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Tech Trends in Beauty: Analyzing the Future of Cosmetic Innovation

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Abstract

This research paper addresses the question of how AI technologies are being adopted in the beauty industry and aims to identify the key factors influencing this adoption. The motivation behind this study is the relatively underexplored nature of technology acceptance in the beauty sector compared to other industries. Existing literature has not thoroughly examined the interaction between key variables in the Technology Acceptance Model (TAM) within the beauty context, nor has it sufficiently explored gender differences in the acceptance of AI beauty tools.

To address these gaps, a qualitative content analysis of nine pieces of online content was conducted to identify key emerging technologies, current trends, and practical applications of AI in the beauty industry. The findings reveal that artificial intelligence (AI) is the most frequently mentioned technology, significantly influencing the industry's transformation. The analysis also highlights significant trends such as personalization, sustainability, and the integration of technological advancements into business practices.

A quantitative study was conducted to test five hypotheses derived from the TAM, examining factors influencing acceptance such as perceived usefulness (PU), perceived ease of use (PEOU), attitude towards using (ATT), and behavioral intention (BI). The results support four hypotheses. The quantitative analysis confirms that PU and ATT are critical drivers of BI, with PU primarily influencing BI through ATT. PEOU positively impacts both PU and ATT, although its direct effect on BI is modest. These findings underscore the importance of enhancing usefulness and ease of use to foster positive user attitudes towards AI.

The study concludes that focusing on these aspects can effectively increase consumer adoption of AI technologies in beauty applications. Future research should explore additional factors and their interactions to develop more comprehensive strategies for technology adoption in this context. This study contributes to a comprehensive understanding of the technological landscape in the beauty sector and provides insights for developing more targeted and effective AI solutions.

Keywords

artificial intelligence, beauty industry, personalization, sustainability, Technology Acceptance Model, user acceptance, gender differences, consumer behavior, innovation

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AI	Artificial Intelligence
AR	Augmented Reality
ATT	Attitude Towards Using
BI	Behavioral Intention
CRM	Customer Relationship Management
IoT	Internet of Things
ML	Machine Learning
NLP	Natural Language Processing
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
TAM	Technology Acceptance Model
VR	Virtual Reality
XR	Extended Reality

Introduction

1.1 Background

Innovations are becoming an integral part of today's life, fundamentally changing people's daily routines. The transformative impact of new technologies is evident across diverse sectors, with significant advancements contributing to meaningful improvements. According to S. Kim, the connection between the physical environment and the cyber environment has fundamentally altered the innovation activities of firms (S. Kim et al., 2021, p. 17).

Due to the rapid integration of technology into cosmetics and beauty products, the beauty industry was revolutionized and underwent a swift change. With the market generating approximately $430 billion in revenue in 2022 and projected to reach $580 billion by 2027 (McKinsey, 2023), the sector is on an upward trajectory across all categories, demonstrating its steady rise. This paradigm shift towards digitalization has propelled the adoption of Beauty Technologies, ushering in a new era in the industry. The rise of big data and Artificial Intelligence (AI) has played a pivotal role in reshaping the beauty landscape (Ustymenko, 2023, p. 3).

According to TechTarget, Beauty tech is the integration of technology into cosmetics and beauty products (TechTarget, 2024). The term Beauty Tech is "the intersection of beauty and technology, applying cutting-edge advancements to transform and elevate the beauty industry" (PerfectCorp, 2023). In other words, Beauty tech refers to the current range of smart beauty products available on the market which primarily focuses on providing information and personalized services to users (Y. J. Lee et al., 2022).

Today's consumers, characterized by their high expectations and a desire for uniqueness, seek products tailored to their specific needs, both physically and emotionally (Saniuk et al., 2020, p. 17). In the era of Industry 4.0, customization expectations are particularly pronounced in specific product groups and according to a survey, respondents expressed a preference for customised standardisation when purchasing items like beauty/cosmetics (31%) (Saniuk et al., 2020, p. 9). This underscores the growing emphasis on personalized experiences and tailored solutions in the evolving landscape of beauty technologies. That is why beauty industry brands are increasingly leveraging different technologies not only to enhance customer experience but also to drive innovation in product development (Ustymenko, 2023, p. 3).

Therefore, this research seeks to explore the practical applications of AI beauty technologies and how they work together with other technologies such as Augmented Reality (AR), Machine Learning

(ML), the Internet of Things (IoT), and the Metaverse to enhance consumer experiences and drive innovation in the beauty industry. By examining these interconnected technologies, the research aims to provide a comprehensive understanding of their collective impact on the beauty sector.

The research will examine current trends shaping the beauty industry, the practical applications of AI technology within the sector, and public perceptions regarding the acceptance of AI beauty technologies. By assessing these variables, the study aims to provide insights that could help industry stakeholders understand the benefits and challenges associated with these technological advancements.

Ultimately, the research has the potential to contribute to the broader understanding of how AI and related technologies can be strategically implemented to meet consumer demands for personalization and innovation in beauty products and services.

1.2 Thesis Outline

This paper is organized as follows. The paper aims to study AI beauty technologies' acceptance and practical applications. In accordance with this goal, the following tasks were defined:

- Consideration of the theoretical basis for the acceptance of technology and consumer behavior towards the adoption of technologies in the beauty industry.
- Analysis of existing AI technologies and their applications within the beauty sector.
- Examination of the integration of AI with AR, ML, IoT, and Metaverse technologies in the beauty sphere.
- Identification and analysis of trends shaping the beauty industry.
- Exploration of public perception and acceptance of AI beauty technologies through survey data.

This thesis is divided into three main parts.

The first part (Background Literature) covers the theoretical basis and literature overview of AI and related technologies existing in the market. It starts with defining the key concepts and frameworks related to technology acceptance models, including the Technology Acceptance Model (TAM) and its relevance to AI in beauty. This section also explores consumer behavior theories that explain how and why consumers adopt new technologies, specifically focusing on the beauty sector.

The second part of the paper (Qualitative Content Analysis) relates to the analysis of industrial white papers and market reports to understand which specific technologies impact the beauty industry, showcasing current trends and practical applications of AI technology.

The third part (Quantitative study) provides an analysis of an online survey conducted to identify the acceptance of AI beauty tools in everyday life. This empirical section involves the collection and analysis of survey data to understand consumer attitudes towards AI beauty technologies. It examines factors influencing acceptance, such as perceived usefulness, ease of use, attitude towards using, and behavioral intention. The findings from the survey are analysed to provide insights into how consumers perceive AI beauty technologies and their willingness to adopt these innovations.

Finally, the Discussion sums up all the findings of the thesis, discussing the implications for industry stakeholders and providing recommendations for future research. It reflects on the practical applications of the research, offering insights into how beauty brands can leverage AI and related technologies to meet consumer demands and stay competitive in the evolving market. The conclusion also identifies potential areas for further investigation, suggesting avenues for future studies to expand on the findings and address any limitations encountered during the research.

2 Background Literature

This chapter provides an overview of the existing technologies within the beauty sector to give a broad understanding of the problem area. It explores how AI technologies are integrated with other advanced applications such as AR, ML, the IoT, and the Metaverse to revolutionize the beauty industry. By examining these technologies, this chapter aims to present a comprehensive view of the current technological landscape and the dynamics shaping consumer experiences and expectations in the beauty market.

2.1 Emerging Technologies in the Beauty Industry

The beauty industry is undergoing a significant transformation, driven by the advent of emerging technologies. These advancements are not only revolutionizing the way products are manufactured and designed but also how consumers interact with brands and personalize their beauty experiences. From the integration of AI and AR to the adoption of sustainable manufacturing practices, the beauty sector is embracing a future where technology enhances every aspect of the industry. This chapter delves into the various technologies that are shaping the beauty industry, examining their impact on production operations, consumer engagement, and environmental sustainability.

Technologies in Production and Manufacturing Operations

Technologies that are leveraged in production and manufacturing operations encompass a range of innovations designed to enhance the efficiency (Yang & Yen, 2019, pp. 346–349) and effectiveness of production processes (Dodevska et al., 2022, pp. 22–23) within the beauty industry. These technologies often involve advanced manufacturing techniques (C.-W. Lee, 2019, p. 54), quality control (Dodevska et al., 2022, pp. 22–23), automation systems (Yang & Yen, 2019, pp. 346–349), and optimization tools (Díaz et al., n.d.) (Yang & Yen, 2019, pp. 346–349).

For instance, by leveraging electrochemical sensors, researchers aim to enhance the safety and quality control of cosmetics in response to the increasing global demand for effective analytical methodologies (Dodevska et al., 2022, pp. 22–23). Such electroanalytical methods offer a promising pathway for the development of reliable sensing devices capable of cost-effective, rapid, and highly selective quantification of various cosmetic ingredients (Dodevska et al., 2022, pp. 22–23). The miniaturization potential of electrochemical systems enables integration into handheld devices and smartphones, facilitating fast and accurate on-site detection (Dodevska et al., 2022, pp. 22–23).

A study made by Amberg & Fogarassy (2019, pp. 12–13) revealed that over 30% of respondents prioritise the purchase of natural cosmetics despite perceived lower effectiveness, highlighting a strong preference for eco-friendly and health-conscious products. As consumer demand for safer and environmentally friendly products continues to rise (Venkataramani et al., 2020, pp. 2–4), some technologies within the beauty sector offer promising avenues for reducing the environmental impact of cosmetic products and empower cosmetic formulators to make sustainable decisions early in the research phase, thereby mitigating the environmental footprint of products and practices (Bom et al., 2020, p. 12). For example, the Sustainability Calculator developed by Bom et al. (2020, p. 12) is a tool that allows one to assess the sustainability of cosmetic products throughout their entire life cycle. It provides a systematic approach to evaluating the positive and negative impacts of various parameters on sustainability, ultimately assisting in decision-making and strategy development to minimize environmental impacts (Bom et al., 2020, p. 12). Another sustainable decision is an In-Mold Decorative Injection Technology in cosmetic containers (C.-W. Lee, 2019, p. 54) which is a sustainable way to address the growing demand for aesthetically pleasing and environmentally friendly packaging solutions. By integrating printing and injection moulding of advanced plastic film patterns, this technology enhances product appearance, wear resistance, and colour diversity while simplifying the production process and reducing costs (C.-W. Lee, 2019, p. 54).

Another aspect is the quality of products, which is addressed through the application of the Analytic Hierarchy Process (AHP) method in cosmetic design (Yang & Yen, 2019, pp. 346–349). This method aims to enhance the global circulation of brands by developing ultra-thin cosmetic products with enhanced temperature tolerance, bacteria resistance, and anti-knock quality. AHP enables the creation of small-volume products tailored to the international market and evolving fashion trends, utilizing automated production to ensure portability and affordability for consumers (Yang & Yen, 2019, pp. 346–349).

Technologies Enhancing Consumer Interaction

On the other side, technologies that focus on enhancing the interaction between beauty brands and consumers, offer personalized experiences and foster a deeper connection with the brand. The emphasis on personalization is underscored by findings from an Accenture survey, indicating that 75% of consumers are inclined to make a purchase when they receive personalized recommendations, underscoring the demand for customization (Accenture, 2016). Similarly, a Forrester study revealed that 77% of consumers have chosen a brand that provides personalized service or experience, indicating a strong preference for tailored interactions (Forrester, 2021). To grasp the current understanding of consumer preferences and behaviors, it is important to specify the term "Personalisation" as the extent to which information is customized to meet the specific requirements of an individual user, playing a crucial role in shaping positive experiences (Bilgihan et al., 2016, p. 110). The demand for personalized services is increasing across various industries, particularly in sectors like cosmetics and healthcare, where there's a growing need for integrated platforms to meet customer preferences effectively (Fatima et al., 2023, pp. 2–3).

Personalized recommendations lie at the heart of beauty technology's capabilities (Revieve, 2021). The fields of AI and ML primarily focus on advancing personalization applications, aiming to optimize user experiences by developing increasingly precise algorithmic decision and prediction models (Zanker et al., 2019, pp. 164–166). For example, AI-powered skincare analysis tools use image processing to assess skin conditions and recommend personalized skincare routines. Virtual try-on features powered by AR allow consumers to see how different makeup products will look on their faces in real-time, enhancing the shopping experience and reducing the uncertainty of online purchases.

Emerging technologies are redefining the beauty industry by enhancing production processes, promoting sustainability, and offering personalized consumer experiences. The integration of AI technologies not only streamlines operations but also meets the evolving demands of eco-conscious and customization-seeking consumers. As these technologies continue to evolve, they hold the potential to further transform the beauty industry, making it more efficient, sustainable, and consumer-centric.

2.2 AI beauty technologies

AI is a technology that involves simulating human intelligence in machines to perform various tasks (Tripathi, 2021, pp. 1–16). AI technologies are utilized in medicine to aid in repetitive tasks traditionally performed by humans, including screening, diagnosis, treatment, and epidemiological analyses (Mintz & Brodie, 2019, pp. 73–81). AI has become a fundamental component of the cosmetics industry, revolutionizing product offerings and transforming customer interactions (Mangtani et al., 2020), (Kato, 2018). In the cosmetics sector, AI techniques such as ML and computer vision have been deployed across multiple domains, ranging from product development to personalized recommendations (Kato, 2018). Statistically, among makeup users, 58% of Gen Z makeup users have utilized an AI filter or AI-powered beauty search tool to aid in selecting a colour cosmetic for purchase, surpassing the 40% of all beauty buyers who have done the same (Herich, 2023, p. 4).

One notable advancement of AI implementation is the development of personalized recommender systems for cosmetics products. These systems leverage AI algorithms to consider a range of factors, including facial features, emotions, and potential skin conditions, to offer tailored product recommendations (Abu-Shanab et al., p. 5). By integrating these elements, the recommender system aims to enhance user satisfaction by providing more relevant and accurate suggestions for cosmetic products (Abu-Shanab et al., p. 5).

AI is a technology that can be not only used independently but also it is encompassing a variety of software and hardware components that facilitate ML, artificial neural networks, deep learning, cognitive computing, and natural language processing (Varriale et al., 2023, p. 3). These diverse technologies collectively enable AI systems to perform complex tasks such as data analysis, pattern recognition, decision-making, and human-computer interaction.

A novel methodology known as Convolutional Neural Networks (CNNs) employs an AI architecture to analyze datasets and extract valuable insights from them. CNN, through extensive training with diverse datasets, excel in processing different types of media and images, enabling them to identify patterns and extract features from input data (N et al., p. 3), (Abishek et al., p. 3). The system's effectiveness was demonstrated through a comprehensive testing phase, including public and expert evaluations, showcasing the potential of AI-driven solutions in the cosmetics industry (Nagarajaiah & Hanakere, 2023, pp. 798–799). AI algorithms are ideal for selecting appropriate products based on a customer's unique personal factors (Nagarajaiah & Hanakere, 2023, pp. 798–799). They can process large volumes of unstructured data, including customer reviews, preferences, purchase history, and social media interactions, to generate insightful recommendations.

Another application of AI technology leveraging a CNN algorithm is a prediction of colour reproduction on the user's lips before applying lipstick (Cahyono et al., 2023, p. 5). By comparing the accuracy with and without CNN utilization, the study demonstrated the CNN algorithm's superior performance, particularly in accounting for the user's natural lip colour. This accurate prediction of colours holds significant promise for enhancing the effectiveness of virtual lipstick applications (Cahyono et al., 2023, p. 5).

The integration of AI with other advanced technologies, such as big data analytics, digital applications, the IoT, and robotics, significantly enhances competitive advantage (Varriale et al., 2023, p. 14). These integrated systems not only enhance operational efficiency but also significantly improve customer satisfaction, energy efficiency, and risk management.

Augmented Reality (AR)

Some technologies within the beauty sector aim to enhance personalization by offering personalized product visualization displays, allowing users to virtually try on makeup and fashion products tailored to their face and body, thereby enhancing their shopping experience (Taylor & Francis, 2023, p. 9). AR is one of the most popular technologies, with “the potential to transform the shopping experience”

(Duncan et al., 2013). AR represents an augmented version of reality, integrating digital images, sounds, or other sensory inputs into the real-world environment (Haidi et al., 2022, p. 2). Leveraging multimedia, 3D modelling, real-time tracking, intelligent interaction, sensing capabilities, and enhanced realism, AR technologies enhance users' perceptions of the physical world through simulation.

By leveraging AI, AR can become more intuitive and responsive to user interactions, increasing the adaptability and versatility of AR systems (Sahu et al., 2021, p. 3). AI enhances AR through advanced image and object recognition, allowing AR applications to understand and interact with the physical environment more effectively.

In the realm of AR technology within the beauty industry, a study conducted by Bialkova & Barr (2022, p. 5), delves into the critical interplay between user satisfaction and purchase intention. Participants who reported a heightened level of satisfaction demonstrated a stronger inclination towards purchasing compared to their less satisfied counterparts (Bialkova & Barr, 2022, p. 6). A key revelation from the study underscores the significance of factors such as interactivity, realism, ease of use, and immersion in shaping AR experience evaluation, consequently influencing user satisfaction (Bialkova & Barr, 2022, p. 6). This pivotal finding underscores the imperative for the industry to craft AR experiences that prioritize these elements, enhancing the overall consumer journey and, consequently, boosting purchase likelihood (Bialkova & Barr, 2022, p. 6).

A notable application of AR in the beauty industry involves the use of facial recognition technology by virtual artists. These artists enable customers to digitally try on various cosmetic products by scanning their faces using the app's facial recognition feature (Haidi et al., 2022, p. 3). Among Gen Z individuals, virtual makeup try-on apps are the most popular, with 31% reporting that they have experimented with this type of application (Herich, 2023, p. 4). This immersive experience allows customers to visualize how different products would appear on their skin, facilitating more informed purchasing decisions by experimenting with different cosmetic colours virtually (Haidi et al., 2022, p. 3).

Another application of AR technology lies in the hairstyling industry, where AR applications offer females access to a broader range of hairstyle information and choices(W.-C. Wang et al., 2011, p. 3), facilitating more informed decisions about their personal appearance and grooming preferences. By addressing the challenge of quickly and accurately segmenting hair, the system enables realistic hair colour augmentation in real-time (Levinshtein et al., 2018, pp. 2–4). Leveraging a modified MobileNet CNN architecture trained on crowd-sourced hair segmentation data, the system achieves impressive accuracy and detail in hair matting while running at over 30 frames per second on an iPad

Pro tablet (Levinshtein et al., 2018, pp. 2–4). This breakthrough technology not only enhances user experience but also demonstrates the potential of deep learning in real-time image processing on resource-constrained mobile platforms, opening the way for innovative applications in various industries beyond beauty (Levinshtein et al., 2018, pp. 2–4).

The integration of AR within the beauty industry signifies a monumental shift in how consumers engage with products and brands. AR's ability to merge the digital with the physical world offers unprecedented opportunities for personalization, allowing users to virtually try makeup and fashion products tailored to their unique features. As AR continues to evolve, its integration with AI will further enhance its capabilities, making it an indispensable tool for the beauty industry, driving both consumer engagement and sales.

Machine Learning (ML)

ML, a subset of AI, enables machines to learn from data without explicit programming, mirroring human cognitive processes by using experiential data to inform decision-making (Vatiwutipong et al., 2023, p. 2). The efficiency of the ML algorithm is noteworthy, as it swiftly and accurately identifies users' skin conditions. This empowers users to gain a deeper understanding of their skin quality, enabling them to make informed decisions and select products that align with their needs. Ultimately, this approach aims to prevent potential skin damage resulting from the use of incompatible or unsuitable skincare products (Li et al., 2020, p. 2).

Deep learning (DL) as a subfield of ML exhibits superior performance in the field of medicine (Khan et al., 2020, p. 13), specifically in dermatology (Murphree et al., 2022, p. 10) compared to the traditional ML method. In the age of big data, deep learning techniques have become increasingly powerful for tasks like image classification and detection compared to traditional approaches that rely on predefined rules to extract features (W.-S. Huang et al., 2018, p. 4).

For instance, the cloud-based skin analysis system not only detects various skin issues but also utilizes big data analysis to recommend maintenance solutions, such as brush head types, skincare products, and cosmetics (W.-S. Huang et al., 2018, p. 2). Deep learning is pivotal in accurately classifying a vast number of skin and scalp images, mitigating subjective errors inherent in experience-based rules. This comprehensive approach integrates cloud computing, image processing, ML, and big data analysis to offer holistic beauty solutions (W.-S. Huang et al., 2018, p. 2). The hardware architecture consists of a handheld device for image input, a display device for output, and cloud analysis software for calculation, ensuring seamless integration and user-friendly operation (W.-S. Huang et al., 2018, p. 2). Another image analyzer which was described by Xiao et al. (2020, pp. 9–11) utilizes ML algorithms, enhancing surface texture information and offering real-time analysis of facial skin features like hairs, smoothness, and scars. Through its ability to retrain neural networks on user-specific data, the tool holds promise for low-cost skin disease diagnosis.

Another example is a skin intelligence recommendation platform which is leveraging both ML and deep learning (DL) algorithms to address the challenges posed by the extensive variety of cosmetic products in the market and the diverse nature of individual skin conditions (Li et al., 2020). The subsequent classification of skin conditions utilizes image processing algorithms to preprocess and extract features, enabling the training of multi-label classification models (Li et al., 2020). This predictive model offers personalized maintenance knowledge and product recommendations based on the user's skin condition, aiding in the selection of suitable skin care products and ingredients (Li et al., 2020). Through rapid and accurate skin condition identification, users can make informed decisions to mitigate potential skin damage caused by unsuitable products (Li et al., 2020).

ML represents a transformative technology within the beauty sector, offering sophisticated tools for skin analysis and personalized product recommendations. As ML continues to advance, its application in the beauty industry will undoubtedly lead to more personalized, efficient, and effective beauty solutions, setting new standards for consumer satisfaction and product innovation.

Internet of Things (IoT)

IoT refers to a network of interconnected physical devices like sensors and controllers that perform tasks such as data transfer and process control (Gopal et al., 2023). The data generated by IoT devices is kept in the IoT cloud, where it is analyzed by the AI model, assisting in decision-making and achieving the best outcomes from the AI and IoT integration (Juyal et al., 2021, p. 10541). Its application spans various fields including healthcare, where it facilitates the connection of medical devices for monitoring purposes, such as capturing images of the affected skin and storing data in the cloud for analysis and diagnosis (Juyal et al., 2021, p. 10541).

One compelling use case of the IoT within the beauty industry is enabled skin sensor technology that could represent a significant advancement in personalized sun safety and UV exposure monitoring (Ramani et al., 2023, p. 2). By continuously tracking UV radiation levels in real-time and analyzing environmental factors, such as temperature and humidity, the system generates tailored recommendations for sun protection measures (Ramani et al., 2023, p. 2). This proactive approach not only increases individual awareness of UV-related hazards but also has the potential to mitigate the incidence of sunburn and skin cancer by promoting informed choices regarding outdoor activities. With its ability to remotely collect data, analyze patterns, and provide personalized recommendations, the technology stands poised to significantly improve public health outcomes associated with UV radiation exposure, making outdoor experiences safer and healthier for individuals worldwide (Ramani et al., 2023, p. 2).

A new concept which lies within the IoT ecosystem, the Internet of Mirrors (IoM) (Fatima et al., 2023, pp. 3–4) , integrates smart mirror interfaces and embedded sensors over a connected network to offer personalized services and visualize user metrics based on sensed data. These smart mirrors can sense, visualize, and interact with users and other IoM components, forming a collective ecosystem encompassing computing, storage, data exchange, and resource management. The IoM ecosystem involves users and smart mirror interfaces at its core, categorized into three elements: sensing and transmission, network and communication, and application layers (Fatima et al., 2023, pp. 3–4).

In the realm of the IoM, various scenarios and use cases illustrate the transformative potential of this technological ecosystem in enhancing everyday activities and human interactions. One such scenario involves enhanced beauty consultations, where smart mirrors equipped with advanced image processing and computer vision capabilities analyze customers' facial features and physiological data to offer personalized makeup recommendations (Fatima et al., 2023, pp. 12–13). This technology enables customers to virtually try on makeup products in real time, receiving immediate feedback and suggestions based on their preferences and skin analysis. Another compelling use case is found in employee training, where smart mirrors facilitate interactive sessions for trainees, providing real-time feedback and guidance on makeup techniques through AR guides and haptic feedback (Fatima et al., 2023, pp. 12–13). Additionally, IoM devices offer eco-friendly inventory management solutions for beauty retail stores by tracking customer interactions and preferences, optimizing inventory planning, and reducing waste through accurate demand predictions (Fatima et al., 2023, pp. 12–13). Remote dermatological treatment and skin health analysis represent another promising application, allowing users to receive personalized consultations and treatment plans based on comprehensive skin and physiological data collected by smart mirrors and wearable devices. Lastly, IoM devices integrated into smart homes offer all-inclusive remote living support, serving as central control hubs for security, environmental control, and health monitoring, while also acting as personal assistants for various tasks and recommendations (Fatima et al., 2023, pp. 12–13).

Overall, by leveraging IoT-based skin monitoring systems, real-time diagnostics and monitoring of skin diseases, aim to enhance the diagnostic cycle by offering real-time monitoring of skin conditions. It can provide valuable insights into trends and changes in skin parameters, enabling the recommendation and sale of appropriate cosmetics, moisturizers, cleansers, and other skincare products tailored to individual needs. This integration of IoT technology not only enhances skin care services but also contributes to a more personalized and effective approach to cosmetic product recommendations and sales (Sharma & Juyal, 2020, p. 4263).

Metaverse

The metaverse, a concept once confined to science fiction literature, is rapidly transitioning into a tangible reality, bridging the gap between the physical and virtual worlds. As highlighted by Macedo et al. (2022, p. 12), the metaverse represents a groundbreaking platform with vast implications across societal and economic domains. Originating in 1992 from Neal Stephenson's novel "Snow Crash," the term signifies a virtual universe surpassing the confines of reality. In contemporary contexts, the metaverse has evolved into a digital landscape where individuals and businesses interact, create, and explore (Cheng et al., 2022, p. 11).

Maintaining the metaverse requires the support of big data and substantial computing power, including technologies such as cloud computing and AI networks (Cheng et al., 2022, p. 10). In the realm of cosmetics, the metaverse offers unprecedented opportunities for companies to engage with consumers, redefine marketing strategies, and navigate intellectual property challenges. (Y. Kim & Jung, 2022a, p. 2) underscore the emergence of branded virtual spaces within the metaverse, where cosmetics companies construct immersive environments for brand promotion and consumer engagement. These virtual worlds, ranging from replicas of physical stores to entirely novel spaces, serve as platforms for interactive experiences and marketing initiatives.

Recognizing the metaverse's transformative impact, beauty companies such as Amore, LG H&H, and L'Oréal are actively integrating into this digital landscape (Y. Kim & Jung, 2022b, p. 3). One significant benefit is that conventional Metaverse can be leveraged for marketing through virtual storefronts, interactive ads, and virtual influencers, offering an immersive environment that engages a wider audience (Jamshidi et al., 2023, p. 21). Additionally, the Meta-Metaverse enhances marketing by analyzing customer behavior, targeting specific subgroups, and optimizing strategies to predict future market trends and measure campaign effectiveness (Jamshidi et al., 2023, p. 21).

Overall, the digital landscape offers a new frontier for consumer engagement, brand promotion, and innovative marketing strategies. The creation of branded virtual spaces allows cosmetics companies to offer immersive experiences, bridging the gap between the virtual and physical worlds. As the metaverse continues to evolve, it will reshape the way consumers interact with beauty brands, providing a dynamic platform for creativity, engagement, and commerce.

2.3 Technology Acceptance Model

The public's acceptance of technology is critical to its effective application (Liu & Tao, 2022, p. 9). Understanding users' perceptions regarding new technology adoption can facilitate its further growth and implementation (Taherdoost, 2019). Therefore, understanding what influences public acceptability of AI beauty technologies should be a requirement for their widespread deployment (Liu & Tao, 2022, p. 9).

To grasp the current understanding of the research stream "Acceptance of technology", it is important to specify the term "Acceptance" as "an antagonism to the term refusal and means the positive decision to use an innovation" (Simon, 2001, p. 179). As technology plays an increasingly crucial role in various aspects of modern life, the need for its acceptance becomes even more pronounced.

To understand the factors influencing the acceptance of beauty technologies, it is crucial to examine the behavioral aspects of information systems' acceptance. Numerous theoretical models have been developed to analyze the determinants of information technology acceptance. Various studies have proposed different theories and models to describe and explain user acceptance, each identifying unique factors that contribute to this process (Taherdoost et al., pp. 219–223) in the Information technology (IT) area.

TAM stands as one of the most extensively utilized frameworks for understanding user acceptance of technology (King & He, 2006). Its widespread adoption is attributed not only to its simplicity and comprehensibility but also to its ease of understanding rather than its practical applicability (King & He, 2006).

Developed by Davis in 1989, the TAM was primarily designed to assess users' acceptance or rejection of computer technology (Davis et al., 1989, p. 983). Its development aimed to pinpoint the factors pivotal in shaping the technology acceptance process, particularly external influences on users' thoughts, attitudes, and behavioral intentions.

The Technology Acceptance Model is an adaptation of the Theory of Reasoned Action (TRA) (Ajzen, 1991), specifically designed to analyze user acceptance of Information Systems (IS) (Rondan-Cataluña et al., 2015). According to the TAM, the adoption of technology is forecasted by users' behavioral intentions, which, in turn, are influenced by their perceptions of the technology's usefulness in task performance and the ease of its use (Davis et al., 1989). Davis (1989) conducted a series of experiments to assess the TAM by examining perceived ease of use (PEOU) and perceived usefulness (PU) as independent variables and system usage as the dependent variable (Ma & Liu, 2004, p. 60). This framework should encompass key aspects related to individual customers' intentions and adoption of AI Beauty Technology.

However, over the years, various iterations and extensions of TAM have been developed to address the specific contexts and nuances of different technological domains. The TAM model has been evolving beyond its original focus on computer acceptance in workplaces. Now it has been widely applied across diverse contexts, as a concise framework for predicting user acceptance (Rondan-Cataluña et al., 2015).

In the initial version of the model, "PU" and "PEOU" were identified as two primary factors that have influence on the adoption of computer technologies (Davis et al., 1989). PEOU and PU stand out as the central constructs in TAM (Chen et al., 2013, p. 112). Throughout the evolution of this model, it expanded to four main elements, as delineated by Rese et al. (2017): PU, PEOU, attitude towards use (ATT), and behavioral intentions (BI) towards use. BI to use a technological innovation is proposed to be influenced by both the user's attitude towards use the system and the system's perceived usefulness (Davis, 1989). PU and PEOU primarily shape users' decisions to accept or reject technologies, as noted by Davis (1989). While these two factors are associated with the features of the application itself, the other elements focus on the application's impact on the consumer.

Despite its age, TAM continues to attract significant interest in research, particularly in consumer studies on mobile application usage (G. Huang & Ren, 2020, pp. 157–158).

2.4 Acceptance of AI technology

TAM is the most frequently utilized framework for assessing acceptance, demonstrating the highest predictive accuracy in determining BI towards AI adoption (Kelly et al., 2023, p. 30). PU, performance expectancy, attitudes, trust, and effort expectancy have all been shown to significantly and positively influence BI, willingness, and usage behavior of AI across various industries (Kelly et al., 2023, p. 30). In user acceptance analysis, two key variables - usefulness and usability - are frequently highlighted since they enhance the perceived convenience and applicability of new technologies, directly influencing users' attitudes towards adopting or purchasing new products (Petschnig et al., 2014).

Previous research on the acceptance and usage behavior of AI beauty technology has laid a foundation for understanding how users interact with these technologies (Netscher et al., 2023, p. 544). It explored the impact of AI on consumer behavior, particularly looking at how age influences the perception and acceptance of AI technologies in cosmetics (Netscher et al., 2023, p. 544). It was found that younger customers tend to enjoy using these tools more and are more likely to use them compared to older customers. Younger users also feel more confident in using computers and have fewer concerns about using AI technology (Netscher et al., 2023, p. 544). The study also revealed that when people see others around them accepting AI technology, they are more likely to find it easy to use (Netscher et al., 2023, p. 544). Additionally, if someone sees themselves reflected in the use of AI technology, they are more likely to think it's useful for buying cosmetics (Netscher et al., 2023, p. 544). These studies provided valuable insights into the factors influencing user acceptance, such as age, subjective norms, and perceived enjoyment.

Furthermore, in the following chapter, five hypotheses will be formulated to examine users' acceptance of AI beauty tools. This approach will allow for a detailed analysis of how variables such as usefulness and ease of use influence user attitudes and behaviors towards AI in the beauty industry, thereby filling the existing research gaps and contributing to a more nuanced understanding of technology acceptance across different demographics, including gender differences.

2.4.1 Structural Model Specification

Perceived Usefulness

PU is defined as "the degree to which an individual believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). This concept suggests that the adoption of computer technology could notably improve professional efficacy in the workplace (Davis et al., 1989). In the realm of innovative technologies, PU refers to the benefits users could get from adopting the application (T.-L. Huang & Liao, 2015, p. 273). Davis concluded that PU has the most significant influence on users' intention to accept new technologies (Davis et al., 1989, p. 982). In current research PU signifies the degree to which users believe these technologies would enhance their beauty routine.

Numerous studies affirm that PU positively influences ATT AI technology across various industries. For instance, Zhong et al. (2020, p. 1344) found that PU significantly affects attitudes in the hotel industry. Research in e-commerce also shows that PU significantly enhances user attitudes towards AI (C. Wang et al., 2023, p. 13). In the media industry context, it was found that PU has a significant impact on attitudes towards using cloud computing technologies, suggesting that the perceived benefits of AI drive positive attitudes across different technological contexts (Tavakoli et al., 2022, p. 17). This correlation suggests that when users find AI technologies beneficial, they are more likely to adopt and use them and their attitudes improve.

To evaluate the positive impact of these variables, the following hypothesis is proposed:

H1: Perceived Usefulness will positively influence Attitudes Towards AI in Beauty.

Perceived Ease of Use

PEOU is defined as "the degree to which an individual believes that using a particular system would be free of physical and mental effort (Davis, 1989, p. 320). PEOU encompasses an individual's comfort and ease while navigating new technology (Davis, 1989) as well as their perception of the difficulty in using and understanding it (T.-L. Huang & Liao, 2015). Usability, as defined in the literature, can be viewed in two dimensions (Baek & Yoo, 2018): ease of use and learning for one group, and efficiency in achieving specific goals for another.

Davis has highlighted that PEOU significantly influences the intention to adopt new technologies and fosters sustainable relationships with them (Davis, 1989). PEOU, in particular, has both direct and indirect positive effects on the intention to use various mobile services and technologies, including mobile applications (Kuo & Yen, 2009, p. 109). Researchers supported that PEOU positively impacts PU (Nair & MukundaDas, 2012, p. 4) as well as PEOU has a significant effect on ATT (Nair & MukundaDas, 2012, p. 4). Therefore, in this research, PEOU refers to the extent to which users perceive AI beauty technologies as effortless to use, while attitude is defined as the degree to which a user is interested in using AI beauty tools.

Davis in his research revealed that PEOU indirectly influences technology acceptance through its impact on PU (Davis, 1989). As a result, when consumers perceive technology as useful and easy to use, they are more likely to engage in sustainable relationship behavior with it, as proposed by the relationship marketing paradigm (Chiou & Shen, 2012).

Research consistently confirms that PEOU positively influences PU in the acceptance of AI. Pillai et al. (2020, p. 9) demonstrated this relationship in the retail sector, while Seo & Lee (2021, p. 9) found similar results in the service industry, and Huarng et al. (2022, p. 5) observed the influence of PEOU on PU in healthcare. Similarly, in the area of AI-based smart healthcare services, when consumers find AI technology user-friendly, they are more likely to perceive it as highly useful (Liu & Tao, 2022, p. 9). Educational (Zhang et al., 2023, p. 11) and e-commerce (C. Wang et al., 2023, p. 12) research confirms that PEOU significantly impacts PU, indicating that when AI technologies are easy to use, users perceive them as more useful.

Additionally, Zhong et al. (2020, p. 1344) highlighted the positive impact of PEOU on attitudes in the hotel industry. As well as studies in e-commerce (C. Wang et al., 2023, p. 12) and media industries (Tavakoli et al., 2022, p. 17) demonstrate that PEOU positively influences attitudes towards AI, suggesting that user-friendly AI applications lead to more favorable attitudes.

Prior research on the acceptance of AI technology in the cosmetic sector concluded that ease of use enhances the technology's applicability in everyday scenarios, leading to higher usability levels (Yustikarani & I Putu Wahyu, 2023, p. 145).

Hence, two hypotheses are created to evaluate whether PEOU could affect the ATT and PU of the AI-beauty tools in decision-making behavior:

H2: Perceived Ease of Use will positively influence Attitudes Towards AI in Beauty.

H3: Perceived Ease of Use will positively influence Perceived Usefulness.

Behavioral intention to use (BI)

BI is defined as the extent of an individual's intention to engage in a particular behavior, representing the subjective likelihood of performing that behavior (Fishbein & Ajzen, 1977). When applied to technology, BI to use an application is considered a rational predictor of future usage (Jackson et al., 1997). Therefore, understanding BI is crucial for anticipating the future use of mobile applications. This intention can be formed for various systems, applications, or technological tools.

Researchers have supported that PU has a positive influence on BI in the acceptance of AI in various sectors. Vărzaru (2022, p. 8) demonstrated this relationship in the financial industry, while it was found that PU significantly affects BI in the service industry (Seo & Lee, 2021, p. 9) as well as in AI-based smart healthcare services (Liu & Tao, 2022, p. 9).

Studies, such as those by Zhong et al. (2020, p. 1344), have shown that a positive attitude towards AI significantly influences BI in the hotel industry.

Moreover, studies in education (Zhang et al., 2023, p. 11) and e-commerce (C. Wang et al., 2023, p. 12) reveal that PU has a strong positive effect on the intention to use AI, showing that perceived benefits drive user adoption.

To study the possible influence of PU on BI, and to test the degree the which positive attitude could affect user BI, the following hypotheses are created below:

H4: Attitude towards use will positively influence Behavioral Intention to Use.

H5: Perceived Usefulness has a direct and positive effect on Behavioral Intention to Use.

2.4.2 Measurement Model Specification

In quantitative research part, a model based on the relevant literature was developed to examine the acceptance of AI in the beauty industry. This model is visually represented in Figure 1.

This model is reflective, where the direction of the arrows goes from the construct to the indicators. Reflective measurement models are characterized by the assumption that all indicator items are caused by the same construct, meaning they stem from the same domain (Hair et al., 2016, p. 61). Consequently, indicators associated with a particular construct should be highly correlated with each other. Additionally, individual items should be interchangeable, allowing any single item to be omitted without changing the meaning of the construct, provided the construct maintains sufficient reliability.

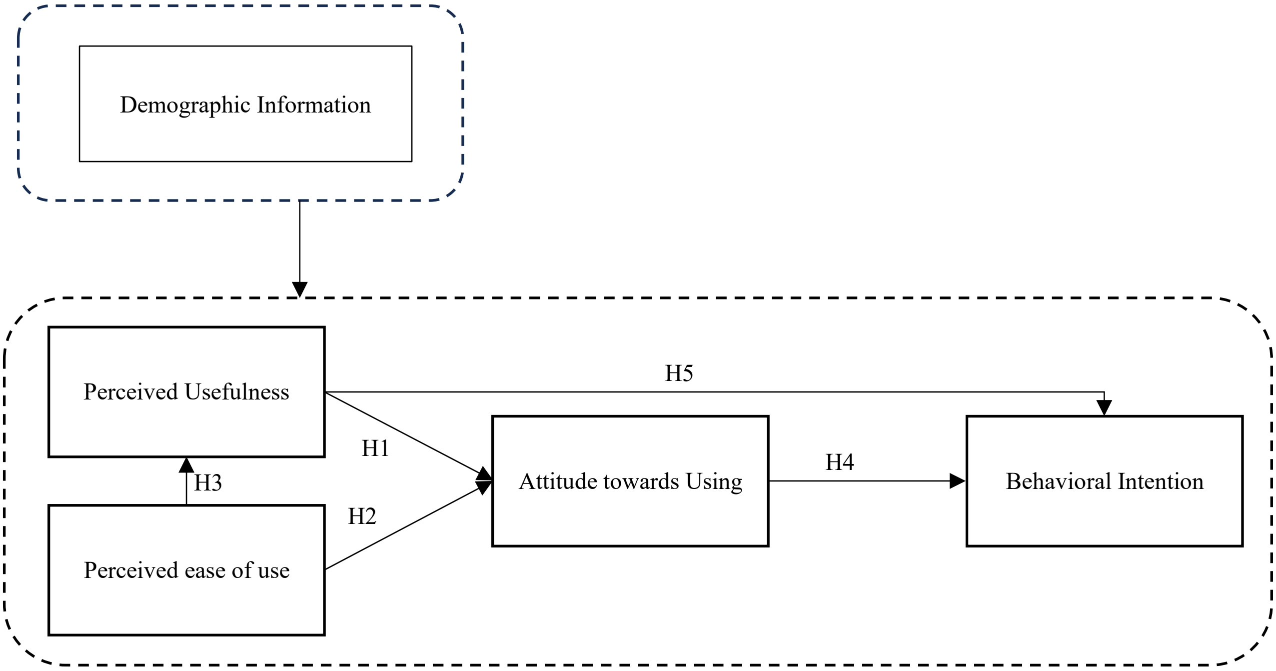


Figure 1 Determinants from the technology acceptance model (adapted from Davis et al., 1989)

By utilizing this reflective measurement model, the study aims to provide a comprehensive understanding of how PU, PEOU, and other determinants influence the attitude towards using AI technologies, which in turn affects the BI to adopt these technologies in the beauty sector.

The Table 1 summarizes key literature on the Technology Acceptance Model across various industries, highlighting the constructs covered in each study.

Table 1 Summary of literature sources

Name of the paper	*Industry*	*Technology Covered*	*Perceived Usefulness*	*Perceived Ease of Use*	*Behavioral Intention*	*Attitude towards use*
Construction and empirical research on acceptance model of service robots applied in hotel industry	Hotel	AI	x	x	x	x
Shopping intention at AI-powered Automated Retail Stores	Retail	AI	x	x		
The Emergence of Service Robots at Restaurants: Integrating Trust, Perceived Risk, and Satisfaction	Service	AI	x	x	x	
Adoption model of healthcare wearable devices	Healthcare	AI, IoT	x	x		
Customer Intention to Use AI Technology on Beauty Industry	Beauty	AI	x	x		
Assessing Artificial Intelligence Technology Acceptance in Managerial Accounting	Finance	AI	x	x	x	
The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services	Healthcare	AI	x	x	x	
AI in Cosmetics. Determinants Influencing the Acceptance of Product Configurators	Beauty	AI	x	x		
Explaining the effect of artificial intelligence on the technology acceptance model in media: a cloud computing approach	Media	Cloud Computing, AI	x	x		
An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce	E-commerce	AI	x	x	x	x
Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis	Education	AI	x	x	x	

The summarized literature reveals extensive studies on TAM constructs such as Perceived Usefulness, Perceived Ease of Use, Behavioral Intention, and Attitude towards use across multiple industries. Technology acceptance research in the beauty industry is relatively underexplored compared to its application in other sectors. While extensive studies have been conducted in fields like healthcare and retail, there is a notable gap in understanding how these models apply specifically to the beauty industry.

Moreover, while the current state of research within the beauty industry provides valuable insights into age-related differences, they have not thoroughly examined other important aspects of technology acceptance, such as the relationship between key variables in the Technology Acceptance Model. Previous research in the beauty industry has not fully explored how these variables of TAM interact to influence the acceptance of AI-based beauty tools.

Additionally, there is a notable gap in the literature regarding gender differences in the acceptance of AI in the beauty industry. While some studies have acknowledged the role of gender in technology acceptance, there has been limited research specifically addressing how males and females differ in their perceptions and acceptance of AI beauty tools. This gap is significant because understanding gender differences can help in developing more targeted and effective AI solutions that cater to the specific needs and preferences of different user groups.

To address the identified gaps in the literature, this research paper employs a qualitative content analysis aimed at answering three key research questions:

RQ1: What are the key emerging technologies currently impacting the beauty industry?

RQ2: Which trends are currently shaping the beauty industry?

RQ3: What are the practical applications of AI technology that exist in the beauty industry?

By exploring these questions, the study provides a comprehensive understanding of the technological landscape within the beauty sector.

3 Methodology

The following chapter outlines the research design and approaches used in this study. It begins with a detailed explanation of the overall research design, emphasizing the reasons for utilizing a mixed-methods approach. The chapter then delves into the qualitative content analysis, describing the search strategy employed to identify relevant content, followed by the process of inductive coding using QCAmap software, and addressing issues of reliability and validity to ensure robust findings. Next, it presents the quantitative study, detailing the structured questionnaire used to gather data and analyze the acceptance of AI beauty technologies. This comprehensive methodology provides a clear roadmap for how the research was conducted and ensures transparency and replicability of the study.

3.1 Research design

To address the central research questions comprehensively, a mixed-methods approach was employed, integrating both qualitative and quantitative techniques. By employing these mixed methods, the study aims to provide a comprehensive understanding of the emerging technologies, trends, and practical applications of AI in the beauty industry, while also assessing public perception and acceptance of these innovations.

The following diagram (Figure 2) outlines the comprehensive methodology employed to address the central research questions of this study. By systematically following these six phases of analysis, the study aims to thoroughly investigate and answer the research questions as well as check pre-defined hypotheses. This methodology ensures a rigorous and structured approach, integrating both qualitative and quantitative methods to provide a holistic understanding of the subject matter.

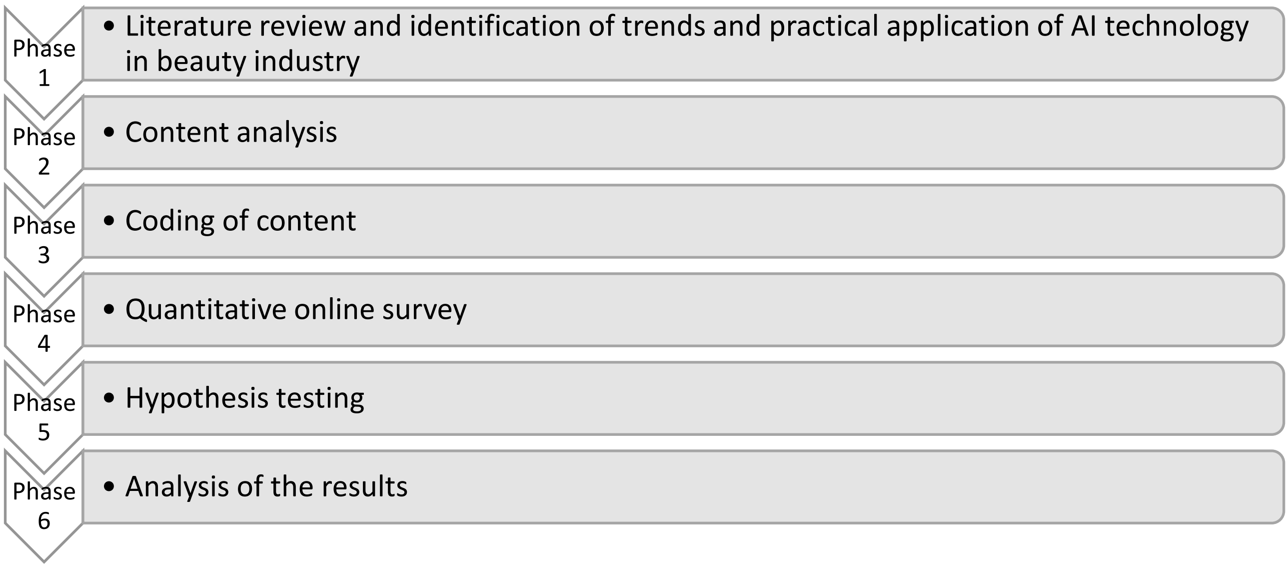


Figure 2 Research phases (own source)

By combining these methods, the study provides a comprehensive examination of the current state and potential future of AI technologies in the beauty industry. The qualitative analysis offers in-depth insights into emerging trends and technologies, while the quantitative study quantifies the public's acceptance and attitudes towards these innovations. Mixed-methods approach ensures a robust and holistic understanding of the research problem, enabling the formulation of actionable recommendations for stakeholders in the beauty industry.

3.2 Qualitative Content Analysis

Qualitative content analysis, inspired by quantitative methods, emphasizes the interpretative character of the assignment of text categories (Mayring, 2014, p. 10). By using this technique, valuable websites, online articles, or white papers were analysed. In total 9 content were undertaken for qualitative content analysis.

The qualitative content analysis aimed to answer the following research questions:

RQ1: What are the key emerging technologies currently impacting the beauty industry?

RQ2: Which trends are currently shaping the beauty industry?

RQ3: What are the practical applications of AI technology that exist in the beauty industry?

3.2.1 Search strategy

In conducting qualitative content analysis, a systematic search strategy was employed to identify relevant content pieces from the beauty tech industry. The goal was to gather comprehensive and authoritative materials that reflect current trends and technological advancements. This strategy involved several stages, starting from a broad search to a focused selection process, ensuring the inclusion of high-quality and relevant data sources.

Initial Search and Selection

The initial search phase aimed to cast a wide net, identifying a broad range of potential sources. Searches were conducted across various platforms, including industry-specific websites, consulting firm portals, and online databases of white papers. Key search terms included "BeautyTech," "cosmetic technology," "AI in the beauty industry," and "beauty innovation." This initial search gathered a total of 50 content items, encompassing white papers, scientific articles, and industry reports.

Screening Based on Titles and Abstracts

The next phase involved a more focused screening process. Out of the initial 50 content items, 24 were selected based on their titles and abstracts. This step was crucial in filtering out materials that did not directly address the research questions or were not relevant to the BeautyTech field. Criteria for inclusion at this stage were centred on the relevance to technological advancements in the beauty industry and the potential contribution to understanding industry trends.

Detailed Evaluation and Final Selection

The final selection phase involved a thorough evaluation of the full texts of the 24 shortlisted items. This detailed review further narrowed down the selection to 9 content pieces that met all inclusion criteria and provided substantial insights into BeautyTech. Figure 3 illustrates the search strategy process of selecting Items for qualitative content analysis.

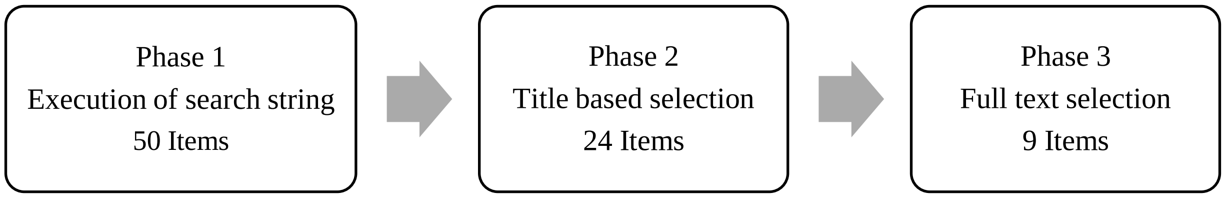


Figure 3 Search strategy phases

By employing a rigorous search strategy and a systematic selection process, this research ensured the inclusion of high-quality, relevant content for qualitative analysis, thereby enhancing the reliability and validity of the findings. The table below (Table 2) illustrates specific criteria for selecting final items.

Table 2 Overview of Inclusion and Exclusion Criteria for Content

Inclusion criteria	*Exclusion criteria*
Whitepapers from Start-Ups and corporations, operating in the field of BeautyTech	Websites that can’t be accessed in English
Websites from national offices	Non-serious Websites
Websites from consulting firms that address the research questions	Advertising Websites
Online scientific papers	Private Blogs
Published between January 2019 and February 2024	Focused mainly on medical treatments and not on beauty technologies
Available in full-text	
Online Articles from official sources	

In this study, specific inclusion and exclusion criteria were applied to ensure the relevance and quality of our content. White papers from startups and corporations in the BeautyTech field, websites from national offices, and consulting firms addressing central research questions were included in the section on inclusion criteria to ensure a comprehensive and authoritative analysis of the current trends and developments in the BeautyTech field. White papers are typically produced by industry leaders, consulting firms, and startups, offering in-depth insights and detailed information that is both relevant and current. These documents often provide expert perspectives, data-driven analysis, and strategic foresight that are essential for understanding the nuances of existing trends and technologies as well as real examples and use cases in the beauty industry.

Conversely, non-serious websites, advertising sites, private blogs, and sources primarily focused on medical treatments rather than BeautyTech were excluded. Differentiation between beauty technologies and medical technologies is based on their primary objectives and applications. Medical Technologies are aimed at diagnosing, treating, and managing medical conditions, diseases, and skin illnesses. Examples include medical devices and treatments such as laser therapy, Botox injections, and other dermatological procedures. While Beauty Technologies focuses on enhancing aesthetic appeal and improving the consumer experience in non-medical contexts. The technologies in this category are designed to analyze skin conditions, provide beauty recommendations, and offer VR and AR experiences for makeup and skincare. For instance, AI and ML can be used to analyze skin data and provide personalized beauty tips, while AR can enable users to virtually try on makeup products before purchase.

Websites that could not be accessed in English were also excluded to maintain consistency and comprehensibility. This approach helped us focus on high-quality, pertinent data while avoiding biased or irrelevant information.

The content examined is listed in detail in the following Table 3. This documents a systematic approach and enables replication of the research. The author and the date of access are noted.

Table 3 Overview of dataset uploaded on QCAmap

ID	*Year*	*Type*	*Name*	*Company name/Author*	*Access date*
Item 1	2023	White paper	Unveiling the future of beauty	Designit a Wipro company	23.03.2024
Item 2	2021	White paper	The New Beauty Rules: Playing to Win in a Changing Category	Carat, a Dentsu company	23.03.2024
Item 3	2023	White paper	VIVA TECHNOLOGY 2023	L’Oréal	23.03.2024
Item 4	2019	White paper	Gen Z: Building New Beauty	WGSN Beauty & Insight	26.03.2024
Item 5	2023	Website	Advanced AI: The Next Frontier In Beauty Technology	Sampo Parkkinen Forbes Councils Member	26.03.2024
Item 6	2023	Website	Hyper-personalization in the Beauty Industry How Customization is Reshaping the Cosmetics Industry	Sia Partners	28.03.2024
Item 7	2022	Website	New technology innovations shaping beauty industry	Vinay Kavde Senior Consulting Partner, Wipro, Limited	28.03.2024
Item 8	2020	Whitepaper	Beauty inside retail	Valtech	29.03.2024
Item 9	2023	Website	What Is Beauty Tech - The Complete Guide 2024	Perfect Corp.	29.03.2024

Source: Own research, 2024, n = 9

3.2.2 Inductive coding with QCAmap

The presented work is conducted with an inductive category-building approach to understand the research topic and answer the defined research questions. Inductive category development is a qualitative research method where themes and patterns emerge directly from the data, rather than from pre-existing theories (Bell et al., 2022, pp. 24–25). It is crucial that when inductive content analysis is performed, the data needs to be as unstructured as possible (Dey, 1993, p. 16).

In the current work, analysis began with detailed observations and systematical examination of the data to identify emerging themes, which were then grouped into broader categories, ultimately leading to new theoretical insights. This method supports the development of grounded theories based on actual data, ensuring that the findings are original and well-founded. By synthesizing diverse data sources, including white papers, websites, and online articles, inductive coding facilitates a comprehensive analysis of technologies and trends that impact the beauty industry.

QCAmap was chosen as the primary tool for data analysis due to its robust capabilities in qualitative content analysis. QCAmap, a software specifically designed for qualitative research, offers a structured and systematic approach to coding and analyzing textual data. The text content is analysed, and findings are categorized accordingly (Bell et al., 2022, pp. 20–23). This approach was chosen because of the research objective and the research environment.

For the coding method, a combination of in vivo coding and concept coding was used to identify the categories. In Vivo coding uses words or short phrases from the participant´s language in the data record as codes . While concept coding leverages a word or short phrase that represents a suggested meaning broader than a single item or action (Miles et al., 2013, p. 66). This combination means that individual words or short sequences of a statement reflect the content of the text. In addition, a generic term or concept can also summarize the text content instead of the literal transfer.

3.2.3 Reliability and Validity

In assessing the quality of qualitative research, traditional criteria such as validity, reliability, and objectivity, commonly used in the positivist paradigm, are not entirely suitable (Jana Bradley, 1993). Qualitative content analysis, being interpretive, requires different criteria to judge its rigour and trustworthiness. Lincoln & Guba (1985) proposed four criteria specifically tailored for evaluating qualitative research: credibility, transferability, dependability, and confirmability. These criteria provide a comprehensive framework for ensuring the trustworthiness of qualitative content analysis.

Credibility

Credibility pertains to the accuracy and truthfulness of the research findings in representing the social phenomena under study (Jana Bradley, 1993, p. 436). It involves activities like prolonged engagement, persistent observation, triangulation, peer debriefing, and member checking to ensure that the findings accurately reflect the data (Lincoln & Guba, 1985). For this research, credibility was enhanced by sourcing white papers from reputable industry leaders, ensuring the data was both relevant and authoritative. Inductive coding with QCAmap allowed themes to emerge directly from the data, minimizing researcher bias and accurately representing the trends and technologies in the BeautyTech field. Detailed documentation of the coding process and peer debriefing further supported the credibility of the findings.

Transferability

Transferability refers to the extent to which the findings of a study can be applied to other contexts or settings (Kyngäs et al., 2020, p. 2). It involves providing detailed, rich descriptions of the research context and data so that other researchers can assess the applicability of the findings. In this study, transferability was addressed by thoroughly documenting the data sources, including authors and access dates, and systematically detailing the data collection and analysis process. This transparency enables other researchers to replicate the study or apply the findings to similar contexts in the BeautyTech industry.

Dependability

Dependability focuses on the stability and consistency of the research process over time (Kyngäs et al., 2020, p. 4). It requires thorough and transparent documentation of the research methodology and any changes that occur during the study. Dependability in this research was ensured by using a clear and systematic coding process with QCAmap, which offers robust capabilities for qualitative content analysis. The combination of in vivo coding and concept coding provided a reliable framework for identifying and categorizing themes. The consistent application of coding procedures and detailed documentation of the research process contributed to the dependability of the findings.

Confirmability

Confirmability involves ensuring that the findings are shaped by the data and not by researcher bias or personal motivations (Kyngäs et al., 2020, p. 2). It is achieved through practices such as audit trails, where the research process is documented in detail and can be reviewed by others. In this study, confirmability was maintained by grounding the results in the data collected and minimizing researcher bias through inductive category development. The overlap of identified criteria with those documented in other studies further validated the findings, demonstrating that they were reflective of the data rather than the researcher's interpretations. Peer debriefing and systematic coding procedures also supported confirmability by providing an external check on the research process.

3.3 Quantitative study

The second method employed is a quantitative study, conducted through a structured questionnaire designed to test the theoretical model of technology acceptance.

Questionnaire development

To set up the questionnaire, the tool Umfrageonline.com was used due to its user-friendly interface and its capability to accommodate unlimited questions. The questionnaire employed a mixed approach for responses, incorporating multiple-choice answers for demographic questions and a Likert scale for other questions (Thompson, 2018).

The structured questionnaire was divided into four parts, comprising a total of 30 questions designed to test the theoretical model. The first section collects demographic data about the participants to gain insights into the respondents. In the second section, participants should have rated their skills and knowledge about technology and AI from their perspective. Since respondents might not have prior experience with AI beauty tools, the third part provided a comprehensive explanation of AI technology in the beauty industry, including real examples, use cases, photos, and descriptions of potential advantages and disadvantages. As an example, three the most popular technologies were chosen: Personalized recommendation system, Virtual try-on app and skincare analysis platform. Detailed overview of technology description can be found in Appendix 1. The last section measures the constructs included in the research model and is further divided into four subsections: PEOU, PU, BI, and ATT.

The four parts of the questionnaire are as follows (Appendix 1):

- Part A: Demographic Information
- Part B: Technology Knowledge and Background in AI
- Part C: Explanation of AI Beauty Tools
- Part D: Technology Acceptance Model

All items were measured using a seven-point Likert scale ranging from 1 "strongly disagree" to 7 "strongly agree", providing respondents with a full spectrum of agreement or disagreement from their perspective. All questions were mandatory, ensuring no missing data.

The constructs were derived from existing literature and adapted to the context of this study. All the constructs were previously tested survey instruments, leveraging well-established psychometric measures (Straub, 1989). Most constructs were operationalized by modifying previously validated scales. The scales for PU, ATT, and PEOU were adapted from Davis (1989) while measures for BI were adapted from Venkatesh et al. (2012). By modifying these previously validated scales, analysis ensured that survey instruments were both reliable and valid within the scope of this study.

It includes:

- Perceived Usefulness: 6 items
- Perceived Ease of Use: 6 items
- Behavioral Intention: 4 items
- Attitude towards use: 6 items

An overview of questions is presented in Appendix 1, detailed questionnaire items and their sources are presented in Appendix 2, codebook in Appendix 3.

Data Collection, Preparation, and Evaluation

The study was disseminated through various online channels, including WhatsApp, email, and online community platforms, over four weeks (28 days). After collecting the responses, incomplete questionnaires were excluded from the analysis. Data analysis was conducted using JASP and SmartPLS 4 software tools. These programs were chosen for their robust features and user-friendly interfaces, which are particularly well-suited for handling complex statistical analyses and structural equation modelling.

JASP is an open-source statistical software that provides a comprehensive suite of analysis tools. It is particularly advantageous for its ease of use and its ability to perform a wide range of statistical tests, including descriptive statistics, t-tests, ANOVA, and regression analysis.

SmartPLS 4, on the other hand, is specialized software for Partial Least Squares Structural Equation Modeling (PLS-SEM). This method is ideal for exploring complex relationships between variables, which is crucial for testing the TAM hypotheses in this study.

For the current analysis, JASP was used for initial data screening and basic statistical analysis, while SmartPLS 4 was leveraged for the more sophisticated modelling required for hypothesis testing. This dual approach enhances the reliability and validity of the study's findings, providing a comprehensive understanding of the factors influencing the acceptance of AI technologies in the beauty industry.

4 Results

The following chapter presents the findings from both the qualitative and quantitative components of the study. It starts with the results of the qualitative content analysis, summarizing the key themes and insights derived from the analyzed content. This is followed by the results of the quantitative study, beginning with descriptive statistics that provide an overview of the demographic data. The chapter then details the data analysis process, including the assessment of the structural model to test the theoretical framework, and concludes with multigroup analyses to explore potential differences among various participant groups.

4.1 Results of Qualitative Content Analysis

This section offers a detailed overview of the qualitative results derived from the content analysis of 9 pieces of online content, providing insights into the existing AI application within the beauty sector. The aim was to systematically analyse and compare information from diverse sources to contribute to a comprehensive understanding of key emerging technologies currently impacting the beauty industry, the practical applications of these technologies and the current trends that are shaping the beauty sector.

RQ1: What are the key emerging technologies currently impacting the beauty industry?

In the content analysis, the primary objective was to identify relevant sources that describe the emerging technologies that have an impact on the beauty industry. This comprehensive analysis involved a detailed examination of the selected articles to determine which technologies are being discussed and their perceived impact on the sector.

The findings indicate that AR and AI are the most frequently mentioned technologies, with 8 out of the 9 reviewed articles highlighting their importance. These technologies are leading the transformation within the beauty industry.

Virtual try-on technology, mentioned in 66% of the documents, highlights the industry's move towards more interactive and immersive customer experiences. This technology leverages AR and AI to enable users to virtually apply cosmetics, which is crucial for online shopping and reducing return rates.

Technologies like Big Data, Virtual Reality (VR), and 3D Printing, each mentioned in 33% of the documents, are also playing significant roles.

The following table (Table 4) and accompanying diagram (Figure 4) visually represent the technologies identified and their respective occurrences in the analysed documents.

Table 4 Category statistic RQ1

Category Name	*Absolute Count*	*% of Documents*
Big data	3	33
Machine Learning	2	22
Cloud Computing	1	11
Internet Of Things	1	11
Smart sensors	1	11
Advanced Customer Relationship Management (CRM) technologies	1	11
Natural Language Processing (NLP)	1	11
Virtual try-on	6	66
Virtual Reality	3	33
Nanotechnology	1	11
Biotechnology	2	22
Extended reality (XR)	1	11
3D technology	2	22
Metaverse	2	22
Wearable accessory	1	11
Augmented Reality	8	88
Artificial Intelligence	8	88
3D Printing	3	33

The following word cloud (Figure 4) visually represents all technologies, with the size of each word corresponding to the amount of content mentioning the technology.

Figure 4 Key emerging technologies within the beauty industry
Source: Own research based on analysed content Item 1 – Item 9

The diverse range of identified technologies illustrates the multifaceted nature of technological advancements within the beauty sector, each playing a pivotal role in its ongoing evolution.

RQ2: Which trends are currently shaping the beauty industry?

The analysis revealed several significant trends, each contributing uniquely to the industry's transformation. The following table (Table 5) lists these trends along with their absolute counts and the percentage of documents in which they were mentioned.

Table 5 Category Statistics RQ2

Category Name	*Absolute Count*	*% of Documents*
Personalization	9	100
Digital beauty	2	22
Diversity and inclusivity	4	44
Sustainability	6	66
Creativity	4	44
Beauty and health	3	33
Phygital	5	55
At-home beauty (devices and self-care)	3	33
Transparency	4	44
Social media	4	44
Direct to consumer	1	11
Digital Twin or Avatars	3	33
Technological advancements	8	88
Customer experience and engagement	6	66

Personalization is the most prominent trend, mentioned in 100% of the documents. This trend reflects the industry's shift towards tailoring products and services to individual consumer preferences and needs. Technological advancements are also highly significant, mentioned in 88% of the documents. This trend encompasses the integration of cutting-edge technologies like AI, AR, VR, and IoT into beauty products and services, enhancing the overall consumer experience and operational efficiency of beauty brands.

Sustainability and customer experience are another major trend, highlighted in 66% of the documents. This reflects the increasing consumer demand for eco-friendly and ethically produced beauty products as well as emphasizing the importance of creating meaningful and interactive experiences for consumers.

The Phygital trend, appearing in 55% of the documents, represents the blending of physical and digital experiences. This trend includes the use of AR and VR for virtual try-ons, as well as integrating online and offline shopping experiences to provide a seamless consumer journey.

Diversity and inclusivity, Creativity, Transparency, and social media are each mentioned in 44% of the documents. These trends highlight the industry's focus on representing diverse beauty standards, fostering creativity in product development and marketing, maintaining transparency about product ingredients and processes, and utilizing social media platforms for brand promotion and consumer interaction.

Other notable trends include Beauty and health, At-home beauty (devices and self-care), and Digital Twins or Avatars, each mentioned in 33% of the documents. These trends indicate a growing interest in the intersection of beauty and wellness, the convenience of at-home beauty treatments, and the use of digital representations for virtual interactions and product testing.

Digital beauty and direct-to-consumer are mentioned less frequently, in 22% and 11% of the documents respectively. Digital beauty focuses on the digitalization of beauty products and services, while the direct-to-consumer model highlights the shift towards selling products directly to consumers, bypassing traditional retail channels.

The following bubble diagram (Figure 5) visually represents the current trends, with the size of each bubble corresponding to the number of papers mentioning each trend.

Figure 5 Trends that are shaping the beauty industry

Source: Own research based on analysed content Item 1 – Item 9

The analysis highlights the diverse and dynamic nature of trends shaping the beauty industry, with personalization and technological advancements leading the way. These trends are not only transforming how beauty products are developed and marketed but also redefining consumer expectations and experiences.

RQ3: What are the practical applications of AI technology that exist in the beauty industry?

The last question delves into the various ways AI is being utilized to revolutionize the beauty sector. The analysis highlights the innovative and diverse applications of AI, showcasing how it enhances consumer experiences and operational efficiency. Key practical applications include AI-driven skin and hair diagnostics, which use deep learning and AR to provide personalized recommendations based on individual health metrics. Additionally, virtual try-on tools leverage AI and AR to allow users to experiment with different makeup looks in real-time, significantly improving the online shopping experience. This section underscores the transformative impact of AI on the beauty industry, emphasizing its role in driving personalization, enhancing customer interaction, and fostering creativity in product development.

Key practical applications identified include:

1. **Self / Skin and Hair Diagnostics**: Utilizing AI, deep learning techniques, and AR, tools like PerfectCorp's AI Skin Diagnostic Solution analyze skin health metrics to deliver personalized product recommendations. This application has had a significant impact, with 8 out of 9 documents mentioning it, accounting for 88% of the content.

2. **Personalized Product Recommendations**: AI systems craft tailored skincare routines based on individual user needs, considering factors like skin type and specific concerns. This use case leverages AR and ML, reflecting its importance in 77% of the documents reviewed.

3. **Virtual Try-On / Virtual Mirror**: AR technology enables users to try makeup products virtually, offering a real-time simulation of different looks. This application, combined with ML, was noted in 88% of the documents, highlighting its widespread adoption.

4. **Shade Matching - Foundation Shade Finder Technology**: AI-powered solutions help consumers find their ideal foundation shade quickly and accurately. This application, supported by Big Data, was mentioned in 33% of the documents.

5. **3D Digital Avatars**: AI and ML are used to create digital avatars for marketing and customer engagement, as seen in initiatives involving digital supermodels and virtual brand ambassadors. This trend was noted in 33% of the documents.

6. **AI-Powered Beauty Advice**: Platforms like YouCam Tutorial use AI to provide personalized beauty advice and education in a digital format, enhancing user experience with AR. This application appeared in 33% of the documents.

7. **3D Fitting Room**: AR technology facilitates virtual makeup tests and styling sessions, mentioned in 11% of the documents.

8. **AI-Created Fragrances**: AI and Big Data are employed to develop new fragrances, exemplified by IBM's collaboration with Symrise. This innovative application was noted in 11% of the documents.

9. **AI-Generated Makeup**: AI analyzes large datasets, such as Instagram images, to create new makeup looks, highlighting its creative potential.

10. **E-Makeup / Virtual Makeup Line for Zoom Calls and Teams**: Leveraging AR, brands like L'Oréal Paris have launched virtual makeup lines for video calls, reflecting a significant trend in 22% of the documents.

11. **Smart Product Search**: Advanced CRM technologies using AI and ML enhance product search capabilities and real-time ordering, as noted in 11% of the documents.

The diagram below (Figure 6) visually represents the various AI technologies utilized in this sector, highlighting not only the use of AI but also the integration of additional technologies.

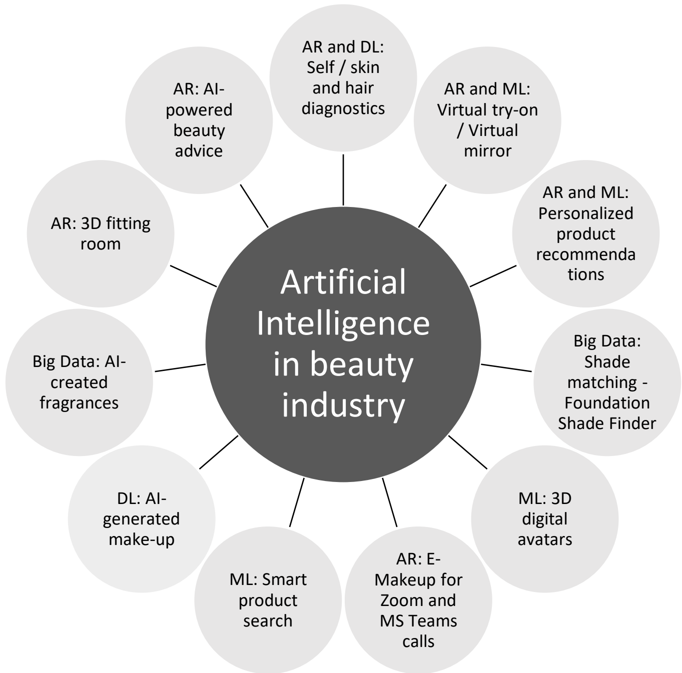


Figure 6 Practical application of AI technology within the beauty industry
Source: Own research based on analysed content Item 1 – Item 9

The analysis of 3 research questions within qualitative content reveals significant insights into the emerging technologies, trends, and practical applications of AI in the beauty industry. AI is significantly influencing areas such as virtual try-ons, personalized product recommendations, and skin diagnostics.

The integration of AI with other technologies like AR, ML, and Big Data has been particularly noteworthy, enhancing the overall performance and capabilities of these technologies. This comprehensive examination demonstrates the transformative potential of AI and its synergistic effects when combined with other technological advancements.

4.2 Results of the Quantitative Study

The following chapter will present the findings derived from the structured questionnaire used to assess public acceptance of AI beauty technologies. It will detail the descriptive statistics, data analysis, structural model assessment, and multigroup analyses conducted on the survey data. This chapter aims to provide a comprehensive understanding of the quantitative insights into consumer perceptions and behaviors related to AI in the beauty industry.

4.2.1 Descriptive Statistics

As a subset of the population, the sample data represents a group of people of all genders with the shared attribute of being employees or students. A total of 118 questionnaires were collected, out of which 101 were completed and used for data analysis, resulting in an overall full response rate of 85.6%. After also subtracting participants who did not complete the survey in full, the sample size amounts to 101.

This working sample (n = 101) consists of 72 respondents who identify as "female" (~71%), and 29 as "male" (~29%) (Table 6). In the further course, for the sake of simplicity, the group of participants identifying as female will be referred to as "female or women", and those identifying as male will be referred to as "male or men". The age groups of 20-25 and 26-30 were the most represented, each with 44.5% of respondents as shown in Table 6. It is shown that 29 women and 16 men, took part in these specific age groups (Appendix 4). It is noticeable that 5 women participated in the age group 56-60 while no male participants were taking part in the survey in the same age range (Appendix 5).

The highest level of education completed by most participants is a bachelor's degree (40.5%), followed by a master's degree (32.6%), 2% of the participants hold a doctorate (Appendix 6). About the industries of the companies in which the participants work, it can be stated that the industry "Information Technology" employs the most participants (~26%). This sector is followed by "Healthcare" (10%) and "Finance" (10%) (Appendix 7). In addition, around 38% of the respondents have chosen "other" as the industry they employ.

Table 6 Description of the Sample

Variable		*Frequency*	*n = %*
Gender	Male	29	28.713
	Female	72	71.287
	Diverse	0	0
Age group	20-25	45	44.554
	26-30	22	21.782
	31-35	10	9.901
	36-40	3	2.97
	41-45	5	4.95
	46-50	2	1.98
	51-55	4	3.96
	56-60	5	4.95
	61-65	5	4.95
	Over 65	0	0
Highest level of education completed	High school or equivalent	17	16.832
	Professional training	5	4.95
	Bachelor’s degree	41	40.594
	Master’s degree	33	32.673
	Doctorate	2	1.98
	other	3	2.97
Sector of work	Information Technology	26	25.743
	Healthcare	10	9.901
	Automotive	2	1.98
	Education	4	3.96
	Real Estate	5	4.95
	Finance	10	9.901
	Government	2	1.98
	Manufacturing	4	3.96
	Other	38	37.624

The second part of the survey assessed participants' familiarity with practical applications of AI technology, their level of technological background, and their general familiarity with AI technology. The data reveal varying levels of familiarity and experience among respondents (Table 7).

The majority of participants, 59 (~ 58.4%), rated their level of tech background and knowledge as Intermediate, indicating a moderate understanding of technology concepts. A smaller number, 22 (21.8%), identified themselves as Beginners, having basic familiarity with technology and only 11 respondents (10.9%) considered themselves Experts with advanced knowledge of technology.

The sample (n = 101) consists of 32 (~31.6%) respondents who are familiar with 1-2 practical applications of AI technology in the beauty industry (question E03) while the majority, 64 participants (63.4%), were not familiar with these applications.

Lastly, previous experience with AI in the beauty and cosmetic industry was limited among the participants, with 94 respondents (93.1%) indicating they had no prior experience, and only 7 respondents (6.9%) having some experience in this area.

Table 7 Technological background

Variable		*Frequency*	*n = %*
Level of tech background and knowledge	Expert	11	10.891
	Intermediate	59	58.416
	Beginner	22	21.782
	Non-technical	9	8.911
Familiarity with AI technology	Not familiar	5	4.95
	Slightly familiar	8	7.921
	Somewhat familiar	19	18.812
	Moderately familiar	20	19.802
	Fairly familiar	29	28.713
	Highly familiar	13	12.871
	Very familiar	7	6.931
Familiarity with practical applications of AI technology in the beauty industry	Familiar with 1-2 practical applications	32	31.683
	Not familiar with the practical applications	64	63.366
	Familiar with multiple applications	5	4.95
Previous experience with AI in the beauty and cosmetic industry	No	94	93.069
	Yes	7	6.931

4.2.2 Data analysis

The Partial Least Squares (PLS) technique was employed for data analysis in this study. PLS is a type of structural equation modelling (SEM) technique that is particularly suited for analyzing and measuring latent, unobserved concepts using multiple observed indicators (Jöreskog & Wold, 1982), (W. Chin & Marcoulides, 1998, pp. 295–336). This technique is effective in confirming the validity of the constructs within a specific instrument and assessing the structural relationships among these constructs (W. W. Chin, 1998, pp. 7–16), (Gefen et al., 2000). The path coefficients have been calculated with the PLS-SEM algorithm. The significance of each path parameter as well as the mediated impact of construct were tested using 5000 bootstrap subsamples (Hair et al., 2011, pp. 139–152). The statistical software SmartPLS4 was utilized to evaluate both the measurement and structural models of the research.

4.2.2.1 Data Distribution

Skewness and kurtosis are essential measures for evaluating the distribution of data in a dataset. Skewness assesses the asymmetry of the distribution, indicating whether the data tails off more to one side (Hair et al., 2016, p. 76). A skewness value greater than +1 or less than -1 suggests a significantly skewed distribution (Hair et al., 2016, p. 76). Kurtosis measures the "peakedness" of the distribution, with values greater than +1 indicating a distribution that is too peaked, and values less than -1 indicating a distribution that is too flat (Hair et al., 2016, p. 76). Ideally, values for both skewness and kurtosis close to zero signify a normal distribution, although this is rare in practical data analysis (Hair et al., 2016, p. 76).

In this study, the skewness and kurtosis values for the indicators of constructs such as PU, PEOU, BI, and attitude towards use are all within the acceptable range of -1 to +1 (Table 10). This indicates that the data distributions for these constructs are neither excessively skewed nor overly peaked.

For the construct "PU," the skewness values ranged from -0.231 to -0.869, indicating slight negative skewness across all items, but remaining within the acceptable range. The kurtosis values ranged from -0.290 to 0.966, also falling within the acceptable range, suggesting that the data do not deviate significantly from normality.

Similarly, for "PEOU," skewness values ranged from -0.663 to -0.894, and kurtosis values ranged from -0.354 to 0.724, both within acceptable limits. This indicates that the distribution of responses for these items also adheres to normal distribution assumptions.

For the "BI" construct, skewness values ranged from -0.382 to -0.882, and kurtosis values ranged from -0.808 to 0.471. These values indicate a normal distribution of responses.

Finally, for the "ATT" construct, skewness values ranged from -0.364 to -0.969, and kurtosis values ranged from -0.703 to 0.562, all within the acceptable range, indicating the normal distribution of responses.

4.2.2.2 Internal Consistency Reliability

Cronbach's Alpha

Cronbach's alpha was employed to test the internal consistency of the questionnaire items. The Cronbach's alpha values for each construct indicated good internal consistency (Appendix 9), as all values were above the recommended minimum level of 0.7 (table 9) (W. Chin & Marcoulides, 1998, pp. 295–336) (Nunnally, 1978).

The column "Cronbach's alpha if Item Deleted" represents the reliability coefficient for the internal consistency of the scale if the individual item is removed (Gliem & Gliem, 2003, p. 86). This is a crucial measure as it helps identify any items that may not be contributing positively to the overall reliability of the construct.

The Cronbach's alpha values if any item were deleted ranged from 0.858 to 0.932, suggesting excellent internal consistency for all constructs and that the removal of any single item would not significantly improve the reliability (Table 10).

Composite Reliability

Given the limitations of Cronbach's alpha, it is technically more suitable to use composite reliability as an alternative measure of internal consistency reliability (Hair et al., 2016, p. 126).

Composite reliability (CR) was also calculated to further assess the reliability of the constructs. This metric assesses the internal consistency of the construct indicators, similar to Cronbach's Alpha but provides a more accurate estimate when indicators have different loadings. Hair et al. (2016, p. 127) recommends a CR value of 0.70 or higher. The highest CR value was observed for "ATT" (0.949), while the lowest was for "PU" (0.920) (Table 10). All CR values exceeded the recommended threshold of 0.70, confirming good construct reliability.

4.2.2.3 Convergent Validity

Convergent validity refers to the degree to which a measure positively correlates with other measures of the same construct (Hair et al., 2016, pp. 127–128). Researchers assess the convergent validity of reflective constructs by examining the outer loadings of the indicators and the average variance extracted (AVE).

Outer Loadings

Outer loadings represent the correlation between each observed variable and its underlying latent construct. Loadings above 0.70 indicate that the observed variable sufficiently reflects the latent construct (Hair et al., 2016, p. 128). For example, all indicators for PU have loadings above this threshold, with values ranging from 0.773 to 0.860. This demonstrates that each indicator reliably measures the construct it is intended to represent.

Average Variance Extracted (AVE)

Convergent validity was further assessed through the Average Variance Extracted (AVE) (Appendix 8). This criterion is described as the average of the squared loadings of the indicators associated with the construct, calculated by summing the squared loadings and dividing by the number of indicators (Hair et al., 2016, p. 129). According to Hair et al. (2010), an AVE value greater than 0.50 is indicative of sufficient convergent validity. AVE values indicate that a substantial portion of variance is captured by the constructs, with the lowest AVE being 0.657 for "PU" and the highest being 0.766 for "BI." All values were well above the cut-off value of 0.50, thus establishing convergent validity for all constructs.

4.2.2.4 Discriminant Validity

Discriminant validity tests whether constructs that are supposed to be unrelated are distinct from one another. Two main methods were employed: the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker criterion.

Heterotrait-Monotrait Ratio (HTMT)

HTMT values indicate the discriminant validity between constructs (Hair et al., 2016, p. 133). Values below 0.85 suggest that the constructs are distinct (Henseler et al., 2015). In this study, all HTMT values are below this threshold, indicating good discriminant validity (**Error! Reference source not found.**). For instance, the HTMT value between PU and ATT is 0.904, which is slightly above the conservative threshold but still within acceptable bounds considering the conceptual similarity of the constructs. The HTMT confidence intervals for all pairs of constructs do not include 1, further confirming discriminant validity.

Table 8 Heterotrait-Monotrait Ratio

	ATT	*BI*	*PEOU*	*PU*
ATT				
BI	0.895			
PEOU	0.624	0.569		
PU	0.904	0.756	0.644	

Fornell-Larcker Criterion

According to this criterion, the square root of each construct's AVE should be greater than its highest correlation with any other construct (Hair et al., 2016, p. 131). This study's results satisfy this criterion, confirming discriminant validity (Table 9). For example, the square root of the AVE for ATT is 0.870, higher than its correlations with BI (0.826), PEOU (0.583), and PU (0.831).

Table 9 Fornell-Larcker Criterion

	ATT	*BI*	*PEOU*	*PU*
ATT	*0.870*			
BI	*0.826*	*0.875*		
PEOU	*0.583*	*0.521*	*0.821*	
PU	*0.831*	*0.687*	*0.587*	*0.811*

In the following table (Table 10) there are shown results summarizing all data for Reflective Measurement Models.

Table 10 Results Summary for Reflective Measurement Models

							Convergent Validity		*Internal Consistency Reliability*		*Discriminant Validity*
Constructs	*Indicators*	*Mean*	*SD*	*Excess kurtosis*	*Skewness*	*Cronbach's alpha (α) if Item Deleted*	*Loadings*	*Average variance extracted (AVE)*	*Cronbach's alpha*	*Composite reliability*	*HTMT confidence interval does not include 1*
PU	PU1	4.683	1.281	0.966	-0.617	0.880	0.795	0.657	0.895	0.899	Yes
	PU2	4.693	1.454	0.096	-0.685	0.881	0.795				
	PU3	4.564	1.479	-0.290	-0.631	0.870	0.851				
	PU4	4.802	1.298	-0.014	-0.231	0.879	0.786				
	PU5	4.990	1.309	0.943	-0.869	0.884	0.773				
	PU6	4.673	1.450	-0.100	-0.619	0.866	0.860				
PEOU	PEOU1	5.059	1.427	0.138	-0.770	0.882	0.811	0.674	0.902	0.911	Yes
	PEOU2	4.980	1.496	0.084	-0.687	0.904	0.701				
	PEOU3	5.040	1.469	0.305	-0.850	0.875	0.856				
	PEOU4	5.149	1.360	-0.012	-0.778	0.878	0.856				
	PEOU5	5.356	1.390	-0.354	-0.663	0.875	0.869				
	PEOU6	5.089	1.422	0.724	-0.894	0.889	0.820				
Behavioral Intention	BI1	4.762	1.666	-0.388	-0.580	0.874	0.861	0.766	0.899	0.903	Yes
	BI2	4.752	1.691	-0.429	-0.613	0.865	0.868				
	BI3	5.069	1.457	0.471	-0.882	0.858	0.894				
	BI4	4.356	1.614	-0.808	-0.382	0.872	0.878				
Attitude towards use	ATT1	5.119	1.517	0.111	-0.808	0.922	0.884	0.757	0.935	0.937	Yes
	ATT2	4.802	1.592	-0.152	-0.655	0.912	0.929				
	ATT3	5.337	1.464	0.537	-0.969	0.932	0.816				
	ATT4	4.604	1.617	-0.591	-0.404	0.922	0.874				
	ATT5	5.158	1.553	0.562	-0.994	0.925	0.865				
	ATT6	4.663	1.637	-0.703	-0.364	0.927	0.849				

The mean scores for PU ranged from 4.564 to 4.990, with standard deviations between 1.281 and 1.479, indicating a moderate spread of responses. The overall Cronbach's alpha was 0.895, indicating good internal consistency.

The means for PEOU ranged from 4.980 to 5.356, with standard deviations from 1.360 to 1.496, suggesting participants generally found the technology easy to use. The overall Cronbach's alpha for PEOU was 0.902, indicating good internal consistency.

The mean scores of constructs BI ranged from 4.356 to 5.069, with standard deviations between 1.457 and 1.691, showing a moderate to high intention to use the technology. The overall Cronbach's alpha for BI was 0.899, indicating good internal consistency.

The means of ATT ranged from 4.604 to 5.337, with standard deviations from 1.464 to 1.637, indicating a generally positive attitude towards use the technology. The overall Cronbach's alpha for ATT was 0.935, indicating excellent internal consistency.

4.2.3 Structural Model Assessment

Collinearity Analysis

In the first step of the structural model assessment, potential collinearity issues were examined among the predictor constructs. Collinearity can distort the results by inflating the variances of parameter estimates, making it crucial to evaluate the Variance Inflation Factor (VIF) values for each predictor construct (Hair et al., 2016, p. 207).

According to the findings (Table 11), the VIF values for all constructs, except one, were below the commonly accepted threshold of 5. Specifically, the VIF value for ATT2 was slightly above this threshold at 5.251. Despite this, the slight elevation in the VIF for ATT2 does not pose a critical issue for collinearity in our structural model. Hence, we can confidently proceed with further analysis without significant concerns about multicollinearity affecting our results.

Table 11 Collinearity Statistic (VIF)

	VIF
ATT1	3.732
ATT2	5.251
ATT3	2.524
ATT4	4.201
ATT5	3.213
ATT6	3.952
BI1	2.336
BI2	2.733
BI3	3.012
BI4	2.452
PEOU1	2.325
PEOU2	1.860
PEOU3	2.742
PEOU4	3.076
PEOU5	3.421
PEOU6	2.146
PU1	2.021
PU2	1.966
PU3	3.026
PU4	2.226

Coefficient of Determination (R^2 Values)

The R^2 value, also known as the coefficient of determination, is a crucial metric in assessing the predictive accuracy of the structural model. It represents the proportion of variance in the endogenous constructs that is explained by their respective predictor constructs, with values ranging from 0 to 1 (Hair et al., 2016, p. 214). Higher R^2 values indicate greater predictive accuracy.

In the current model, the R^2 value for PU was found to be 0.345, indicating a relatively weak predictive accuracy. On the other hand, the R^2 values for ATT and BI were 0.705 and 0.682, respectively. These values suggest moderate predictive accuracy, highlighting that a substantial portion of the variance in these constructs is explained by their predictors.

Effect Size (f^2 Values)

To gain further insights into the impact of each predictor construct on the endogenous constructs, the effect size (f^2) values were examined (Table 12). The effect size indicates the change in the R^2 value when a specific exogenous construct is excluded from the model. Higher f^2 values denote a greater impact on the predictor construct (Hair et al., 2016, p. 216).

In the current analysis, ATT had a high effect size of 0.664 on BI, signifying a strong influence. Conversely, the effect size of PU on BI was negligible (0.000), suggesting no significant impact. The effect size of PEOU on ATT was relatively small (0.047), while its effect on PU was substantial (0.526), indicating that PEOU significantly influences PU but has a minor effect on ATT.

Table 12 Effect Sizes

	ATT	*BI*	*PEOU*	*PU*
ATT		0.664		
BI				
PEOU	0.047			0.526
PU	1.238	0.000		

Path Coefficients

Path coefficients provide a direct measure of the strength and direction of relationships between constructs in the model. These coefficients are essential in understanding the hypothesized relationships. Assuming a 5% significance level, our analysis revealed that all relationships in the structural model were significant, except for the path from PU to BI ($p = 0.998$), which was not significant (Table 13). Specifically, the path from ATT to BI had a coefficient of 0.826 with a t-statistic of 7.623, indicating a strong and significant relationship. Similarly, the path from PEOU to PU had a coefficient of 0.587 and a t-statistic of 7.689, signifying a significant positive relationship. The path from PU to ATT was also strong and significant, with a coefficient of 0.746 and a t-statistic of 11.766.

However, the path from PU to BI was almost zero and not significant, indicating no direct influence of PU on BI.

Total Effects

The total effects analysis provides a comprehensive view of the overall impact of exogenous constructs on endogenous constructs, considering both direct and indirect effects (Table 13). These results highlight the significant role of ATT in influencing BI, indicating that users' attitudes towards technology substantially drive their BI. PU also had a notable total effect, primarily through its influence on ATT.

Table 13 Significance Testing Results

Path direction	*Original sample (O)*	*Sample mean (M)*	*Standard deviation (STDEV)*	*T statistics (|O/STDEV|)*	*P values*	*Significance ($p < 0.05$)?*
ATT -> BI	0.826	0.828	0.108	7.623	0.000	Yes
PEOU -> ATT	0.145	0.147	0.074	1.962	0.050	Yes
PEOU -> PU	0.587	0.592	0.076	7.689	0.000	Yes
PU -> ATT	0.746	0.744	0.063	11.766	0.000	Yes
PU -> BI	-0.000	-0.001	0.136	0.003	0.998	No

Bootstrapping Results

Bootstrapping is a resampling technique that provides additional insights into the stability and reliability of the path coefficients (Table 14). By analyzing the bootstrapping results, there was obtained a detailed overview of the relationships in the model, including standard errors, bootstrap mean values, t-values, and p-values. The bootstrapping confidence intervals, derived from the Bias-Corrected and Accelerated method, provided further validation of our findings.

For example, the path from ATT to BI had a bootstrapped mean of 0.828 with a 95% confidence interval ranging from 0.624 to 1.048, confirming its significance. Similarly, the path from PEOU to PU had a bootstrapped mean of 0.592 with a confidence interval from 0.425 to 0.726, further validating its significance. The non-significant path from PU to BI had a bootstrapped mean close to zero, with a confidence interval spanning negative and positive values, indicating no significant effect.

Table 14 Path coefficients

Path direction	*Original sample (O)*	*Sample mean (M)*	*2.5%*	*97.5%*
ATT -> BI	0.826	0.828	0.624	1.048
PEOU -> ATT	0.145	0.147	0.000	0.294
PEOU -> PU	0.587	0.592	0.425	0.726
PU -> ATT	0.746	0.744	0.609	0.856
PU -> BI	-0.000	-0.001	-0.281	0.251

The structural model sheds light on the critical factors influencing BI to use AI in beauty. The significant role of attitudes towards technology and PU underscores the need for strategies that enhance these perceptions. By focusing on improving user attitudes and PU, stakeholders can effectively drive the adoption of AI technologies in the beauty industry. Future research should explore additional factors and their interactions to further refine our understanding of technology adoption in this context.

As shown in Table 13, 4 hypotheses were supported and 1 was rejected.

H1: Perceived Usefulness will positively influence Attitudes Towards AI in Beauty.

Accepted. The analysis supports Hypothesis H1, indicating that PU positively influences attitudes towards AI in beauty. This relationship is confirmed by a significant path coefficient of 0.746 ($p < 0.001$), demonstrating that as users perceive AI to be useful, their attitudes towards using AI in beauty improve. The high effect size ($f^2 = 1.238$) further reinforces the substantial impact of PU on ATT. This result implies that to foster positive attitudes towards AI in beauty applications, it is crucial to highlight the practical benefits and usefulness of the technology. Users need to see clear advantages in adopting AI, such as enhanced efficiency, better results, or convenience, to develop favourable attitudes.

H2: Perceived Ease of Use will positively influence Attitudes Towards AI in Beauty.

Accepted. Hypothesis H2 is also supported, with the data showing that PEOU positively influences attitudes towards AI in beauty. The path coefficient for PEOU to ATT is 0.145 ($p = 0.050$), which, while smaller than the PU to ATT path, is still statistically significant at the 5% level. The effect size ($f^2 = 0.047$) is relatively modest, indicating a minor yet positive impact. This suggests that making AI technologies user-friendly and easy to use can slightly improve users' attitudes. However, while ease of use is important, its impact on attitudes is not as strong as the PU. Therefore, usability should be considered a supportive factor rather than the primary driver of positive attitudes.

H3: Perceived Ease of Use will positively influence Perceived Usefulness.

Accepted. Hypothesis H3 is confirmed by a significant path coefficient of 0.587 ($p < 0.001$) from PEOU to PU, demonstrating that PEOU positively influences PU. The substantial effect size ($f^2 = 0.526$) indicates that ease of use plays a critical role in shaping perceptions of usefulness. This finding suggests that when AI technologies in beauty are easy to use, users are more likely to perceive them as useful. This underscores the importance of designing intuitive and accessible AI interfaces to enhance the perceived value of the technology. Simplifying the user experience can directly contribute to the perception that AI is beneficial and practical.

H4: Attitude towards use will positively influence Behavioral Intention to Use.

Accepted. Hypothesis H4 is strongly supported, as evidenced by a significant path coefficient of 0.826 ($p < 0.001$) from ATT to BI. The high effect size ($f^2 = 0.664$) indicates a robust positive influence of attitudes on BI to use AI in beauty. This finding highlights that users' positive attitudes towards AI significantly drive their intention to adopt and use the technology. It suggests that interventions aimed at improving attitudes, such as educational campaigns, testimonials, and demonstrations of AI benefits, can effectively increase users' willingness to use AI in beauty. Positive attitudes are a crucial determinant of adoption intentions, reinforcing the need to foster favourable perceptions.

H5: Perceived Usefulness has a direct and positive effect on Behavioral Intention to Use.

Rejected. Contrary to expectations, Hypothesis H5 is not supported by the data. The path coefficient from PU to BI is -0.000 ($p = 0.998$), indicating no significant direct effect of PU on BI. The effect size ($f^2 = 0.000$) is also negligible. This surprising result suggests that while PU strongly influences attitudes (H1), it does not have a direct impact on the intention to use AI in beauty. Instead, its influence is likely mediated through attitudes. This finding implies that users' decisions to adopt AI in beauty are more strongly driven by their overall attitudes rather than their direct assessment of usefulness. Therefore, strategies should focus on shaping positive attitudes to indirectly leverage the PU.

Figure 7 summarizes results extracted from SmartPLS 4.

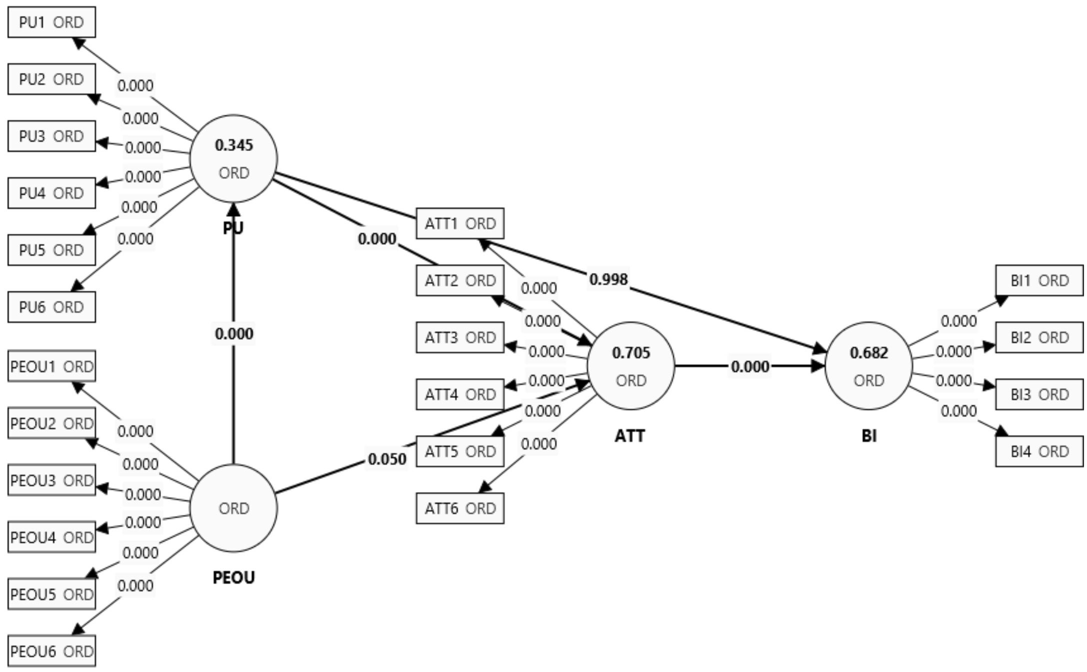


Figure 7 Determinants from the technology acceptance model (SmartPLS 4)

Results summary

The result of this study shows that PU and ease of use are both important, but their roles differ. PU has a strong direct impact on attitudes, which in turn significantly drives BI. PEOU enhances PU and also contributes to attitudes, although to a smaller extent. The direct impact of PU on BI is not significant, suggesting that the path to adoption is primarily through attitudes.

To promote the adoption of AI in beauty, it is essential to focus on enhancing the PU and ease of use of the technology. Educational and promotional efforts should aim to highlight the practical benefits and make the technology as user-friendly as possible. By fostering positive attitudes through these means, stakeholders can effectively increase users' willingness to adopt AI technologies in beauty applications. Future research could further explore additional factors and potential mediators to refine these insights and develop more targeted strategies for encouraging technology adoption.

4.2.4 Multigroup analyses

The results of multi-group analyses in Table 15 indicated that some of the path coefficients of the theoretical hypotheses differed by gender.

H1: Perceived Usefulness will positively influence Attitudes Towards AI in Beauty.

The analysis indicates that PU positively influences attitudes towards AI in beauty for both females and males, with path coefficients of 0.749 and 0.840, respectively. Both relationships are highly significant ($p < 0.001$). However, the difference between males and females is not statistically significant ($p = 0.547$). This means that while both genders perceive the usefulness of AI as a strong influencer of their attitudes, there is no significant difference between the strength of this perception across genders.

H2: Perceived Ease of Use will positively influence Attitudes Towards AI in Beauty.

For females, PEOU significantly influences attitudes towards AI in beauty with a path coefficient of 0.210 ($p = 0.006$). However, this relationship is not significant for males (path coefficient = -0.116, $p = 0.616$). The difference in path coefficients between males and females is -0.326, with a marginal t-value of 1.752 and a p-value of 0.083, indicating a trend towards significance. This suggests that PEOU plays a more crucial role in shaping attitudes towards AI in beauty for females compared to males.

H3: Perceived Ease of Use will positively influence Perceived Usefulness.

The relationship between PEOU and PU is significant for both females and males, with path coefficients of 0.582 and 0.648, respectively, and p-values less than 0.001. The difference in path coefficients (0.066) is not statistically significant ($p = 0.685$). This indicates that both genders equally perceive that ease of use enhances the usefulness of AI in beauty, with no significant gender-based differences in this perception.

H4: Attitude towards use will positively influence Behavioral Intention to Use.

Both females and males exhibit a strong positive influence of attitude on BI to use AI in beauty (BI), with path coefficients of 0.750 and 0.667, respectively, and p-values less than 0.001. The difference between genders is not significant ($p = 0.748$). This suggests that positive attitudes towards AI in beauty are equally important for driving BI to use the technology across both genders.

H5: Perceived Usefulness has a direct and positive effect on Behavioral Intention to Use.

The direct effect of PU on BI to use AI in beauty (BI) is not significant for either females (path coefficient = 0.150, $p = 0.374$) or males (path coefficient = 0.098, $p = 0.652$). The difference between genders is also not significant ($p = 0.860$). This suggests that PU does not directly drive the intention to use AI in beauty for either gender, indicating that its influence may be mediated through other factors such as attitudes.

Table 15 Multi-group analysis by gender

Hypothesis	*Path direction*	*Path coefficient Female*	*Path coefficient Male*	*P value Female*	*P values Male*	*Difference (Male-Female)*	*t value (|Male vs Female|)*	*p-value (Male vs Female)*
H1	PU -> ATT	0.749	0.840	0.000	0.000	0.091	0.605	0.547
H2	PEOU -> ATT	0.210	-0.116	0.006	0.616	-0.326	1.752	0.083
H3	PEOU -> PU	0.582	0.648	0.000	0.000	0.066	0.406	0.685
H4	ATT -> BI	0.750	0.667	0.000	0.000	-0.083	0.322	0.748
H5	PU -> BI	0.150	0.098	0.374	0.652	-0.052	0.176	0.860

The multigroup analysis by gender (Table 15) reveals nuanced differences and similarities in how males and females perceive and intend to use AI in beauty. Both genders agree on the importance of PU in shaping attitudes, and the influence of attitudes on BI is similarly strong across both groups. However, PEOU plays a more significant role in influencing attitudes for females compared to males. The direct impact of PU on BI is not significant for either gender, suggesting that its role in driving intentions is more complex and likely mediated through attitudes. These insights highlight the importance of tailoring strategies to enhance PEOU, especially for female users, to foster positive attitudes and subsequently drive the adoption of AI in beauty applications.

5 Discussion

The present study proposed a theoretical research model to examine the roles of PU, PEOU, and attitudes towards AI in the context of the beauty industry. This model is based on the Technology Acceptance Model, which has been widely used to understand user acceptance of technology. The results of this study provide strong support for the validity of the proposed model, as it explained significant portions of the variance in attitudes and BI towards using AI in beauty applications. It was found that PU and PEOU influenced attitudes directly, while attitudes had a significant effect on BI. Interestingly, PEOU also had a significant direct effect on PU, reinforcing the interconnectedness of these constructs. These results offer both important theoretical and practical implications.

5.1 Practical implications

The findings of this study have several practical implications for the beauty industry, particularly for companies considering the integration of AI technologies into their products and services. Firstly, the strong influence of PU on attitudes suggests that companies should emphasize the practical benefits of AI, such as personalized recommendations, enhanced customer experiences, and improved product efficacy. By clearly communicating these advantages, companies can foster positive attitudes towards AI among consumers, which in turn can drive their BI to use AI-powered beauty solutions.

Secondly, the significant role of PEOU indicates that companies should invest in making their AI technologies user-friendly. This includes intuitive interfaces, easy-to-understand functionalities, and seamless integration with existing beauty routines. By reducing the perceived complexity of AI, companies can enhance its PU and positively influence consumer attitudes.

Furthermore, the multigroup analysis revealed gender differences in the acceptance of AI in beauty. Specifically, PEOU was more influential for females than males in shaping attitudes towards AI. This suggests that companies should tailor their marketing and product design strategies to address the specific needs and preferences of female consumers, potentially through targeted usability improvements and gender-specific features.

Overall, the beauty industry stands to benefit significantly from the adoption of AI technologies. By understanding and leveraging the factors that influence consumer acceptance, companies can develop more effective strategies to promote AI adoption, enhance customer satisfaction, and ultimately drive business growth.

5.2 Further research and limitations

While this study provides valuable insights into the acceptance of AI in the beauty industry, it also has limitations that suggest avenues for future research. One limitation is the scope of the study, which focused primarily on PU, PEOU, and attitudes. Future research could expand this model by incorporating additional factors that may influence AI acceptance, such as trust, perceived risk, and social influence.

Another interesting avenue for future research is to explore the impact of AI characteristics, such as transparency, explainability, and personalization, on consumer acceptance. Given the increasing concern over data privacy, future studies could also investigate how perceptions of privacy and security affect the willingness to adopt AI in beauty applications.

Moreover, long-term studies could provide deeper insights into how consumer attitudes and intentions evolve with continued exposure to AI technologies. This would help to understand the prospects of AI acceptance and identify any changes in consumer perceptions that may arise as AI becomes more embedded in everyday beauty routines.

Additionally, while the multigroup analysis by gender provided valuable insights, future research could examine other demographic variables such as age, cultural background, and technological proficiency. Understanding how these factors influence AI acceptance could help in developing more targeted and effective strategies for different consumer segments.

Finally, experimental studies could be conducted to test the effectiveness of different AI features and marketing strategies in real-world settings. This would provide practical evidence of what works best in promoting AI adoption in the beauty industry.

Conclusion

This research aimed to explore the integration and acceptance of AI technology in the beauty industry, focusing on the emerging technologies, current trends, and practical applications that are reshaping the sector. The research employed a mixed-methods approach, combining qualitative content analysis and quantitative surveys to provide a comprehensive understanding of the topic.

The qualitative content analysis addressed three primary research questions: identifying key emerging technologies, understanding the trends shaping the industry, and examining practical applications of AI technology in the beauty sector. The findings revealed that technologies like Augmented Reality, Artificial Intelligence, Virtual Try-On, Big Data, and 3D Printing are pivotal in transforming the beauty landscape. Personalization, sustainability, and the integration of physical and digital experiences (phygital) were highlighted as major trends driving innovation and consumer engagement.

The quantitative study further investigated user acceptance of AI beauty tools leveraging the Technology Acceptance Model as a robust framework for understanding these dynamics (Davis, 1989). The structural model assessment and hypothesis testing revealed that the total effects analysis highlights the significant role of user attitudes in driving behavioral intention to adopt AI technologies in the beauty industry. Perceived usefulness also plays a crucial role, primarily through its influence on ATT rather than directly on BI. Perceived ease of use enhances PU and has a moderate effect on ATT, underscoring the importance of user-friendly AI technologies. These findings suggest that strategies to promote AI adoption should focus on improving PU and making the technology more intuitive. Future research should explore additional factors influencing AI adoption in the beauty sector to further refine our understanding and enhance targeted strategies.

Overall, this thesis contributes to the existing body of knowledge by providing insights into the technological advancements and consumer behaviors in the beauty industry. It highlights the importance of personalization and user-centric design in developing AI applications and underscores the need for further research on gender differences in technology acceptance. The findings have practical implications for beauty brands, technology developers, and marketers aiming to leverage AI to enhance customer experiences and drive innovation in the industry.

Appendix

Appendix 1 Survey guide

Question Block A: Demographical questions

1. What gender do you identify as?
   a. female
   b. male
   c. diverse
2. What is your age group?
   a. under 18
   b. 18-24
   c. 25-34
   d. 35-44
   e. 45-54
   f. 55-64
   g. 65 or older
3. What is the highest level of education you have completed?
   a. Primary/Elementary School
   b. High School or equivalent
   c. Professional training
   d. Bachelor's degree
   e. Master's degree
   f. Doctorate
   g. other
4. Which sector do you work/study in?
   a. Education
   b. Healthcare
   c. Technology
   d. Finance
   e. Government
   f. Manufacturing
   g. Retail
   h. Hospitality
   i. Arts and Entertainment
   j. Other

Question Block B: General Questions

1. How would you rate your level of tech background or knowledge?
   a. Expert: I have extensive knowledge and experience in technology.
   b. Intermediate: I have a moderate understanding of technology concepts.
   c. Beginner: I have a basic familiarity with technology.
   d. Non-technical: I have limited knowledge of technology.
2. How familiar are you with Artificial Intelligence (AI) technology?
   a. (Liker scale answer)
3. Are you familiar with the practical applications of AI technology in the beauty industry?
   a. Yes, I am very familiar with multiple applications.
   b. I am somewhat familiar with 1-2 practical applications of AI in beauty.
   c. No, I am not familiar with the practical applications of AI in beauty.
4. Have you ever used AI in beauty?
   a. Yes
   b. No

Question Block C: Explanation of AI Beauty Tools

1. Personalized recommendations and Hyper-personalization:
   - AI algorithms analyze customer data (past purchases, skin type) to suggest tailored products
   - AI tools can predict personalized outcomes with different skincare products
     Example: HautAI's SkinGPT
2. Virtual try-on:
   - Augmented reality (AR) technology enables virtual makeup and skincare try-ons, allowing customers to experiment without in-store sampling.
     Example: L'Oréal's Modiface app, Sephora Virtual Artist
3. Skincare analysis:
   - AI-driven skincare analysis apps use image recognition and machine learning to recommend products based on individual skin concerns.
     Example: Neutrogena's Skin360 web app

Potential Advantages of AI in the beauty industry:

- Time-saving personalized recommendations for efficient skincare routines
- Enhanced shopping experiences through interactive virtual try-on features
- Access to expert-level skincare analysis and guidance at any time
- Empowerment through increased knowledge and understanding of skincare needs

Potential Disadvantages of AI in the beauty industry:

- Potential concerns regarding data privacy and security in AI-driven systems
- Risk of over-reliance on AI recommendations, potentially overlooking individual preferences
- Limited accessibility to AI-powered beauty tools for those without internet or technological resources
- Possibility of AI-generated content reinforcing unrealistic beauty standards

Appendix 2 Questionnaire items

Definition and source of literature for the constructs

Constructs		Operational definition	Source of literature
PU	PU1	I believe that incorporating AI-powered beauty tools into my beauty routine will help me achieve better results.	(Davis, 1989)
	PU2	The potential economic benefits of using this technology are attractive to me.	(Davis, 1989)
	PU3	I expect that using this technology will simplify and improve my beauty routines.	(Davis, 1989)
	PU4	The potential advantages of AI-powered beauty tools outweigh their potential disadvantages.	(Davis, 1989)
	PU5	Overall, AI-powered beauty tools are advantageous.	(Davis, 1989)
	PU6	Using AI-powered beauty tools would enhance the effectiveness of my beauty routines.	(Davis, 1985)
PEOU	PEOU1	I don't think interacting with AI-powered beauty tools requires a lot of mental effort.	(Davis, 1989)
	PEOU2	I don't think that interacting with AI-powered beauty tools might be frustrating for me.	(Davis, 1989)
	PEOU3	I don't think that I might become confused when I start using AI-powered beauty tools.	(Davis, 1989)
	PEOU4	I think AI-powered beauty tools are easy to use.	(Davis, 1989)
	PEOU5	I think learning how to use AI-powered beauty tools is easy for me.	(Davis, 1989)
	PEOU6	I find it easy to understand how to use AI-powered beauty tools effectively.	(Davis, 1989)
Behavioral Intention	BI1	When this technology is available, I will recommend my relatives and friends.	(Venkatesh et al., 2012, pp. 157–178)
	BI2	I am willing to participate in the pilot application of AI-powered beauty tools.	(Venkatesh et al., 2012, pp. 157–178)
	BI3	I will try it when AI-powered beauty tools become available.	(Venkatesh et al., 2003)
	BI4	I will regularly use AI in Beauty technology in my beauty routine when it becomes available.	(Venkatesh et al., 2003)
Attitude towards use	ATT1	I like the idea of using AI-powered beauty tools.	(Davis, 1989)
	ATT2	It is a positive influence for me to use AI-powered beauty tools.	(Davis, 1989)
	ATT3	I think it is a trend to use AI-powered beauty tools.	(Davis, 1989)
	ATT4	I think it is valuable for me to use AI-powered beauty tools.	(Davis, 1989)
	ATT5	Using AI-powered beauty tools is a good idea.	(Davis, 1989)
	ATT6	Using AI-powered beauty tools in my beauty routine is favourable.	(Davis, 1989)

Appendix 3 Codebook

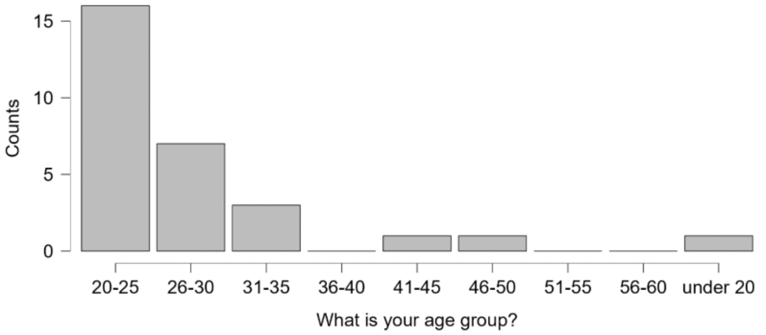
Part of Survey	Code	Question Represented
Demographics	D01	Gender
	D02	Age Group
	D03	Highest Level of Education
	D04	Sector of work
Experience	E01	Level of tech background
	E02	Level of familiarity with AI technology
	E03	Level of familiarity with the practical applications of AI beauty technology
	E04	Previous experience with AI beauty technology
Measurement (Likert Scale)	01	Strongly Disagree
	02	Disagree
	03	Slightly Disagree
	04	Neutral
	05	Slightly Agree
	06	Agree
	07	Strongly Agree

Appendix 4 Frequencies for the question "What is your age group?"

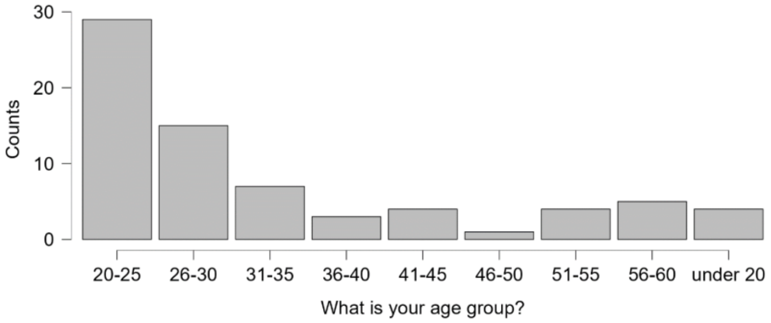
What gender do you identify as?	What is your age group?	Frequency	Per cent	Valid Percent	Cumulative Percent
Male	20-25	16	55.172	55.172	55.172
	26-30	7	24.138	24.138	79.310
	31-35	3	10.345	10.345	89.655
	36-40	0	0.000	0.000	89.655
	41-45	1	3.448	3.448	93.103
	46-50	1	3.448	3.448	96.552
	51-55	0	0.000	0.000	96.552
	56-60	0	0.000	0.000	96.552
	under 20	1	3.448	3.448	100.000
	Missing	0	0.000		
	Total	29	100.000		
Female	20-25	29	40.278	40.278	40.278
	26-30	15	20.833	20.833	61.111
	31-35	7	9.722	9.722	70.833
	36-40	3	4.167	4.167	75.000
	41-45	4	5.556	5.556	80.556
	46-50	1	1.389	1.389	81.944
	51-55	4	5.556	5.556	87.500
	56-60	5	6.944	6.944	94.444
	under 20	4	5.556	5.556	100.000
	Missing	0	0.000		
	Total	72	100.000		

Appendix 5 Age groups

Male

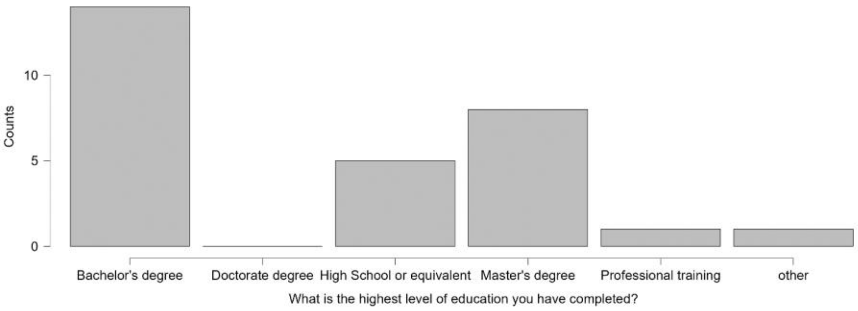


Female

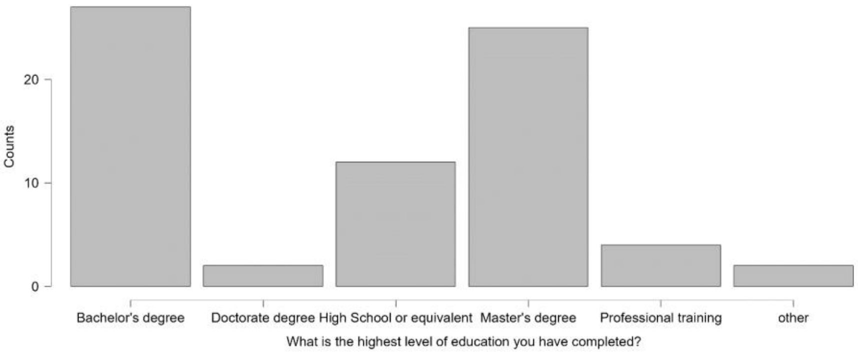


Appendix 6 Level of education

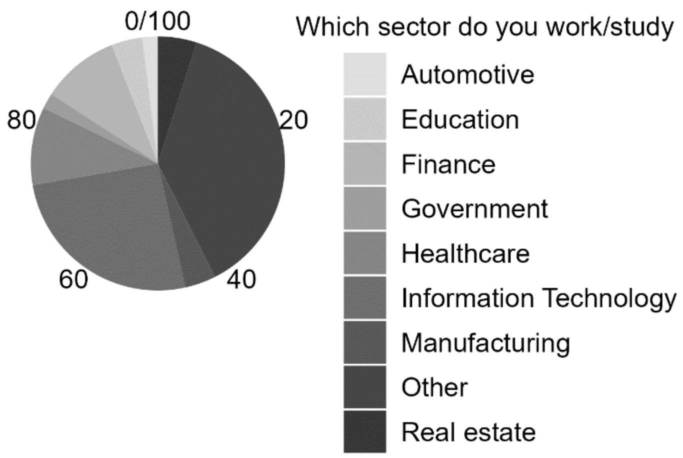
Male



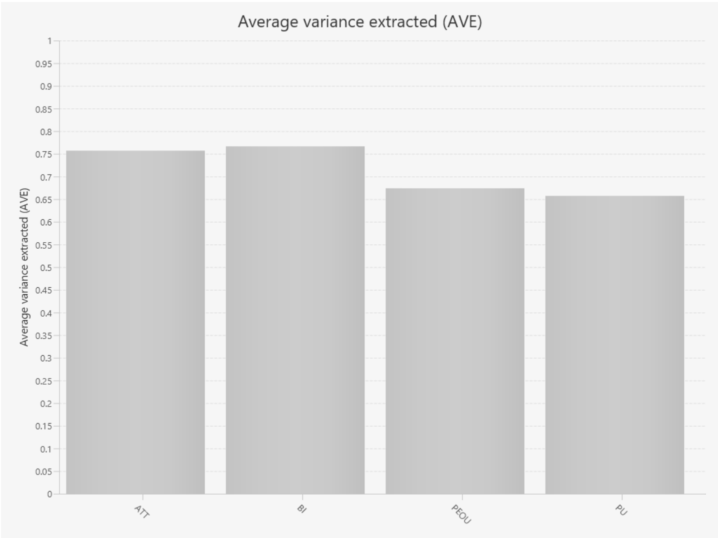
Female



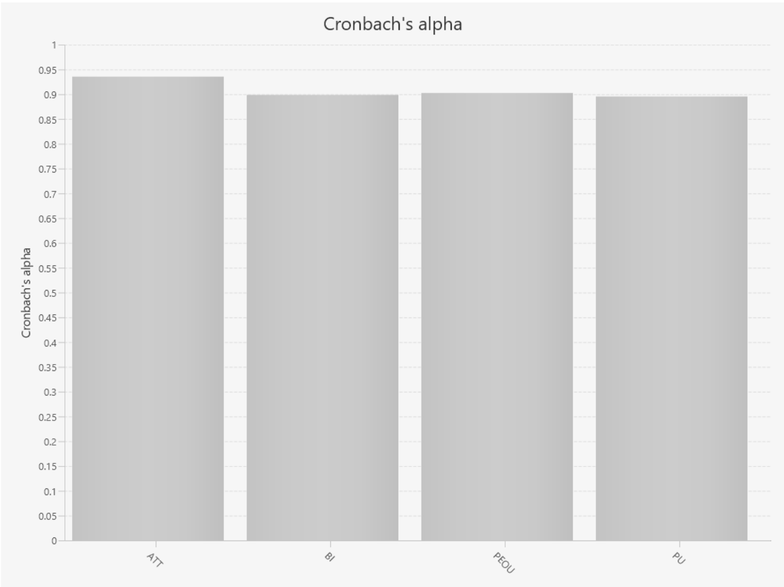
Appendix 7 Sector of study/work



Appendix 8 Average Variance Extracted (AVE)



Appendix 9 Cronbach's alpha



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