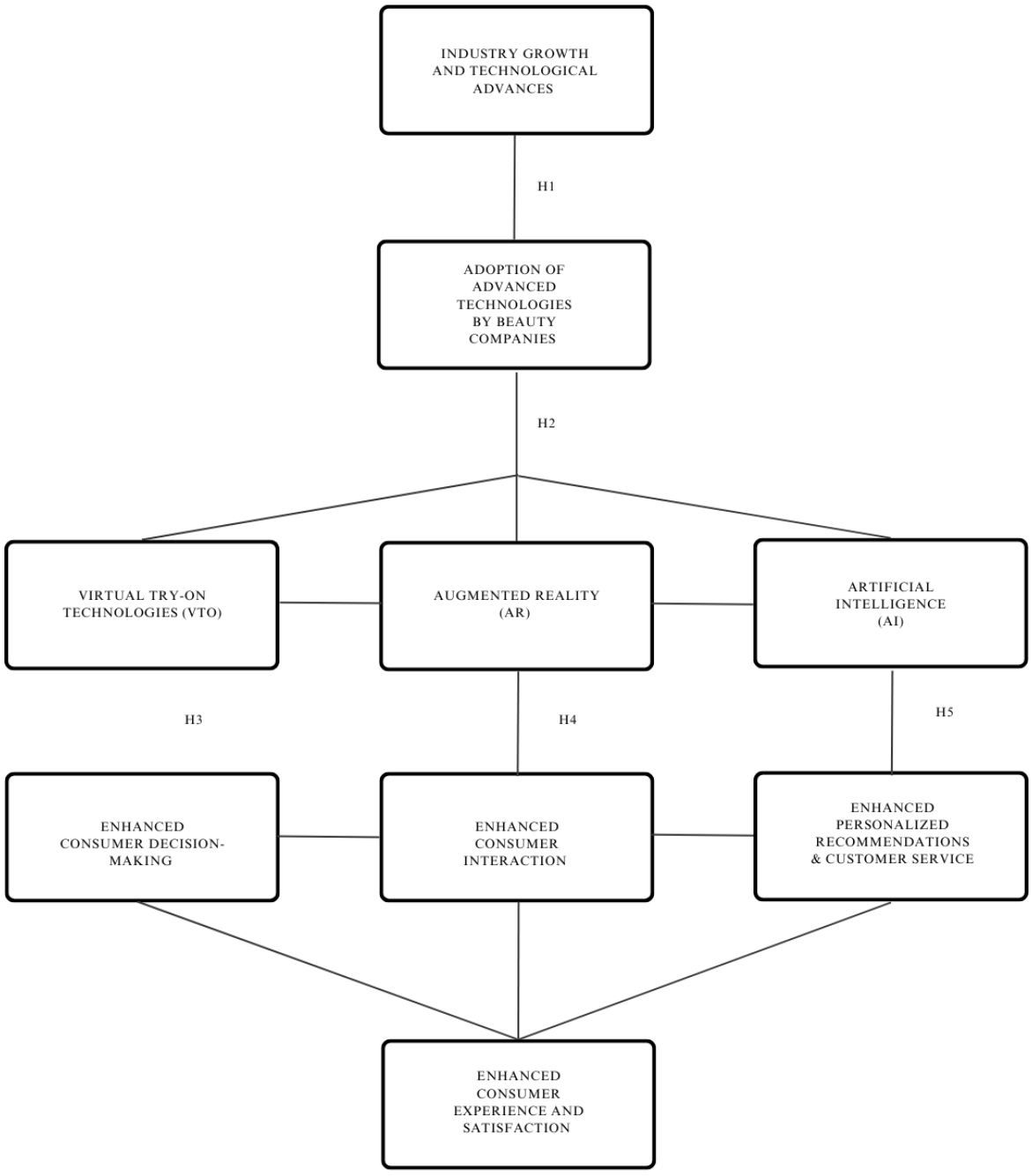
The conceptual model illustrates the relationship between the independent variables and the dependent variable, demonstrating how each hypothesis is connected to these variables.

2.4.1 CONCEPTUAL FRAMEWORK

The conceptual model is illustrated in Figure 1, followed by an explanation of the rationale behind the variables used to substantiate our working hypotheses.

FIGURE 1

Conceptual Model



Industry Growth and Technological Advances

H1: The robust growth of the cosmetics industry, driven by technological advancements and influencer collaborations, positively impacts consumer perceptions and engagement with beauty brands (Petruzzi, 2024; Binwani & Ho, 2019; Ridder, 2020).

Adoption of Advanced Technologies by Beauty Companies

H2: The adoption of advanced technologies such as AR and AI by beauty companies like L'Oréal significantly enhances consumer engagement and satisfaction with their products and services (Paris, 2014; Li et al., 2008; Mangtani et al., 2020).

Virtual Try-On Technologies (VTO)

H3: The implementation of Virtual Try-On (VTO) technologies in the beauty industry positively impacts consumer decision-making processes and enhances their overall shopping experience (Fiore et al., 2005; Pantano et al. (2017); Willems et al., 2017).

Augmented Reality (AR)

H4: The use of Augmented Reality (AR) technology in the beauty industry enhances consumer interaction and satisfaction by providing immersive and interactive product experiences (Rauschnabel, 2018; Dacko, 2017; Mangtani et al., 2020).

Artificial Intelligence (AI)

H5: The integration of Artificial Intelligence (AI) in the beauty industry significantly improves consumer satisfaction through personalized recommendations and enhanced customer service (Booth, 2014a, p. 30).

2.5 A L'ORÉAL COMPANY

Given that the focus of this research will be the company L'Oréal, it is appropriate to briefly characterize this company. L'Oréal is a French personal care giant, recognized as the world's largest cosmetics company, with a diverse product range that includes hair color, skincare, sun protection,

make-up, perfume, and hair care products. Pioneering the luxury beauty landscape, L'Oréal expanded significantly between 1957 and 1983 under François Dalle's leadership, marking its entry into the global market and establishing the Grand L'Oréal. Strategic brand acquisitions continued under Lindsey Owen-Jones from 1988 to 2005, cementing L'Oréal's position as a world leader in cosmetics, with this period introducing iconic products and expanding the brand portfolio. Under Jean-Paul Agon since 2006, the company emphasized diversity and inclusion with a mission of "Beauty for All," growing through acquisitions and committing to ethical and socially responsible initiatives, highlighting sustainable development (De L'élégance, 2023).

Regarding the L'Oréal Annual Report (2023), L'Oréal Luxe, a division of L'Oréal, focuses on delivering unique and exceptional product experiences through 23 brands, including Lancôme, Yves Saint Laurent, and Giorgio Armani, creating personalized relationships with consumers via direct-to-consumer channels and exclusive services. As of 2003, L'Oréal operates in over 130 countries, owns 36 brands, and consistently demonstrates double-digit growth with a substantial investment in research and development. With over 1,400 services available online, L'Oréal is pioneering Beauty Tech. The Group's experts use technology, data, and artificial intelligence to develop services that deliver an unrivalled degree of personalization, revolutionizing how consumers discover, try, and receive advice about products, both online and in brick-and-mortar points of sale. For example, Lancôme's E-Shade Finder uses a selfie video and an algorithm to analyze over 22,000 skin tones, creating bespoke foundation shades, while its Skin Screen analysis service uses AI to measure 13 clinical parameters of skin health, providing personalized skincare routines (Prates, 2024).

Reaffirming its commitment to personalized, inclusive, and responsible beauty, L'Oréal introduced innovations at Viva Technology in Paris, such as advanced skin and hair diagnostics, a GenAI-powered personal beauty assistant, a revolutionary infrared light hairdryer, a micro rejuvenation skincare device, and the most realistic skin-like technology platform for scientific research and product testing. Strategic partnerships with companies like BreezoMeter and Verily further expand L'Oréal's expertise, demonstrating how environmental factors impact skin aging and developing applied technologies in beauty and dermatology. These technologies, combined with initiatives like the CREAITECH Gen AI Beauty Content Lab and partnerships with Meta and content creators, illustrate L'Oréal's dedication to shaping the future of beauty through tech. With a strong focus on sustainability, L'Oréal measures and reduces the environmental impact of its digital activities, reinforcing its leadership in beauty tech and sustainable development (Prates, 2024).

3. METHODOLOGY

This study aims to understand the impact of emerging technologies in the beauty industry on consumer experience and satisfaction. Data was gathered through an online survey that included both quantitative and qualitative questions. The survey was distributed to a diverse group of participants, ensuring a comprehensive representation of various demographics and user experiences, even if it is a convenience sample. The questionnaire was available from April 12 to June 5 and received a total of 230 responses, of which 108 were valid.

3.1 QUESTIONNAIRE DESIGN AND MEASUREMENT

A data collection instrument was developed following the research model, incorporating items from existing studies in the relevant literature.

The Frequency of purchase and consumer behavior items were based on Solomon (2020). Effectiveness and satisfaction with Virtual TryOn (VTO) technologies were drawn from Fiore et al. (2005), Pantano et al. (2017) and Willems et al. (2017), while accuracy and realism of VTO simulations were inspired by Rauschnabel (2018) and Mangtani et al. (2020).

Consumer interaction with brands through VTO technologies were approached by Mangtani et al. (2020) and Bullinger et al. (2011), and social influence and recommendation of VTO technologies were derived from Rauschnabel (2018) and Mariani et al. (2023).

Predictions about the future of AR and VTO technologies took cues from (Bona et al., 2019) and Rauschnabel (2018), and the inclusion and personalization capabilities of VTO referenced Griffin (2015) and McElroy et al. (2007). Privacy concerns related to VTO and chatbots were guided by Mick & Fournier (1998), while the positive influence of chatbots on shopping experiences and trust in chatbot information was inspired by Mariani et al. (2023), Troyer (2019), and Uzialko (2023).

The impact of chatbots on customer retention and brand relationships referenced Mariani et al. (2023) and Mangtani et al. (2020), preferences for AR devices and platforms were based on Rauschnabel (2018), and factors influencing willingness to use VTO and chatbots drew from Fiore et al. (2005) and Mariani et al. (2023). Satisfaction with VTO and chatbots was also inspired by Fiore et al. (2005) and Mariani et al. (2023).

The items were measured using a seven-point Likert scale, ranging from 1 “strongly disagree” to 7 “strongly agree” and the Net Promoter Score from 0 “Not at all satisfied” to 10

"Extremely satisfied". In addition, ranking order questions were used, as well as multiple choice and detachment control.

Table 1 illustrates the sources and justifications for each question in the questionnaire used in the study. Each question is linked to specific references from the literature, providing a foundation for its inclusion.

Table 1

Questionnare References

QUESTION	SOURCE/REFERENCE	COMMENT/JUSTIFICATION
How did you first learn about augmented reality (AR) technologies in the beauty industry?	Olmedo (2013); Azuma (1997)	Based on the introduction and historical development of AR.
How often do you usually buy beauty products?	Solomon (2020)	Related to consumer behavior and purchase frequency.
When using virtual try-on (VTO) technologies to try beauty products, I feel more confident in making purchase decisions.	Fiore et al. (2005); Pantano et al. (2017)	Based on the effectiveness of VTO in enhancing purchase decision confidence.
Using virtual try-on (VTO) features increased my satisfaction when trying beauty products.	Fiore et al. (2005); Willems et al. (2017)	Related to the impact of VTO on consumer satisfaction.
Makeup simulations through virtual try-on (VTO) technologies accurately match real-life results.	Rauschnabel (2018); Mangtani et al. (2020)	Based on the accuracy and realism of VTO simulations.
Using virtual try-on (VTO) technologies to try beauty products increased my interaction with brands.	Mangtani et al. (2020); Bullinger et al. (2011)	Related to increased brand interaction due to VTO usage.
I would recommend using virtual tryon (VTO) technologies to try beauty products to friends and family.	Rauschnabel (2018); Mariani et al. (2023)	Based on the recommendation of VTO technologies and their social influence.
I believe augmented reality (AR) technologies in the beauty industry will completely replace traditional shopping experiences in the future.	(Bona et al., 2019); Rauschnabel (2018)	Based on predictions about the future of AR shopping experiences.
I believe virtual try-on (VTO) technologies can help make the beauty industry more inclusive by better meeting the needs of different skin types and tones.	Griffin (2015); McElroy et al. (2007)	Related to inclusion and personalization enabled by VTO technologies.
I feel my privacy is compromised when using virtual try-on (VTO).	Mick & Fournier (1998)	Based on discussions about technological paradoxes and privacy concerns.
The presence of chatbots positively influences my overall online beauty product shopping experience.	Mariani et al. (2023); Troyer (2019)	Based on the positive influence of chatbots on shopping experiences.

I trust the information provided through chatbots.	Troyer (2019); Uzialko (2023)	Related to trust in information provided by chatbots.
The presence of chatbots on online beauty platforms increases my likelihood of purchasing again from that website.	Mariani et al. (2023); Troyer (2019)	Based on the influence of chatbots on customer retention.
Using chatbots increased my relationship with brands.	Mangtani et al. (2020); Mick & Fournier (1998)	Related to strengthening relationships with brands through chatbots.
I would recommend online beauty platforms with integrated chatbots to friends and family.	Mariani et al. (2023); Troyer (2019)	Based on the recommendation of chatbot technologies and their social influence.
I believe chatbot technologies will completely replace traditional shopping experiences in the future.	Mariani et al. (2023); Uzialko (2023)	Based on predictions about the future of shopping experiences with chatbots.
I feel my privacy is compromised when using chatbots.	Mick & Fournier (1998)	Based on discussions about technological paradoxes and privacy concerns.
What device do you prefer to use to try beauty products with augmented reality (AR) technologies?	Rauschnabel (2018)	Based on discussions about AR devices.
What aspects of virtual try-on (VTO) technologies do you consider most important to enhance the consumer experience in the beauty industry? (Select up to three options)	Fiore et al. (2005); Willems et al. (2017)	Based on identifying important aspects to improve VTO experiences.
What aspects of chatbot technologies do you consider most important to enhance the consumer experience in the beauty industry? (Select up to three options)	Mariani et al. (2023); Troyer (2019)	Based on identifying important aspects to improve chatbot experiences.
Have you ever had a negative experience using augmented reality (AR) technologies to try beauty products? If so, please describe briefly.	Mick & Fournier (1998); Bullinger et al. (2011)	Related to discussions about technological paradoxes and resistance.
What are the main benefits you see in using augmented reality (AR) technologies to try beauty products? (Select up to three options)	Rauschnabel (2018); Mangtani et al. (2020)	Based on identifying benefits of AR technologies.
Do you have any concerns or reservations about using augmented reality (AR) technologies to try beauty products? If so, please share your concerns or comments.	Mick & Fournier (1998); Bullinger et al. (2011)	Based on concerns about using AR technologies.
Rank the following augmented reality (AR) platforms or applications in order of preference, with 1 being the most preferred and 5 the least preferred	Rauschnabel (2018); Mangtani et al. (2020)	Based on preferences for AR platforms.
Rank the following areas in terms of where you would like to see more applications of augmented reality (AR) in the beauty industry	Rauschnabel (2018); Mangtani et al. (2020)	Based on preferences for areas of AR application.

What factors influence your willingness to try a beauty product using virtual try-on or chatbots?	Fiore et al. (2005); Mariani et al. (2023)	Based on factors influencing the willingness to use VTO and chatbots.
Considering your experience with Virtual Try-On (VTO) and Chatbots on online beauty platforms, how satisfied are you with these features? Rate from 1 (not satisfied) to 10 (extremely satisfied)	Fiore et al. (2005); Mariani et al. (2023)	Related to evaluating satisfaction with VTO and chatbots.

Responses were analyzed to identify variables aligned with hypotheses on AR's impact on consumer interaction, satisfaction, and industry growth.

From questionnaire items, variables like "AR_Technologies_vs_Traditional_Shopping" and "Purchase_Frency" were formulated to measure beliefs about AR and purchasing behavior. Additional variables such as "Confidence_Decision" and "Satisfaction_VTO" were designed to assess the influence of VTO technologies on purchase decisions and consumer satisfaction. These variables supported hypotheses on technology adoption and consumer engagement. Although some questions were not used to create variables, they provided significant insights into consumer perceptions within the beauty industry, enriching the researcher's understanding and guiding future research directions.

AR_Technologies_vs_Traditional_Shopping (AR technologies vs traditional shopping experiences): Derived from the question "I believe that augmented reality (AR) technologies in the beauty industry will completely replace traditional shopping experiences in the future." This variable represents participants' beliefs about the potential of augmented reality (AR) technologies to replace traditional shopping experiences within the beauty industry, relating to the overarching theme of enhancing consumer interaction and satisfaction through immersive and interactive product experiences (H4).

Recommend_Online_Beauty_Chatbots (Recommend online beauty platforms with integrated chatbots to friends and family): Derived from the question "I would recommend online beauty platforms with integrated chatbots to friends and family." This variable indicates the likelihood that participants will recommend online beauty platforms featuring integrated chatbots to their friends and family, relating to the overarching theme of improving consumer satisfaction through personalized recommendations and enhanced customer service (H5).

Ease_of_Use (Ease of use): Derived from the question "I would recommend online beauty platforms with integrated chatbots to friends and family." This variable captures participants' perceptions of how easy it is to use online beauty platforms with integrated chatbots, relating to the overarching theme of positively impacting consumer decision-making processes and enhancing

their overall shopping experience through the implementation of Virtual Try-On (VTO) technologies (H3).

Purchase_Frequency (Frequency of Beauty Product Purchase): Derived from the question *"How often do you usually buy beauty products?"* This variable represents participants' habitual purchasing behavior concerning beauty products, relating to the overarching theme of industry growth and technological advances (H1).

Confidence_Decision (Confidence in Purchase Decisions): This variable is based on the statement *"When using virtual try-on (VTO) technologies to try beauty products, I feel more confident in making purchase decisions."* It measures the extent to which participants' confidence in making purchase decisions is influenced by virtual try-on technologies, aligning with the idea of enhanced consumer experience and satisfaction (H3).

Satisfaction_VTO (Satisfaction with VTO Experience): Created from the statement *"Using virtual try-on (VTO) features increased my satisfaction when trying beauty products."* It gauges participants' satisfaction levels with virtual try-on features, supporting the hypothesis that VTO technologies positively impact consumer decision-making processes and overall shopping experience (H4).

Accuracy_Simulation (Accuracy of VTO Makeup Simulation): This variable is inferred from the statement *"Makeup simulations through virtual try-on (VTO) technologies accurately match real-life results."* It measures participants' perceptions of the accuracy of makeup simulations through VTO technologies, supporting the adoption of advanced technologies by beauty companies (H2).

Interaction_Brand (Interaction with Brands): Based on the statement "Using virtual tryon (VTO) technologies to try beauty products increased my interaction with brands." It quantifies participants' increased interaction with beauty brands using VTO technologies, aligning with the hypothesis of enhanced consumer engagement due to industry growth and technological advances (H1).

Recommendation_Likelihood (Likelihood of Recommendation): Derived from the statement *"I would recommend using virtual try-on (VTO) technologies to try beauty products to friends and family."* It measures participants' propensity to recommend VTO technologies to others, supporting the idea that advanced technologies positively impact consumer engagement and satisfaction (H2).

Privacy_Concern_Chatbots (Privacy Concerns with Chatbots): Derived from the statement *"I feel my privacy is compromised when using chatbots."* It measures participants' concerns regarding privacy when interacting with chatbots, supporting the overarching theme of industry growth and technological advances (H5).

These variables encapsulate the key dimensions explored in the questionnaire, providing a foundation for testing the hypotheses related to consumer behavior and the impact of advanced technologies in the beauty industry.

3.2 DATA COLLECTION

This study employs a quantitative approach, guided by the notion that qualitative methods for data collection and analysis are not mystical; however, they possess considerable power, particularly when employed to construct novel theories or enhance existing theories (Shah & Corley, 2006) The data collection instrument was a Qualtrics-designed and implemented online questionnaire. The sample was not entirely random, but it was chosen for convenience to ensure diversity. The survey was distributed across multiple channels, including Instagram, Facebook, WhatsApp, and L'Oréal group platforms, to include individuals of diverse genders, nationalities, age groups, occupations, and other pertinent personal attributes.

The respondents provided their informed consent anonymously. Participants responded to an initial inquiry regarding their use of tools such as chatbots or virtual try-ons on online platforms. Participants first responded to an initial inquiry regarding their use of tools such as chatbots or virtual try-ons. If the response was negative, the survey would conclude for the participant. If affirmative, participants were asked to complete the entire survey, focusing on those who had previously had interactions with chatbots or virtual try-on features on online platforms.

3.3 RESPONDENTS

The survey initially garnered 230 responses, with 108 valid responses retained after data cleaning. Key demographic insights reveal that most respondents (66.67%) are aged 1825, indicating a strong representation of young adults. The survey predominantly captures the perspectives of women (81.48%), reflecting their engagement with beauty industry technologies. Educationally, 52.78% hold postgraduate degrees, suggesting informed perspectives on beauty tech innovations. Professionally, 69.44% are full-time employed, and income distribution varies, with a significant portion (25%) earning between 1,001€ and 1,500€ monthly. Most respondents (49.93%) shop for retail items online monthly, highlighting their active engagement with online beauty tech platforms (see Table 2).

Table 2

Demographics

Demographics	Count	%
Age		
Between 18 and 25	72	66,67%
Between 26 and 30	19	17,59%
Between 31 and 40	9	8,33%
Between 40 and 55	8	7,41%
Gender		
Male	20	18,52%
Female	88	81,48%
Educational Qualification		
Highscool	2	1,85%
Technical or vocational education	2	1,85%
Bachelor's degree	47	43,52%
Postgraduate	57	52,78%
Occupation		
Student	22	20,37%
Part-time employee	8	7,41%
Full-time employee	75	69,44%
Unemployed	3	2,78%
AVG Household monthly income		
< 500€	24	22,22%
500€ - 1.000€	20	18,52%
1.001€ - 1.500€	27	25,00%
1.501€ - 2.000€	16	14,81%
> 2.000€	21	19,44%
Frequency of purchasing retail items online		
Daily	2	1,85%
Weekly	13	12,04%
Monthly	55	50,93%
2 to 3 times a year	29	26,85%
Once a year	9	8,33%

4. RESULTS AND DISCUSSION

4.1 MEASUREMENT MODEL

The measurement model analysis was conducted to assess the reliability and validity of the measures. Subsequently, the structural model was examined to determine the relationships and connections within the model.

4.2 LOADINGS

The survey responses were systematically reviewed and coded to facilitate quantitative analysis. Each survey item was assigned a numerical value corresponding to the respondents' answers. This process involved:

4.2.1 CODING THE SURVEY RESPONSES

- For Likert-scale items (e.g., satisfaction levels, agreement levels), responses were numerically coded from 1 (strongly disagree/very dissatisfied) to 5 (strongly agree/very satisfied).
- For ranking items, respondents were asked to order options by importance, and numerical values were assigned based on the rank order provided by each respondent.
- For multiple-choice items, binary coding was applied, with 1 indicating the selection of a specific option and 0 indicating non-selection.

4.2.2 DATA ENTRY IN SPSS

- The coded data were entered into SPSS, creating a structured dataset where each row represented a respondent, and each column represented a survey item.
- Variable names and labels were assigned to ensure clarity and ease of reference during analysis.

4.2.3 VERIFICATION OF SCALE AND DATA CONSISTENCY:

- Each variable was examined to ensure it adhered to the appropriate measurement scale. This involved checking that Likert-scale items maintained their ordinal nature, ranking items were correctly ordered, and binary variables accurately reflected the selection or non-selection of options.

- Descriptive statistics were generated to verify the integrity of the data entry process. Each variable's frequency means, and standard deviations were calculated to identify anomalies or inconsistencies.
-

4.3 CONSTRUCT RELIABILITY AND VALIDITY

Reliability Checks:

The internal consistency of survey items intended to measure the same construct was assessed using Cronbach's alpha. Items with low item-total correlations were scrutinized and considered for exclusion to improve the reliability of the scales. We have conducted tests on all variables integral to validating our hypotheses, specifically focusing on variables Q1, Q32, and Q24.

Scale: Q1: Virtual try-on technology in the beauty industry

Table 3

Case Processing Summary VTO

Case Processing Summary

		N	%
Cases	Valid	108	100,0
	Excluded[a]	0	,0
	Total	108	100,0

a. Listwise deletion based on all variables in the procedure.

Table 4

Rellability Statistics VTO

Reliability Statistics

Cronbach's Alpha	N of Items
,846	8

The Cronbach's Alpha value of 0.846 for the 8-item scale measuring virtual try-on technology indicates strong internal consistency and reliability. This supports the scale's use in further research to investigate user perceptions and the effectiveness of virtual try-on technology.

Scale: Q32: Chatbots Technology on beauty industry

Table 5

Case Processing Summary Chatbots

Case Processing Summary

		N	%
Cases	Valid	108	100,0
	Excluded[a]	0	,0
	Total	108	100,0

a. Listwise deletion based on all variables in the procedure.

Table 6

Reability Statistics Chatbots

Reliability Statistics

Cronbach's Alpha	N of Items
,762	8

The Cronbach's Alpha value of 0.762 for the 8-item scale measuring chatbot technology indicates satisfactory internal consistency and reliability. This supports the scale's validity for further research and analysis into the adoption and impact of chatbot technology on user perceptions and experiences.

Scale: Q24: Features in terms of importance for a satisfactory augmented reality (AR) experience when trying beauty products

Table 7

Case Processing Summary AR

Case Processing Summary

		N	%
Cases	Valid	108	100,0
	Excluded[a]	0	,0
	Total	108	100,0

a. Listwise deletion based on all variables in the procedure.

Table 8

Reability Statistics AR

Reliability Statistics

Cronbach's Alpha	N of Items
,610	5

The Cronbach's Alpha value of 0.610 for the 5-item scale measuring the importance of features for a satisfactory AR experience indicates moderate internal consistency. While the scale is marginally acceptable for exploratory purposes, further refinement and validation are recommended to improve its reliability for more robust research applications.

After conducting the Cronbach's alpha test, we conclude that all variables are suitable for further analysis. However, it is recommended to refine and validate the data from Q24, as its alpha value is only marginally acceptable. Despite this, the data is still adequate for the continuation of the analysis.

Validity Checks:

Exploratory Factor Analysis (EFA) was conducted to identify the underlying factor structure of the dataset. This step involved using the Principal Axis Factoring method with Varimax rotation to interpret the factors more clearly. The rotated factor matrix was examined to ensure that variables loaded appropriately onto distinct factors, reflecting coherent constructs.

For this EFA, we utilized the data provided by the following questions to define the group of variables (factors): Q1 (Virtual try-on technology in the beauty industry), Q32 (Chatbot technology in the beauty industry), Q24 (Features important for a satisfactory AR experience when trying beauty products), Q25 (Brand preference in the beauty industry that use AR), and Q26 (Ranking of areas for more AR applications in the beauty industry). To begin the test, we determined the KMO and Bartlett's Test.

Table 9

KMO and Barlett's Test

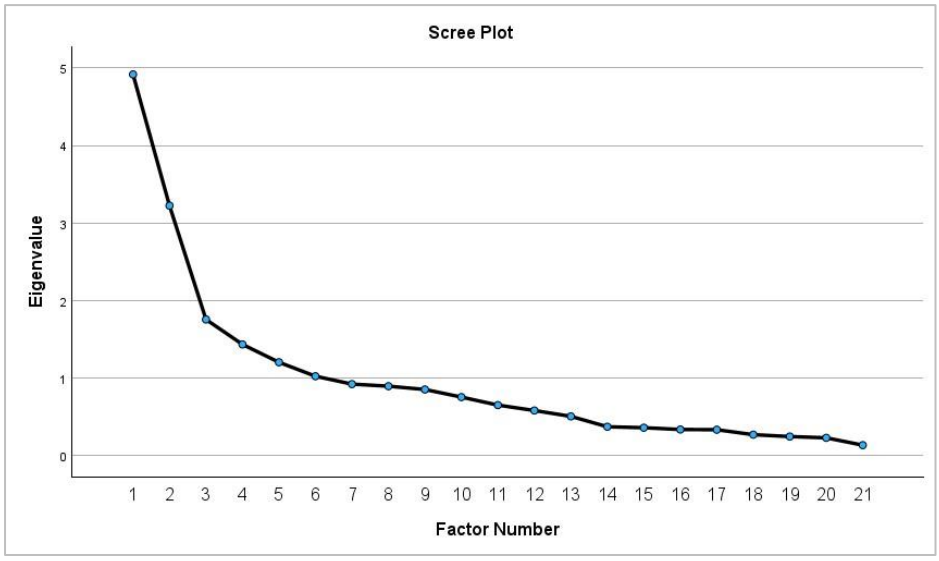
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,763
Bartlett's Test of Sphericity	Approx. Chi-Square	871,266
	df	210
	Sig.	<,001

The KMO measure of 0.763 and the significant result from Bartlett's Test of Sphericity (Chi-Square = 871.266, df = 210, Sig. < 0.001) indicate that the data is suitable for factor analysis. These results provide a solid foundation for identifying and interpreting the dataset's underlying factors, enhancing the overall analysis's robustness. Subsequently, we proceeded to analyze the scree plot.

Figure 2

Scree Plot



Based on the scree plot, extracting six factors could potentially improve the model by capturing additional variance considering the gradual decline up to the sixth factor. This will enhance the model's robustness if the additional factors contribute to a better understanding of the data without adding noise. Subsequently, the communalities were analyzed.

Table 10

Communalities of each variable's

Communalities

	Initial	Extraction
Confidence in Purchase Decisions	,748	,721
Satisfaction with VTO Experience	,787	,798
Accuracy of VTO Makeup Simulation	,668	,721
Interaction with Brands	,584	,577
Likelihood of Recommendation	,639	,634
AR technologies will replace traditional shopping experiences in the future.	,483	,421
VTO technologies can help make the beauty industry more inclusive	,476	,522
Privacy Concerns with VTO	,277	,204
Chatbots helpe me with the interaction of the site	,476	,536
Chatbots positively influences my experience	,464	,392
I trust the information provided to me through chatbots.	,389	,447
Chatbots on online beauty platforms increases my likelihood of purchasing	,510	,839
Chatbots has strengthened my relationship with brands.	,529	,486
Recommend online beauty platforms with integrated chatbots to friends and family.	,553	,711
Believe that chatbots will replace traditional purchases	,269	,295
Privacy Concerns with Chatbots	,322	,401
Ease of use	,434	,520
Accuracy in simulation	,389	,549
Variety of products available	,327	,346
Perfect integration with mobile devices	,382	,319
Personalization options	,228	,204

Extraction Method: Principal Axis Factoring.

The initial communalities represent the proportion of each variable's variance that all factors can explain. The extraction communalities show the proportion of variance that can be explained by the retained factors after factor extraction.

High Communalities (Above 0.6)

These variables are well-explained by the extracted factors, indicating that the factors account for a significant portion of the variance in these items.

Moderate Communalities (Between 0.4 and 0.6)

The extracted factors moderately explain these variables, suggesting that the factors account for a reasonable amount of variance in these items but less strongly than those with high commonalities.

Low Communalities (Below 0.4)

The extracted factors poorly explain these variables, indicating that the factors account for a relatively small portion of the variance in these items. This suggests that these variables might need to be better represented by the factor model and could be considered for removal or further investigation.

The communalities analysis reveals that most variables have moderate to high communalities, indicating that the extracted factors explain a substantial portion of the variance in these items. However, several variables with low communalities suggest that the factor model needs to capture their variance adequately, and these may require further refinement or re-evaluation.

Therefore, we decided to rerun the test, extracting a fixed number of factors. According to the scree plot, this number should be six. This approach yielded new results, enhancing the outcomes provided by the communalities.

The next step involves examining the percentage of variance explained by the factors.

Table 11

Total Variance Explained

Total Variance Explained

Factor	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4,917	23,413	23,413	4,085	19,450	19,450
2	3,224	15,352	38,765	1,785	8,498	27,948
3	1,756	8,361	47,126	1,556	7,412	35,360
4	1,434	6,828	53,954	1,494	7,114	42,474
5	1,204	5,731	59,686	,880	4,192	46,665
6	1,024	4,874	64,560	,844	4,018	50,683
7	,922	4,390	68,950			
8	,895	4,262	73,212			
9	,853	4,060	77,272			
10	,755	3,593	80,865			
11	,651	3,100	83,965			
12	,581	2,768	86,733			
13	,506	2,409	89,142			
14	,372	1,770	90,912			
15	,360	1,712	92,625			
16	,337	1,602	94,227			
17	,334	1,589	95,816			
18	,270	1,284	97,100			
19	,246	1,170	98,270			
20	,229	1,090	99,360			
21	,134	,640	100,000			

Extraction Method: Principal Axis Factoring.

Given the initial eigenvalues and the rotation sums of squared loadings, retaining six factors seems justified:

These six factors explain a significant total variance (64.560% initially, 50.683% after rotation).

While the variance explained by Factors 5 and 6 is lower after rotation, they still contribute to the overall model and might capture additional data dimensions.

Therefore, based on both the scree plot and the variance explained, retaining six factors is a reasonable decision to ensure the model captures the primary dimensions of the dataset without losing potentially meaningful information.

After determining that six factors should be retained, the subsequent step is to analyze the rotated matrix (Table 12).

Table 12

Rotated Factor Matrix[a]

Rotated Factor Matrix[a]

	Factor					
	1	2	3	4	5	6
Satisfaction with VTO Experience	,873					
Confidence in Purchase Decisions	,815					
Likelihood of Recommendation	,769					
Accuracy of VTO Makeup Simulation	,764					
Interaction with Brands	,757					
VTO technologies can help make the beauty industry more inclusive	,569					
AR technologies will replace traditional shopping experiences in the future.	,488					
Recommend online beauty platforms with integrated chatbots to friends and family.		,719				
Chatbots helpe me with the interaction of the site		,713				
I trust the information provided to me through chatbots.		,564				
Chatbots on online beauty platforms increases my likelihood of purchasing			,902			
Chatbots has strengthened my relationship with brands.		,382	,565			
Chatbots positively influences my experience			,421			
Accuracy in simulation				,712		
Ease of use				,671		
Perfect integration with mobile devices				,486		
Privacy Concerns with Chatbots					,579	
Privacy Concerns with VTO						
Believe that chatbots will replace traditional purchases						
Variety of products available						,494
Personalization options						,358

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 9 iterations.

Defining the Groups of Variables (Factors)

To define the groups of variables, we look at the loadings (values) in each column of the rotated factor matrix. High loadings (typically greater than 0.5) indicate that the variable strongly correlates with that factor. Here is how we can group them:

Factor 1 (VTO Experience and Confidence): This factor encompasses variables related to satisfaction with Virtual Try-On (VTO) experiences, confidence in purchase decisions, and AR technologies' perceived future and inclusivity in the beauty industry.

- Satisfaction with VTO Experience: .873
- Confidence in Purchase Decisions: .815
- Likelihood of Recommendation: .769
- Accuracy of VTO Makeup Simulation: .764
- Interaction with Brands: .757
- VTO technologies can help make the beauty industry more inclusive: .569
- AR technologies will replace traditional shopping experiences in the future: .488

Factor 2 (Chatbot Interaction): This factor includes variables related to the interaction and trust in chatbots, how chatbots influence purchase decisions, and recommendations of platforms with integrated chatbots.

- Recommend online beauty platforms with integrated chatbots to friends and family: .719
- Chatbots help me with the interaction of the site: .713
- I trust the information provided to me through chatbots: .564
- Chatbots on online beauty platforms increase my likelihood of purchasing: .902
- Chatbots have strengthened my relationship with brands: .565 (Note: it also loads on Factor 3, but higher on Factor 2)
- Chatbots positively influence my experience: .421

Factor 3 (Accuracy and Ease of Use): This factor is associated with the technical aspects of the VTO experience, including the accuracy of simulations, ease of use, and integration with mobile devices.

- Accuracy in simulation: .712
- Ease of use: .671
- Perfect integration with mobile devices: .486

Factor 4 (Privacy Concerns and Other): This factor includes privacy concerns related to chatbots and the availability of various products and personalization options.

- Privacy Concerns with Chatbots: .579
- Variety of products available: .494
- Personalization options: .358 (Note: relatively low loading; consider reviewing this variable)
- Privacy Concerns with VTO: (This variable did not load strongly on any factor in your matrix)

Based on the current analysis and information, we decided to remove the variables related to personalization options and privacy concerns with VTO, as they exhibit low or no factor loadings.

Through these meticulous steps, the dataset was prepared for subsequent statistical analyses, ensuring that the variables were accurately coded, correctly scaled, and reliably measured. This rigorous data preparation process laid the foundation for robust and valid findings in the study of AR technologies' impact on consumer behavior in the beauty industry.

4.4 VALIDATION OF HYPOTHESIS

- **Industry Growth and Technological Advances**

H1: The robust growth of the cosmetics industry, driven by technological advancements and influencer collaborations, positively impacts consumer perceptions and engagement with beauty brands (Petruzzi, 2024; Binwani & Ho, 2019; Ridder, 2020).

Variables: **Purchase_Frequency**, **Interaction_Brand.**

To begin the analysis of the correlation between the two variables and determine how they influence each other, we will first conduct a test of normality (Table 13).

Table 13

Tests of normality H1

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Frequency of Beauty Product Purchase	,276	108	<,001	,872	108	<,001
Interaction with Brands	,152	108	<,001	,935	108	<,001

a. Lilliefors Significance Correction

Both the Kolmogorov-Smirnov and Shapiro-Wilk tests indicate that the data for the variables "Frequency of Beauty Product Purchase" and "Interaction with Brands" do not follow a normal

distribution ($p < 0.001$ for both tests). Given the data's non-normality, Spearman's rank correlation coefficient test will be used to measure the relationship between these variables.

Table 14

Frequency of Beauty Product Purchase H1

			Frequency of Beauty Product Purchase
Spearman's rho	Interaction with Brands	Correlation Coefficient	,215*
		Sig. (1-tailed)	,013
		N	108

*. Correlation is significant at the 0.05 level (1-tailed).

The Spearman's rho correlation analysis shows a significant positive, though weak, correlation between the frequency of beauty product purchases and brand interaction ($\rho = 0.215$, $p = 0.013$, $N = 108$). This suggests increased interaction with brands is associated with a higher frequency of purchasing beauty products. However, the strength of this relationship is weak, indicating that other factors may also play a significant role in influencing purchase frequency.

In the subsequent step, we conducted the Linear Regression analysis.

Table 15

Variables Entered/ Removed[a] H1

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Frequency of Beauty Product Purchase[b]	.	Enter

a. Dependent Variable: Interaction with Brands

b. All requested variables entered.

Table 16

Model Summary H1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,236[a]	,056	,047	1,573

a. Predictors: (Constant), Frequency of Beauty Product Purchase

The regression model summary indicates that "Frequency of Beauty Product Purchase" is a weak predictor of the dependent variable, explaining only 5.6% of the variance. The weak correlation coefficient (R = 0.236) further supports this conclusion. The adjusted R Square (0.047) being close to the R Square value suggests that adding more predictors could potentially improve the model's explanatory power. The standard error of the estimate (1.573) indicates moderate accuracy of the model's predictions.

Table 17

ANOVA[a] H1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15,474	1	15,474	6,256	,014[b]
	Residual	262,193	106	2,474		
	Total	277,667	107			

a. Dependent Variable: Interaction with Brands

b. Predictors: (Constant), Frequency of Beauty Product Purchase

The ANOVA results indicate that the regression model is statistically significant ($F(1, 106) = 6.256$, $p = 0.014$). This suggests that "Frequency of Beauty Product Purchase" is a significant predictor of "Interaction with Brands."

Table 18

Coefficients[a] H1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,507	,509		6,893	<,001
	Frequency of Beauty Product Purchase	,446	,178	,236	2,501	,014

a. Dependent Variable: Interaction with Brands

The coefficients table reveals a statistically significant positive relationship between "Frequency of Beauty Product Purchase" and "Interaction with Brands." Specifically:

- The unstandardized coefficient (B = 0.446) indicates that for each additional purchase of beauty products, the interaction with brands increases by 0.446 units.
- The standardized coefficient (Beta = 0.236) shows a moderate positive effect.
- The significance level (p = 0.014) confirms that this relationship is statistically significant.

In conclusion, it is correct to affirm that there is a correlation between the variables and the frequency of purchases, which explains the interaction with brands to a certain extent. However, incorporating additional variables into the model would provide a more robust explanation.

- **Adoption of Advanced Technologies by Beauty Companies**

H2: The adoption of advanced technologies such as AR and AI by beauty companies like L'Oréal significantly enhances consumer engagement and satisfaction with their products and services (Paris, 2014; Li et al., 2008; Mangtani et al., 2020).

Variables: **Accuracy_Simulation, Recommendation_Likelihood**

To begin the analysis of the correlation between the two variables and determine how they influence each other, we will first conduct a test of normality.

Table 19

Tests of Normality H2

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Accuracy of VTO Makeup Simulation	,199	108	<,001	,934	108	<,001
Likelihood of Recommendation	,150	108	<,001	,930	108	<,001

a. Lilliefors Significance Correction

Both the Kolmogorov-Smirnov and Shapiro-Wilk tests indicate that the data for the variables "Accuracy of VTO Makeup Simulation" and "Likelihood of Recommendation" do not follow a normal distribution ($p < 0.001$ for both tests). Given the data's non-normality, Spearman's rank correlation coefficient test will be used to measure the relationship between these variables.

Table 20

Correlations H2

Correlations

			Accuracy of VTO Makeup Simulation
Spearman's rho	Likelihood of Recommendation	Correlation Coefficient	,621**
		Sig. (1-tailed)	<,001
		N	108

**. Correlation is significant at the 0.01 level (1-tailed).

The Spearman's rho correlation analysis demonstrates a strong and statistically significant positive relationship between "Accuracy of VTO Makeup Simulation" and "Likelihood of Recommendation" ($\rho = 0.621$, $p < 0.001$, $N = 108$). This suggests that as the perceived accuracy of the VTO makeup simulation increases, so does the likelihood of users recommending the technology.

In the subsequent step, we conducted the Linear Regression analysis (Table 21).

Table 21

Variables Entered/ Removed[a] H2

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Accuracy of VTO Makeup Simulation[b]	.	Enter

a. Dependent Variable: Likelihood of Recommendation

b. All requested variables entered.

Table 22

Model Summary H2

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,611[a]	,373	,367	1,135

a. Predictors: (Constant), Accuracy of VTO Makeup Simulation

The regression analysis demonstrates that the "Accuracy of VTO Makeup Simulation" is a significant predictor of "Recommendation Likelihood," explaining 37.3% of the variance in recommendation likelihood. This suggests that improving the accuracy of VTO simulations can positively impact consumer recommendations.

Table 23

ANOVA[a] H2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	81,185	1	81,185	63,053	<,001[b]
	Residual	136,482	106	1,288		
	Total	217,667	107			

a. Dependent Variable: Likelihood of Recommendation

b. Predictors: (Constant), Accuracy of VTO Makeup Simulation

The ANOVA results for the regression model indicate that the "Accuracy of VTO Makeup Simulation" is a significant predictor of "Likelihood of Recommendation". The model is statistically significant, with an F-statistic of 63.053 and a p-value of less than .001, indicating a robust relationship between the predictor and the dependent variable. These findings support the hypothesis that accurate VTO makeup simulations enhance consumer engagement and satisfaction, leading to a higher likelihood of recommendation.

Table 24

Coefficients[a] H2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2,238	,358		6,255	<,001
	Accuracy of VTO Makeup Simulation	,613	,077	,611	7,941	<,001

a. Dependent Variable: Likelihood of Recommendation

The coefficients analysis reveals that "Accuracy of VTO Makeup Simulation" is a significant and impactful predictor of "Likelihood of Recommendation". The strong positive relationship, indicated by a Beta of .611 and a significant p-value of < .001, highlights the importance of accurate VTO simulations in increasing customer recommendations. These findings support the hypothesis that advanced AR technologies enhance consumer engagement and satisfaction in the beauty industry.

- **Virtual Try-On Technologies (VTO)**

H3: The implementation of Virtual Try-On (VTO) technologies in the beauty industry positively impacts consumer decision-making processes and enhances their overall shopping experience (Fiore et al., 2005; Pantano et al. (2017); Willems et al., 2017).

Variables: **Ease of use, Confidence in Purchase Decisions**

To begin the analysis of the correlation between the two variables and determine how they influence each other, we will first conduct a test of normality.

Table 25

Tests of Normality H3

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Confidence in Purchase Decisions	,140	108	<,001	,939	108	<,001
Ease of use	,203	108	<,001	,881	108	<,001

a. Lilliefors Significance Correction

The normality tests indicate that the distributions of "Confidence in Purchase Decisions" and "Ease of Use" are not normal. Given this non-normality, it is recommended to either transform the data or use non-parametric statistical methods to validate the hypothesis H3. Given the data's non-normality, Spearman's rank correlation coefficient test will be used to measure the relationship between these variables.

Table 26

Correlations H3

Correlations

			Confidence in Purchase Decisions
Spearman's rho	Ease of use	Correlation Coefficient	,333**
		Sig. (1-tailed)	<,001
		N	108

**. Correlation is significant at the 0.01 level (1-tailed).

The Spearman's rank correlation analysis reveals a significant positive relationship between "Ease of Use" and "Confidence in Purchase Decisions" with a correlation coefficient of 0.333. This supports hypothesis H3, indicating that the implementation of user-friendly VTO technologies positively impacts consumer decision-making processes and enhances their overall shopping

experience. The statistical significance of this finding further validates the importance of ease of use in influencing consumer confidence in purchase decisions within the beauty industry. In the subsequent step, we conducted the Linear Regression analysis.

Table 27

Variables Entered/ Removed[a] H3

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Ease of use[b]	.	Enter

a. Dependent Variable: Confidence in Purchase Decisions

b. All requested variables entered.

Table 28

Model Summary H3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,292[a]	,086	,077	1,379

a. Predictors: (Constant), Ease of use

The regression analysis demonstrates that "Ease of Use" has a weak but significant impact on "Confidence in Purchase Decisions", explaining 8.6% of the variance. While this supports hypothesis H3 to some extent, it also highlights the need for incorporating additional variables to fully understand the drivers of consumer confidence in the context of VTO technologies in the beauty industry. The findings suggest that while ease of use is important, a holistic approach considering multiple aspects of the VTO experience will provide a more robust understanding of its impact on consumer decision-making processes.

Table 29

ANOVA[a] H3

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18,856	1	18,856	9,911	,002[b]
	Residual	201,663	106	1,902		
	Total	220,519	107			

a. Dependent Variable: Confidence in Purchase Decisions

b. Predictors: (Constant), Ease of use

The ANOVA results for the regression model indicate that "Ease of Use" is a significant predictor of "Confidence in Purchase Decisions". The model is statistically significant, with an F-statistic of 9.911 and a p-value of .002, indicating a robust relationship between the predictor and the dependent variable. These findings support the hypothesis H3 that the implementation of VTO technologies in the beauty industry positively impacts consumer decision-making processes and enhances their overall shopping experience.

Table 30

Coefficients[a] H3

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2,806	,617		4,547	<,001
	Ease of use	,338	,107	,292	3,148	,002

a. Dependent Variable: Confidence in Purchase Decisions

The coefficients analysis reveals that "Ease of Use" is a significant and impactful predictor of "Confidence in Purchase Decisions". The strong positive relationship, indicated by a Beta of .292 and a significant p-value of .002, highlights the importance of ease of use in increasing consumer confidence in purchase decisions. These findings support the hypothesis H3 that the implementation of VTO technologies in the beauty industry positively impacts consumer decision-making processes and enhances their overall shopping experience.

- **Augmented Reality (AR)**

H4: The use of Augmented Reality (AR) technology in the beauty industry enhances consumer interaction and satisfaction by providing immersive and interactive product experiences (Rauschnabel, 2018; Dacko, 2017; Mangtani et al., 2020).

Variables: **AR_technologies_vs_traditional_shopping, Satisfaction_VTO**

To begin the analysis of the correlation between the two variables and determine how they influence each other, we will first conduct a test of normality.

Table 31

Tests of Normality H4

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
AR technologies will replace traditional shopping experiences in the future.	,119	108	<,001	,925	108	<,001
Satisfaction with VTO Experience	,139	108	<,001	,936	108	<,001

a. Lilliefors Significance Correction

Both the Kolmogorov-Smirnov and Shapiro-Wilk tests indicate that the data for the variables "AR technologies will replace traditional shopping experiences in the future" and "Satisfaction with VTO Experience" do not follow a normal distribution ($p < 0.001$ for both tests). Given the data's non-normality, Spearman's rank correlation coefficient test will be used to measure the relationship between these variables.

Table 32

Correlations H4

Correlations

			AR technologies will replace traditional shopping experiences in the future.
Spearman's rho	Satisfaction with VTO Experience	Correlation Coefficient	,394**
		Sig. (1-tailed)	<,001
		N	108

**. Correlation is significant at the 0.01 level (1-tailed).

The Spearman's rank correlation analysis reveals a significant moderate positive relationship between "Satisfaction with VTO Experience" and the belief that "AR technologies will replace traditional shopping experiences in the future," with a correlation coefficient of 0.394. This suggests that as consumers become more satisfied with VTO experiences, they are more likely to believe that AR technologies will play a dominant role in the future of shopping. The statistical significance of this finding further validates the importance of enhancing VTO experiences to influence consumer perceptions about the future of shopping.

In the subsequent step, we conducted the Linear Regression analysis.

Table 33

Variables Entered/ Removed[a] H4

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AR technologies will replace traditional shopping experiences in the future.[b]	.	Enter

a. Dependent Variable: Satisfaction with VTO Experience

b. All requested variables entered.

Table 34

Model Summary H4

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,391[a]	,153	,145	1,356

a. Predictors: (Constant), AR technologies will replace traditional shopping experiences in the future.

The regression analysis demonstrates that the belief that "AR technologies will replace traditional shopping experiences in the future" has a moderate impact on "Satisfaction with VTO Experience", explaining 15.3% of the variance. While this supports the notion that consumer perceptions about the future of AR technologies influence satisfaction with VTO experiences, it also highlights the need for incorporating additional variables to fully understand the drivers of satisfaction in the context of VTO technologies in the beauty industry.

Table 35

ANOVA[a] H4

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35,190	1	35,190	19,137	<,001[b]
	Residual	194,912	106	1,839		
	Total	230,102	107			

a. Dependent Variable: Satisfaction with VTO Experience

b. Predictors: (Constant), AR technologies will replace traditional shopping experiences in the future.

The ANOVA results for the regression model indicate that the belief that "AR technologies will replace traditional shopping experiences in the future" is a significant predictor of "Satisfaction with VTO Experience". The model is statistically significant, with an F-statistic of

19.137 and a p-value of less than .001, indicating a robust relationship between the predictor and the dependent variable. These findings support the hypothesis that consumer perceptions about the future of AR technologies influence their satisfaction with VTO experiences. The results highlight the need for enhancing consumer awareness and positive perceptions of AR technologies to boost satisfaction with VTO applications

Table 36

Coefficients[a] H4

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3,627	,296		12,272	<,001
	AR technologies will replace traditional shopping experiences in the future.	,293	,067	,391	4,375	<,001

a. Dependent Variable: Satisfaction with VTO Experience

The coefficients analysis reveals that the belief that "AR technologies will replace traditional shopping experiences in the future" is a significant and impactful predictor of "Satisfaction with VTO Experience". The strong positive relationship, indicated by a Beta of .391 and a significant p-value of < .001, highlights the importance of consumer perceptions about the future of AR technologies in increasing satisfaction with VTO experiences. These findings support the hypothesis that positive expectations about the future of AR technologies can enhance consumer satisfaction with current VTO applications.

- **Artificial Intelligence (AI)**

H5: The integration of Artificial Intelligence (AI) in the beauty industry significantly improves consumer satisfaction through personalized recommendations and enhanced customer service (Booth, 2014a, p. 30).

Variables: **Privacy_Concern_Chatbots, Recommend_Online_Beauty_Chatbots**

To begin the analysis of the correlation between the two variables and determine how they influence each other, we will first conduct a test of normality.

Table 37

Tests of Normality H5

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Privacy Concerns with Chatbots	,173	108	<,001	,884	108	<,001
Recommend online beauty platforms with integrated chatbots to friends and family.	,177	108	<,001	,885	108	<,001

a. Lilliefors Significance Correction

The normality tests indicate that the distributions of "Privacy Concerns with Chatbots" and "Recommend online beauty platforms with integrated chatbots to friends and family" are not normal. Given the data's non-normality, Spearman's rank correlation coefficient test will be used to measure the relationship between these variables.

Table 38

Correlations H5

Correlations

			Privacy Concerns with Chatbots
Spearman's rho	Recommend online beauty platforms with integrated chatbots to friends and family.	Correlation Coefficient	,328**
		Sig. (1-tailed)	<,001
		N	108

**. Correlation is significant at the 0.01 level (1-tailed).

The Spearman's rank correlation analysis reveals a significant moderate positive relationship between "Recommend online beauty platforms with integrated chatbots to friends and family" and "Privacy Concerns with Chatbots," with a correlation coefficient of 0.328. This suggests that as privacy concerns increase, so does the likelihood of recommending these platforms. The statistical significance of this finding warrants further investigation to understand the underlying dynamics. These findings highlight the complexity of user perceptions and the multifaceted role of privacy concerns in the recommendation of technology-enhanced platforms.

In the subsequent step, we conducted the Linear Regression analysis.

Table 39

Variables Entered/ Removed[a] H5

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Privacy Concerns with Chatbots[b]	.	Enter

a. Dependent Variable: Recommend online beauty platforms with integrated chatbots to friends and family.

b. All requested variables entered.

Table 40

Model Summary H5

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,358[a]	,128	,120	1,564

a. Predictors: (Constant), Privacy Concerns with Chatbots

The regression analysis demonstrates that "Privacy Concerns with Chatbots" has a moderate impact on "Recommend online beauty platforms with integrated chatbots to friends and family", explaining 12.8% of the variance. While this suggests that privacy concerns are an important factor, it also highlights the need for incorporating additional variables to fully understand the drivers of recommendations for chatbot-integrated platforms in the beauty industry.

Table 41

ANOVA[a] H5

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	38,201	1	38,201	15,620	<,001[b]
	Residual	259,235	106	2,446		
	Total	297,435	107			

a. Dependent Variable: Recommend online beauty platforms with integrated chatbots to friends and family.

b. Predictors: (Constant), Privacy Concerns with Chatbots

The ANOVA results for the regression model indicate that "Privacy Concerns with Chatbots" is a significant predictor of "Recommend online beauty platforms with integrated chatbots to friends and family". The model is statistically significant, with an F-statistic of 15.620

and a p-value of less than .001, indicating a robust relationship between the predictor and the dependent variable. These findings suggest that addressing privacy concerns with chatbots can positively influence the likelihood of users recommending chatbot-integrated beauty platforms. This highlights the need for companies to consider and mitigate privacy concerns to improve user satisfaction and recommendations.

Table 42

Coefficients[a] H5

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2,831	,305		9,281	<,001
	Privacy Concerns with Chatbots	,384	,097	,358	3,952	<,001

a. Dependent Variable: Recommend online beauty platforms with integrated chatbots to friends and family.

The coefficients analysis reveals that "Privacy Concerns with Chatbots" is a significant and impactful predictor of the likelihood to "Recommend online beauty platforms with integrated chatbots to friends and family". The moderate positive relationship, indicated by a Beta of .358 and a significant p-value of < .001, suggests that users who have privacy concerns are still likely to recommend these platforms. This finding highlights the complexity of user attitudes towards chatbots, where privacy concerns coexist with recognition of their benefits. Companies should address privacy concerns while continuing to promote the advantages of chatbot integration to enhance user recommendations.

4.5 MULTIGROUP ANALYSIS

4.5.1. Age range vs virtual try-on technology in the beauty industry

The multivariate tests assess the overall impact of the independent variable Age range on the set of dependent variables. The table includes four different multivariate test statistics: Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root. Each test provides an F-value, degrees of freedom (df), and a significance level (Sig.).

Table 43

Between-Subjects Factors Age Range vs VTO

Between-Subjects Factors

		Value Label	N
Age Range	1	18 to 25 years	72
	2	26 to 30 years	19
	3	31 to 40 years	9
	4	40 to 55 years	8

Table 44

Multivariate Tests[a] Age Range vs VTO

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	,896	142,543[b]	6,000	99,000	<,001
	Wilks' Lambda	,104	142,543[b]	6,000	99,000	<,001
	Hotelling's Trace	8,639	142,543[b]	6,000	99,000	<,001
	Roy's Largest Root	8,639	142,543[b]	6,000	99,000	<,001
Q38	Pillai's Trace	,213	1,287	18,000	303,000	,194
	Wilks' Lambda	,797	1,304	18,000	280,500	,184
	Hotelling's Trace	,243	1,319	18,000	293,000	,174
	Roy's Largest Root	,179	3,010[c]	6,000	101,000	,010

a. Design: Intercept + Q38

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Intercept: The highly significant results across all tests for the intercept confirm that the grand mean significantly impacts the dependent variables.

Age Range: Three out of four multivariate tests (Pillai's Trace, Wilks' Lambda, Hotelling's Trace) are insignificant, suggesting that Age Range does not have a significant overall effect on the dependent variables. However, Roy's Largest Root is significant, indicating that there might be a specific strong effect of Age on at least one of the dependent variables. To determine which variables are affected by age range, lets analyze the next chart.

Table 45

Tests of Between-Subjects Effects Age Range vs VTO

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Confidence in Purchase Decisions	7,983[a]	3	2,661	1,302	,278
	Satisfaction with VTO Experience	5,334[b]	3	1,778	,823	,484
	Accuracy of VTO Makeup Simulation	16,091[c]	3	5,364	2,787	,044
	Interaction with Brands	12,461[d]	3	4,154	1,629	,187
	Likelihood of Recommendation	6,192[e]	3	2,064	1,015	,389
	AR technologies will replace traditional shopping experiences in the future.	43,698[f]	3	14,566	4,150	,008
Intercept	Confidence in Purchase Decisions	1231,079	1	1231,079	602,403	<,001
	Satisfaction with VTO Experience	1323,672	1	1323,672	612,463	<,001
	Accuracy of VTO Makeup Simulation	1220,379	1	1220,379	634,092	<,001
	Interaction with Brands	1355,772	1	1355,772	531,663	<,001
	Likelihood of Recommendation	1419,322	1	1419,322	697,999	<,001
	AR technologies will replace traditional shopping experiences in the future.	1114,174	1	1114,174	317,402	<,001
Age Range	Confidence in Purchase Decisions	7,983	3	2,661	1,302	,278
	Satisfaction with VTO Experience	5,334	3	1,778	,823	,484
	Accuracy of VTO Makeup Simulation	16,091	3	5,364	2,787	,044
	Interaction with Brands	12,461	3	4,154	1,629	,187
	Likelihood of Recommendation	6,192	3	2,064	1,015	,389
	AR technologies will replace traditional shopping experiences in the future.	43,698	3	14,566	4,150	,008
Error	Confidence in Purchase Decisions	212,536	104	2,044		
	Satisfaction with VTO Experience	224,768	104	2,161		
	Accuracy of VTO Makeup Simulation	200,159	104	1,925		
	Interaction with Brands	265,206	104	2,550		
	Likelihood of Recommendation	211,475	104	2,033		
	AR technologies will replace traditional shopping experiences in the future.	365,070	104	3,510		

Total	Confidence in Purchase Decisions	2610,000	108			
	Satisfaction with VTO Experience	2705,000	108			
	Accuracy of VTO Makeup Simulation	2323,000	108			
	Interaction with Brands	2686,000	108			
	Likelihood of Recommendation	2858,000	108			
	AR technologies will replace traditional shopping experiences in the future.	2097,000	108			
Corrected Total	Confidence in Purchase Decisions	220,519	107			
	Satisfaction with VTO Experience	230,102	107			
	Accuracy of VTO Makeup Simulation	216,250	107			
	Interaction with Brands	277,667	107			
	Likelihood of Recommendation	217,667	107			
	AR technologies will replace traditional shopping experiences in the future.	408,769	107			

a. R Squared = ,036 (Adjusted R Squared = ,008)
b. R Squared = ,023 (Adjusted R Squared = -,005)
c. R Squared = ,074 (Adjusted R Squared = ,048)
d. R Squared = ,045 (Adjusted R Squared = ,017)
e. R Squared = ,028 (Adjusted R Squared = ,000)
f. R Squared = ,107 (Adjusted R Squared = ,081)

The analysis shows that the independent variable Age Range significantly affects:

- **Accuracy of VTO Makeup Simulation** ($p = 0.044$)
- **Beliefs about AR Technologies Replacing Traditional Shopping Experiences** ($p = 0.008$)

Managerial Implications:

- **Accuracy of VTO Makeup Simulation**: Since Age range significantly impacts the perceived accuracy, efforts to improve or highlight the accuracy of VTO technology could positively influence user perceptions.
- **AR Technologies**: The belief that AR technologies will replace traditional shopping experiences is significantly influenced by Age Range, suggesting a strong link between user characteristics and their acceptance of future technologies.

4.5.2 Education vs chatbot technology in the beauty industry

The multivariate tests assess the overall impact of the independent variable Education on the set of dependent variables. The table includes four different multivariate test statistics: Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root. Each test provides an F-value, degrees of freedom (df), and a significance level (Sig.).

Table 46

Subjects Factors Education vs Chatbots

Between-Subjects Factors

		Value Label	N
Education	1	High School	2
	2	Technical or Vocational Education	3
	3	Bachelor's degree	47
	4	Postgraduate	56

Table 47

Multivariate Tests[a] Education vs Chatbots

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	,734	33,476[b]	8,000	97,000	<,001
	Wilks' Lambda	,266	33,476[b]	8,000	97,000	<,001
	Hotelling's Trace	2,761	33,476[b]	8,000	97,000	<,001
	Roy's Largest Root	2,761	33,476[b]	8,000	97,000	<,001
Q40	Pillai's Trace	,096	,410	24,000	297,000	,994
	Wilks' Lambda	,906	,409	24,000	281,931	,995
	Hotelling's Trace	,102	,408	24,000	287,000	,995
	Roy's Largest Root	,080	,985[c]	8,000	99,000	,453

a. Design: Intercept + Q40

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Intercept: The intercept is highly significant across all tests ($p < 0.001$), indicating that the overall means of the dependent variables are significantly different from zero.

Education: The independent variable Education does not have a significant multivariate effect on the combined dependent variables, as indicated by all four tests (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, Roy's Largest Root) with p-values greater than 0.05.

Table 48

Tests of Between Subjects Effects Education vs Chatbots

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Chatbots helpe me with the interaction of the site	14,487[a]	3	4,829	1,464	,229
	Chatbots positively influences my experience	11,945[b]	3	3,982	1,294	,280
	I trust the information provided to me through chatbots.	3,667[c]	3	1,222	,383	,766
	Chatbots on online beauty platforms increases my likelihood of purchasing	13,061[d]	3	4,354	1,695	,173
	Chatbots has strengthened my relationship with brands.	10,521[e]	3	3,507	1,167	,326
	Recommend online beauty platforms with integrated chatbots to friends and family.	10,151[f]	3	3,384	1,225	,304
	Believe that chatbots will replace traditional purchases	1,453[g]	3	,484	,145	,932
	Privacy Concerns with Chatbots	1,303[h]	3	,434	,175	,913
Intercept	Chatbots helpe me with the interaction of the site	395,351	1	395,351	119,901	<,001
	Chatbots positively influences my experience	371,162	1	371,162	120,653	<,001
	I trust the information provided to me through chatbots.	356,566	1	356,566	111,596	<,001
	Chatbots on online beauty platforms increases my likelihood of purchasing	299,284	1	299,284	116,492	<,001
	Chatbots has strengthened my relationship with brands.	267,413	1	267,413	89,011	<,001
	Recommend online beauty platforms with integrated chatbots to friends and family.	339,483	1	339,483	122,896	<,001
	Believe that chatbots will replace traditional purchases	181,632	1	181,632	54,514	<,001
	Privacy Concerns with Chatbots	158,329	1	158,329	63,845	<,001
Education	Chatbots helpe me with the interaction of the site	14,487	3	4,829	1,464	,229
	Chatbots positively influences my experience	11,945	3	3,982	1,294	,280
	I trust the information provided to me through chatbots.	3,667	3	1,222	,383	,766
	Chatbots on online beauty platforms increases my likelihood of purchasing	13,061	3	4,354	1,695	,173
	Chatbots has strengthened my relationship with brands.	10,521	3	3,507	1,167	,326
	Recommend online beauty platforms with integrated chatbots to friends and family.	10,151	3	3,384	1,225	,304
	Believe that chatbots will replace traditional purchases	1,453	3	,484	,145	,932
	Privacy Concerns with Chatbots	1,303	3	,434	,175	,913

Error	Chatbots helpe me with the interaction of the site	342,921	104	3,297		
	Chatbots positively influences my experience	319,934	104	3,076		
	I trust the information provided to me through chatbots.	332,296	104	3,195		
	Chatbots on online beauty platforms increases my likelihood of purchasing	267,189	104	2,569		
	Chatbots has strengthened my relationship with brands.	312,442	104	3,004		
	Recommend online beauty platforms with integrated chatbots to friends and family.	287,285	104	2,762		
	Believe that chatbots will replace traditional purchases	346,510	104	3,332		
	Privacy Concerns with Chatbots	257,910	104	2,480		
Total	Chatbots helpe me with the interaction of the site	2022,000	108			
	Chatbots positively influences my experience	2149,000	108			
	I trust the information provided to me through chatbots.	2080,000	108			
	Chatbots on online beauty platforms increases my likelihood of purchasing	1799,000	108			
	Chatbots has strengthened my relationship with brands.	1632,000	108			
	Recommend online beauty platforms with integrated chatbots to friends and family.	1923,000	108			
	Believe that chatbots will replace traditional purchases	1308,000	108			
	Privacy Concerns with Chatbots	1065,000	108			
Corrected Total	Chatbots helpe me with the interaction of the site	357,407	107			
	Chatbots positively influences my experience	331,880	107			
	I trust the information provided to me through chatbots.	335,963	107			
	Chatbots on online beauty platforms increases my likelihood of purchasing	280,250	107			
	Chatbots has strengthened my relationship with brands.	322,963	107			
	Recommend online beauty platforms with integrated chatbots to friends and family.	297,435	107			
	Believe that chatbots will replace traditional purchases	347,963	107			
	Privacy Concerns with Chatbots	259,213	107			

a. R Squared = ,041 (Adjusted R Squared = ,013)

b. R Squared = ,036 (Adjusted R Squared = ,008)

c. R Squared = ,011 (Adjusted R Squared = -,018)

d. R Squared = ,047 (Adjusted R Squared = ,019)

e. R Squared = ,033 (Adjusted R Squared = ,005)

f. R Squared = ,034 (Adjusted R Squared = ,006)

g. R Squared = ,004 (Adjusted R Squared = -,025)

h. R Squared = ,005 (Adjusted R Squared = -,024)

The F-values and significance levels for the corrected model indicate that Q40 does not significantly affect any of the dependent variables (all p-values > 0.05).

No Significant Effect of Education: The lack of significant impact of Education on any of the dependent variables implies that this factor may not be a strong predictor or influencer of chatbot-related perceptions and behaviors.

Future research should investigate other potential factors that might significantly influence user interactions and trust with chatbots.

4.5.3 Occupation vs Ranking of features for a satisfying AR.

The multivariate tests assess the overall impact of the independent variable Occupation on the set of dependent variables. The table includes four different multivariate test statistics: Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root. Each test provides an F-value, degrees of freedom (df), and a significance level (Sig.).

Table 49

Between-Subjects Factors Occupation vs Ranking of features for a satisfying AR.

Between-Subjects Factors

		Value Label	N
Occupation	1	Student	22
	2	Part-time employee	76
	3	Full-time employee	7
	4	Unemployed	3

Table 50

Multivariate Tests[a] Occupation vs Ranking of features for a satisfying AR

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	,897	219,302[b]	4,000	101,000	<,001
	Wilks' Lambda	,103	219,302[b]	4,000	101,000	<,001
	Hotelling's Trace	8,685	219,302[b]	4,000	101,000	<,001
	Roy's Largest Root	8,685	219,302[b]	4,000	101,000	<,001
Q41	Pillai's Trace	,096	,854	12,000	309,000	,595
	Wilks' Lambda	,905	,862	12,000	267,512	,587
	Hotelling's Trace	,105	,869	12,000	299,000	,579
	Roy's Largest Root	,096	2,464[c]	4,000	103,000	,050

a. Design: Intercept + Q41

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Intercept: The intercept is highly significant across all tests ($p < 0.001$), indicating that the overall means of the dependent variables are significantly different from zero.

Occupation: The independent variable Occupation does not have a significant multivariate effect on the combined dependent variables according to most tests (Pillai's Trace, Wilks' Lambda, Hotelling's Trace). However, Roy's Largest Root is marginally significant ($p = 0.050$), suggesting there may be a specific strong effect of Q41 on at least one dependent variable. To determine which variables are affected by Occupation, lets analyze the next chart.

Table 51

Tests of Between Subjects Effects

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Ease of use	9,747[a]	3	3,249	2,170	,096
	Accuracy in simulation	4,132[b]	3	1,377	,529	,663
	Variety of products available	5,472[c]	3	1,824	,691	,560
	Perfect integration with mobile devices	,104[d]	3	,035	,017	,997
Intercept	Ease of use	903,418	1	903,418	603,485	<,001
	Accuracy in simulation	899,027	1	899,027	345,193	<,001
	Variety of products available	657,884	1	657,884	249,059	<,001
	Perfect integration with mobile devices	836,342	1	836,342	422,234	<,001
Q41	Ease of use	9,747	3	3,249	2,170	,096
	Accuracy in simulation	4,132	3	1,377	,529	,663
	Variety of products available	5,472	3	1,824	,691	,560
	Perfect integration with mobile devices	,104	3	,035	,017	,997
Error	Ease of use	155,688	104	1,497		
	Accuracy in simulation	270,859	104	2,604		
	Variety of products available	274,713	104	2,641		
	Perfect integration with mobile devices	205,998	104	1,981		
Total	Ease of use	3577,000	108			
	Accuracy in simulation	3531,000	108			
	Variety of products available	2842,000	108			
	Perfect integration with mobile devices	3225,000	108			
Corrected Total	Ease of use	165,435	107			
	Accuracy in simulation	274,991	107			
	Variety of products available	280,185	107			
	Perfect integration with mobile devices	206,102	107			

a. R Squared = ,059 (Adjusted R Squared = ,032)

b. R Squared = ,015 (Adjusted R Squared = -,013)

c. R Squared = ,020 (Adjusted R Squared = -,009)

d. R Squared = ,001 (Adjusted R Squared = -,028)

The analysis shows that:

Ease of use: F(3, 104) = 2.170, p = 0.096

- Marginally non-significant.

Accuracy in simulation: F(3, 104) = 0.529, p = 0.663

Variety of products available: F(3, 104) = 0.691, p = 0.560

Perfect integration with mobile devices: F(3, 104) = 0.017, p = 0.997

- Not significant for all other variables.

Q41: While Q41 does not significantly impact any of the dependent variables, the effect on ease of use is marginally non-significant (p = 0.096).

Further research should explore other potential factors that might significantly influence user experiences with VTO technology.

4.5.4. Frequency Purchase vs Monthly Income

In the context of technologies such as AR, AI, and others within the beauty industry, analysing the variables of purchase frequency and monthly income is crucial for uncovering significant insights.

Table 52

Test of Normality - Frequency Purchase vs Monthly Income

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Frequency of Beauty Product Purchase	,276	108	<,001	,872	108	<,001
Monthly income (€)?	,146	108	<,001	,886	108	<,001

a. Lilliefors Significance Correction

Both the Kolmogorov-Smirnov and Shapiro-Wilk tests indicate that the data for the variables "Frequency of Beauty Product Purchase" and "Monthly Income (€)" do not follow a normal distribution ($p < 0.001$ for both tests). For this reason, we will conduct Spearman's rank correlation test.

Table 53

Correlation test based on frequency of purchase.

Correlations

			Frequency of Beauty Product Purchase
Spearman's rho	Monthly income (€)?	Correlation Coefficient	,119
		Sig. (1-tailed)	,110
		N	108

The Spearman's rho correlation analysis shows a very weak and non-significant positive relationship between "Frequency of Beauty Product Purchase" and "Monthly Income (€)" ($\rho = 0.119$, $p = 0.110$, $N = 108$). This suggests that there is no significant association between monthly income and the frequency of beauty product purchases.

Table 54

Descriptives

Descriptives

Frequency of Beauty Product Purchase

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
< 500€	24	2,58	,654	,133	2,31	2,86	1	4
500€ - 1.000€	20	2,90	,912	,204	2,47	3,33	1	5
1.001€ - 1.500€	27	2,41	,888	,171	2,06	2,76	1	4
1.501€ - 2.000€	16	3,19	,981	,245	2,66	3,71	1	4
> 2.000€	21	2,76	,700	,153	2,44	3,08	1	4
Total	108	2,72	,852	,082	2,56	2,88	1	5

Income Group Differences: There are differences in the mean frequency of beauty product purchases across different income groups. Notably, individuals in the 1.501€ - 2.000€ income range reported the highest frequency of purchases.

Variability: The standard deviations indicate variability within each income group. The 500€ - 1.000€ and 1.501€ - 2.000€ groups show higher variability compared to other groups.

Overall Trend: On average, the frequency of beauty product purchases across all participants is 2.72, with a standard deviation of 0.852, suggesting moderate frequency overall.

Table 55

ANOVA Frequency of Beauty Product Purchase

ANOVA

Frequency of Beauty Product Purchase

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	7,268	4	1,817	2,658	,037
Within Groups	70,399	103	,683		
Total	77,667	107			

The ANOVA results indicate that there are significant differences in the frequency of beauty product purchases across different income groups ($F(4, 103) = 2.658$, $p = 0.037$). This suggests that monthly income has a significant effect on how frequently individuals purchase beauty products.

Marketing strategies could be tailored to different income groups, recognizing that purchasing behavior varies significantly with income.

Table 56

ANOVA Effect Sizes

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	Upper
Frequency of Beauty Product Purchase	Eta-squared	,094	,000	,181
	Epsilon-squared	,058	-,039	,149
	Omega-squared Fixed-effect	,058	-,038	,148
	Omega-squared Random-effect	,015	-,009	,042

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

The effect size measures indicate that the association between income groups and the frequency of beauty product purchases is relatively small. Eta-squared shows the largest effect, suggesting that income accounts for about 9.4% of the variance in purchase frequency. However, other measures, especially the random-effect omega-squared, indicate a much smaller effect, emphasizing the need for cautious interpretation.

5. CONCLUSIONS AND FUTURE RESEARCH

5.1 THEORETICAL CONTRIBUTIONS

The study contributes to a theoretical understanding of consumer behavior in the beauty industry, particularly concerning the adoption and impact of advanced technologies such as virtual try-on (VTO), Augmented Reality (AR), chatbots, and Artificial Intelligence (AI) Key contributions include:

The research evaluated several constructs related to consumer perceptions and behaviors using rigorous statistical methods such as factor analysis, Cronbach's alpha reliability tests, and exploratory factor analysis. The empirical verification of constructs such as the VTO experience, chatbot interaction, and the impact of AR technology on consumer satisfaction was conducted.

Through factor analysis, the study identified the underlying dimensions that influence consumer attitudes and behaviors in relation to beauty technology adoption. Factors such as VTO experience and confidence, chatbot interaction, and ease of use in AR applications have emerged as crucial determinants impacting consumer decision-making.

The research established significant relationships and correlations between variables such as the accuracy of VTO simulations and the likelihood of recommendation. This indicates how technological advancements impact consumer perceptions and engagement in the beauty industry.

The study employed regression analyses to develop predictive models that highlight the correlations between variables such as purchase frequency, interaction with brands, and satisfaction with beauty technologies. These models provide insight into the factors driving consumer engagement and satisfaction in the digital beauty landscape. They provide insights into the factors driving consumer engagement and satisfaction.

5.2 PRACTICAL IMPLICATIONS

The findings of this investigation provide numerous practical implications for stakeholders in Implementing user-friendly VR and AR technologies can significantly improve consumer engagement and satisfaction. Beauty brands should focus on improving the accuracy and ease of use of their simulations to maximize consumer trust and purchase likelihood.

The integration of chatbots into online beauty platforms has the potential to streamline customer service and enhance brand-consumer interactions. It is possible to improve the overall user experience and satisfaction by addressing privacy concerns while leveraging chatbots for personalized recommendations.

Utilizing advanced technologies to differentiate products and services can yield competitive advantages. Marketing campaigns that highlight technological advancements and their benefits can influence consumer perceptions and increase brand loyalty.

Research and development of AI-driven personalization and virtual experience technologies can prepare beauty companies for future consumer demands. Continual innovation and adaptation to technological advancements will be imperative for maintaining competitiveness in the digital era.

5.3 LIMITATIONS AND FURTHER DEVELOPMENTS

Although this study provides valuable insights, it also exhibits limitations that suggest avenues for further research and development.

The study's sample size and demographic composition may limit its generalizability across diverse consumer segments and geographical regions. Future research may incorporate larger and more diverse samples to validate findings across broader populations.

Given the rapid evolution of beauty technology, the study's findings may be influenced by current technological capabilities. Future research should examine the impact of emerging technologies, such as AI advancements and extended reality, on consumer behaviors and preferences over time.

Exploring cultural influences on consumer perceptions and behaviors toward beauty technologies could provide deeper insights into global market trends and preferences. The application of cross-cultural studies would enhance comprehension of the variances in technological adoption across diverse socio-cultural settings.

The conduct of longitudinal studies to monitor changes in consumer attitudes and behaviors over time would provide valuable insights into the sustainability and long-term impact of beauty technologies. This approach would capture consumer preferences changing and technological adaptation.

By addressing these limitations and furthering these developments, future research can build upon the foundation laid by this study, advancing theoretical frameworks and practical applications in the digital beauty industry.

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APPENDIX A

Appendix a –

Questionnaire

Consent

This questionnaire, with an estimated duration of 7 to 10 minutes, falls within the scope of the Master's in Data Driven Marketing at NOVA IMS, with the main objective of understanding the impact of emerging technologies in the beauty industry on the consumer experience. Therefore, we intend to understand whether the use of these technologies positively influences the shopping experience on e-commerce platforms, as well as investigate whether they are perceived as beneficial by the consumer and whether they have an impact on their satisfaction. This questionnaire is specifically aimed at **all users of e-commerce platforms with integrated chatbots and virtual try-ons.**

If any questions arise while filling out or if you would like more information, do not hesitate to contact us via email 20220143@novaims.unl.pt.

Thank you in advance for your attention and collaboration, Carolina
Folhadela Moreira.

Informed Consent Form

I confirm that I agree to participate in this study. I am aware that my participation is voluntary, and I can stop filling out this questionnaire at any time, without suffering any penalty. I also understand that all data collected will be treated confidentially. I acknowledge that the answers will be analyzed by me and that this study does not involve any significant risks.

Q1. Experience with chatbots or VTO

Have you ever used tools like chatbots or virtual try-ons on online platforms?

- Yes
- No

Q2. How did you first learn about augmented reality AR technologies in the beauty industry?

- Through online advertisements
- On recommendation from friends or family

- In physical stores
- On social networks

Q3. How often do you buy beauty products?

- Daily
- Weekly
- Monthly
- 2 to 3 times a year
- 1 time a year

Q4. Scale - VIRTUAL TRY-ON TECHNOLOGY IN THE BEAUTY INDUSTRY

On a scale from 1 to 7, where 1 represents “Strongly Disagree” and 7 represents “Strongly agree”, please answer

- By using virtual try-on (VTO) technologies to try beauty products, I feel more confident making purchasing decisions.
- Using virtual try-on (VTO) features increased my satisfaction when trying beauty products.
- Makeup simulations carried out using virtual try-on (VTO) technologies accurately correspond to real results.
- Using virtual try-on (VTO) technologies to try beauty products has increased my interaction with brands.
- I would recommend using virtual try-on (VTO) technologies to try out beauty products to friends and family.
- I believe that augmented reality (AR) technologies in the beauty industry will completely replace traditional shopping experiences in the future.
- I believe virtual try-on (VTO) technologies can help make the beauty industry more inclusive, better meeting the needs of different skin types and tones.
- I feel like my privacy is compromised when I use virtual try-on (VTO).

Q5. Scale - CHATBOTS TECHNOLOGY IN THE BEAUTY INDUSTRY

On a scale from 1 to 7, where 1 represents “Strongly Disagree” and 7 represents “Strongly agree”, please answer

- Chatbots make it easier for me to interact with the website.
- The presence of chatbots positively influences my overall experience of purchasing beauty products online.
- I trust the information provided to me through chatbots.
- The presence of chatbots on online beauty platforms increases my likelihood of purchasing from that website again.
- Using chatbots has increased my relationship with brands.
- I would recommend online beauty platforms with built-in chatbots to friends and family.
- I believe chatbot technologies will completely replace traditional shopping experiences in the future.
- I feel like my privacy is compromised when I use chatbots.

Q6. Which device do you prefer to use to try beauty products with augmented reality (AR) technologies?

- Smartphone
- Tablet
- Computer
- Smartwatch
- Other device

Q7. What aspects of virtual try-on (VTO) technologies do you consider most important for improving the consumer experience in the beauty industry? (Select up to three options)

- Accuracy in product simulation
- Variety of products available to try
- Ease of use of applications
- Graphic and visual Quality
- Effective customer support to resolve technical issues

Q8. What aspect of chatbot technologies do you consider most important for improving the consumer experience in the beauty industry? (Select up to three options)

- Quick response to queries
- Ability to provide personalized product recommendations
- Ease of use and navigation

- Offering personalized beauty tips and tutorials
- Ability to resolve problems efficiently
- Human and natural interaction
- 24/7 availability for customer support

Q9. Have you had any negative experiences using augmented reality (AR) technologies to try beauty products? If yes, please describe briefly.

- Yes
- No

Q10. What are the main benefits you see in using augmented reality (AR) technologies to try beauty products? (Select up to three options)

- Greater convenience when trying products before purchasing
- Reduction in time spent in physical stores
- Exploring a wider variety of products
- Personalizing product recommendations
- Better understanding of products before purchase

Q11. Do you have any concerns or reservations about using augmented reality (AR) technologies to try out beauty products? If so, please share your concerns or comments.

- Yes
- No

Q12. Rate the following features in terms of importance for a satisfying augmented reality (AR) experience when trying beauty products:

- Ease of use
- Accuracy in simulation
- Variety of products available
- Seamless integration with mobile devices
- Customization options

Q13. Rank the following augmented reality (AR) platforms or applications in order of preference, with 1 being most preferred and 5 being least preferred:

- L'Oréal Makeup Genius
- Sephora Virtual Artist
- Chanel Beauty Try-On
- MAC Virtual Try-On
- Other

Q14. Rank the following areas in terms of where you would like to see more augmented reality (AR) applications in the beauty industry:

- Facial makeup
- Skin care
- Hair
- Nails
- Fashion and accessories

Q15. What factors influence your willingness to try a beauty product using virtual try-on technologies or chatbots:

- Recommendations from friends/family
- Online reviews
- Previous experience with the product
- Demonstration in physical store
- Virtual experimentation using AR

Q16. Considering your experience with Virtual Try-On (VTO) and Chatbots on online beauty platforms, how satisfied are you with these features? being "not at all satisfied" and 10 being "extremely satisfied":

- Not satisfied at all
- Extremely satisfied

Q17. How much time, on average, do you spend trying out beauty products using augmented reality (AR) technologies per session?

- Less than 1 minute
- 1-5 minutes
- 6-10 minutes
- 11-15 minutes
- More than 15 minutes

Q18. What is your age range?

- Under 18 years old
- 18 to 25 years old
- 26 to 30 years old
- 31 to 40 years old
- Over 40 years

Q19. What is your gender?

- Masculine
- Feminine
- Other (please specify)

Q20. What is your level of education?

- High School
- Technical or Professional Education
- Graduation
- Postgraduate (Specialization, Master's, Doctorate)
- Other (specify)

Q21. What is your current occupation?

- Student
- Full-time employee
- Part-time employee
- Unemployed

- Other (please specify)

Q22. What is your approximate monthly income (in €)?

Less than 500

501 to 1000

1001 to 1500

1501 to 2000

More than 2000

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