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Master Thesis

The effect of Artificial Intelligence and products recommendation on purchase intention: a study of the cosmetics field.

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Abstract

Rapid development and adoption of Artificial Intelligence challenge managers to exploit this transforming technology to enhance the customer experience and therefore their sales. This study aims to explore the effect of Artificial Intelligence on consumers' purchase intention in the cosmetics field. We have decided to narrow our research to digital services powered by Artificial Intelligence, able to recommend products to the users. We have defined two different types of skin analysis: via a selfie or via a questionnaire; and two different types of recommended products: products already existing in a brand's product range or personalized products, tailored to each consumer. Using four different scenarios, based on a type of skin analysis and a type of recommended product, we have analyzed 11 different constructs: *Rapidity*, *Enjoyment*, *Innovativeness*, *Trust*, *Perceived Ease of Use*, *Perceived Usefulness*, *Behavioral Intention*, *Technology Adoption Propensity*, *Involvement Into Product Category*, *Attitude Toward the Brand* and *Purchase Intention.* Findings indicate that there is a positive effect of *Rapidity* and *Enjoyment* on *Perceived Ease of Use*, but that *Perceived Ease of Use* does not have a significant effect on *Behavioral Intention* or *Purchase Intention*. Besides, *Innovativeness* and *Trust* positively affect *Perceived Usefulness*, which in turn positively affects *Behavioral Intention* and *Purchase Intention*. Also, *Behavioral Intention* itself has a positive impact on *Purchase Intention*. Finally, *Technology Adoption Propensity* does not have a significant effect on *Behavioral Intention* and *Involvement Into Product Category* does not have a significant effect on *Purchase Intention*, but *Attitude Toward the Brand* positively affects *Purchase Intention*.

Keywords: Artificial Intelligence, products recommendation, purchase intention, cosmetics, skincare, usefulness, ease of use, behavioral intention

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1. Introduction

The cosmetics market is a large market. Consumers are left with hundreds of different brands to choose from and even more products. If we only consider Europe, there are 462,083 cosmetics brands (BoldData, n.d.). This huge amount of brands and products can disservice companies and even cause them to lose a sale. When consumers have to choose from many options, the action of making a choice becomes effortful and might even discourage the consumer from making a choice. On the other hand, when consumers are offered personalized recommendations, they are more likely to choose this option and to not engage in comparison shopping. (André et al., 2018)

Thus, with this wide variety of products, cosmetics brands are developing new tools and experiences to help consumers in their customer decision journey and on their side consumers are looking for recommendations to help them make the right choice. 58% of consumers are more likely to buy from a brand that offers an online quiz that recommends specific products that fit their needs, and 45% of consumers are more likely to buy from a brand that uses Virtual Reality or Artificial Intelligence that allow them to try on products online. (Nosto, 2020).

Today, more and more cosmetics brands are using Artificial Intelligence (AI) in order to propose personalized recommendations to consumers and help them make the right choice.

Indeed, one of the main evolutions of the cosmetics industry is the concept of personalization. This need for personalization has been observed in different industries and is now becoming a priority in the cosmetics industry. To respond to this new need, some brands have developed solutions based on AI. (Sharma, 2020).

The use of AI in the cosmetics industry can take different forms and can be integrated in the online purchasing experience or in the in-store purchasing experience.

A first application of AI in the cosmetics field is the use of AI-based virtual try-on which development was accelerated during the pandemic. With this type of technology, the customer can virtually visualize how the product will look like on their skin. The AI helps the consumers to know where to apply the product and how it looks, but the AI doesn't recommend any product in particular. It is the consumer who chooses which product they want to try-on. An example of this technology is L'Oreal Virtual Try On, which allows patients to virtually try various makeup products and styles from the comfort of their home.

Another application of AI is the use of a questionnaire which uses machine learning: the consumer has to respond to a questionnaire which leads to a selection of recommended products. For example, the brand PROVEN Beauty proposes a beauty quiz, developed by a dermatologist, on its website. The quiz includes multiple questions regarding the customer's age, skin type, skincare concerns, current topical prescriptions, ethnic background and geographic location. Thanks to the consumer's responses, PROVEN proposes a unique skincare regimen tailored to the customer's skin type and cosmetics needs.

There is also the use of AI-based recommendation thanks to uploaded images. The consumer uploads a picture of its face on a company website or takes a live-selfie and then the company recommends products that will target the skin issues identified on the uploaded picture. The Vichy Skin Consult AI was developed to assess skin conditions. After uploading a picture, the consumer is provided with information about their skin quality and a customized product regimen.

Finally, there is the use of a material device, which has the ability to physically scan and analyze the quality of a patient's skin and uses AI to recommend a product. For example, Visia Skin Analysis evaluates eight different skin characteristics and selects a personalized treatment regimen from its built-in library of skin care products. (Elder et al., 2021).

However, there is little research on the technology acceptance of AI, how people react to this new technology, and its impact on consumer purchase intention in the field of cosmetics.

Thus, our master thesis has a double objective. Firstly, we aim to determine the different characteristics and factors that lead a consumer to use Artificial Intelligence in the cosmetics field, and then to a purchase intention. Secondly, we intend to compare two different kinds of Artificial Intelligence that represent two different types of skin analysis (via a questionnaire or via a selfie), and two different types of recommended products (products already existing from the products range of a brand or completely new and personalized products, tailored to the consumer), to discover which are the most effective to lead to a potential sale.

For this study, separating men and women was necessary. Indeed, Procter & Gamble's owned beauty brand Olay did a research and found that 78% of men would never buy their own skincare products. They consider that stealing some of their girlfriend's products is enough to satisfy their need (https://www.olay.com/). Thus, men do not have the same purchase journey as women, and are not influenced by the same factors. As a result, investigating men's willingness to use AI-based services and buy skincare products from it cannot be studied with the same conditions as for women. Thus, for our research, we have decided to focus on women.

2. Literature review and hypotheses

2.1. Cosmetics

Cosmetics represent products that are used on the human body with the intention to clean, beautify, promote attractiveness or alter the appearance of the person using it (FDA, 2021). It includes skincare products, hygiene products, hair care products, makeup, fragrances and hair removal products.

Regarding skincare products, they are defined as products that you use to keep your skin healthy and attractive (Cambridge Dictionary, n.d.). They include creams, emulsions, lotions, gels oils and scrubs for the skin, beauty masks, bath and shower preparation (salts, foams, oils, gels), sunscreen products, anti-wrinkle products, shaving products (soaps, foams, lotions) and makeup removal products.

When purchasing a cosmetic product, customers pay attention and are influenced in their purchasing decision by the product price, the seller's performance, the product style, the brand, the consumer's income, product reviews, recommendations and the product ingredient list (Rieg et al., 2018; Galetić & Požega, 2019).

Indeed, sales professionals have an influence on consumer purchase decisions when buying cosmetics products. It was found that their influence is the highest when they have certain attributes, being credibility, concern for customer's needs, product knowledge, courtesy and attention (Rieg, et al., 2018).

When purchasing a skincare product, some people choose a product by themselves without any professional advice which often leads them to not choosing the right product for their face. This results in them not finishing the product or even only using it a couple of times before realizing their skin has a bad reaction to the product.

2.2. Purchase intention

Purchase intention is defined as the degree to which the consumer is willing to pay and his attitude and orientation toward the purchase of a particular good or service (Bhagat et al., 2022).

Many factors can lead consumers to a purchase intention, such as advertising — via different channels: social media, TV, billboards, magazines, search engine advertising, newsletters etc — (Long Yi, 2011), word-of-mouth and e-word-of-mouth (Jalilvand and Samiei, 2012), brand loyalty (Büyükdağ, 2021), brand trust (Dabholkar and Sheng, 2012), brand equity (Senthilnathan and Tharmi, 2012), attitude toward the product — defined as the consumer's evaluation of the product — or subjective norms — defined as the perceived social pressure to buy or not to buy the product (Ajzen & Fishbein, 1980).

Also, the purchase intention of a consumer can lead to a purchase, but it is not always the case. Morwitz et al (2007) showed that purchase intentions are more closely linked with sales for existing goods than for new ones, for durable products than for non-durable ones, for short time horizons than for long time ones and when respondents are invited to indicate their intentions to purchase specific brands or models than when they are invited to indicate their intentions to buy at the product category level. Thus, marketing managers can rely on consumers' purchase intention to predict sales but they should remain careful in their calculations and take into consideration the category of products they are working on to predict these sales.

2.3. Artificial Intelligence

Using computers and machines, Artificial Intelligence replicates the ability of the human brain to solve problems and make decisions (IBM, n.d.). More precisely, even if a large number of definitions of Artificial Intelligence have appeared since the 1950s, John McCarthy (2007) defines AI as the science and engineering of making intelligent machines, especially intelligent computer programs. It is linked to the analogous task of using computers to figure out human intelligence, but AI is not limited to methods that are biologically observable.

Artificial Intelligence has human-like intelligence and is able to solve complicated problems, which explains why it is now present and has an important place in every sector. The mechanism of Artificial Intelligence is based on its capacity to solve a problem thanks to algorithms (Lee and Choi, 2016).

Artificial Intelligence, since its appearance in the 1950s, has seen huge changes. Nowadays, there exist multiple forms of AI and every industry uses at least one of its forms (Huang et al., 2019), and the use of Artificial Intelligence has not only enhanced the sales but also the brand value of firms, with enhanced customer experience (Shim et al., 2001). Indeed, the use of Artificial Intelligence has improved the satisfaction level of customers, since it has provided them with a better and more personalized shopping experience (Polacco and Backes, 2018).
Also, the abilities and potential of Artificial Intelligence have aroused curiosity among consumers, who are consequently extensively using AI (Shankar, 2018).

2.4. Artificial Intelligence and purchase intention

Artificial Intelligence seems to increase customers' purchase intentions. Indeed, websites that use AI are useful to consumers because they are time-saving as well as providing them with the best alternatives (Bhagat et al., 2022).

Actually, Artificial Intelligence helps consumers in filtering, removing and choosing the most suitable option, thus reducing the search cost and search time of customers, which eventually leads to an effective decision (Bleier et al., 2020). As a result, most customers who use Artificial Intelligence make profits by meeting their demands with the optimal use of money and time (Kim and Kim, 2017). Also, online sites which offer the help of Artificial Intelligence to their customers make them much more confident when carrying out a purchase decision because it makes the process risk-free (Haenlein et al., 2019). Thereby, nowadays AI is becoming one of the most important facets for customers when they have to make a decision about purchasing and consumption (Park, 2009).

All in all, research showed that since Artificial Intelligence’s goal is to develop programs that possess the ability to solve problems in the same as than humans would, it increases consumers’ decision-making capacities toward purchase intention (Liu et al., 2019; Astawa and Sukawati, 2019; Qian and Xu, 2019) and that a good virtual experience positively impacts customers’ purchase intentions (Pantano et al., 2017). When consumers use a recommendation agent online, they experience more satisfaction, greater trust as well as higher purchase intentions toward the product recommended by the recommendation agent (Dabholkar and Sheng, 2012).

Also, Grewal et al (2017) showed that there exists a strong and positive correlation between online shopping sites that are able to provide the help of Artificial Intelligence technology to their consumers with consumers’ purchase intention.

Finally, relying on the technology acceptance model, Kim et al (2021) showed that perceived usefulness and perceived ease of use, with the help of Artificial Intelligence technology, positively influence consumers’ purchase intention.

2.5. Perceived ease of use

In 1989, Davis developed the Technology Acceptance Model (TAM) to better predict and explain the predictors of user acceptance of technology. TAM postulates that two factors, which are perceived usefulness and perceived ease of use, are particularly important to determine if consumers will accept this or that new technology.

Davis defines perceived ease of use as the extent to which a user considers that no effort is required to use a particular system.

A user’s perception of ease of use can be influenced by a variety of factors. Firstly, the individual's previous experience with similar technologies plays a key role. Venkatesh and Davis (2000) found that participants with prior experience with computers were more likely to rate a new software application as easier to use than those without experience. Secondly, it is important to consider whether technology is perceived to be compatible with the user's preferences and needs (Yousafzai et al., 2007). Thirdly, there is evidence that cultural factors can influence perceived ease of use. For example, Gefen et al. (2000) found that American students perceived e-learning systems to be easier to use than Israeli students. The authors suggested that this may be due to cultural differences in attitudes toward technology.

All in all, when consumers perceive a particular technology to be easy to use, it is more likely to be adopted by users, and it should positively affect their intentions to purchase (Har Lee et al., 2011).

H1a*: Consumers with a higher perceived ease of use of the AI-based application will have a greater behavioral intention to use the application.*

H1b*: Consumers with a higher perceived ease of use of the AI-based application will have a greater purchase intention regarding the recommended products.*

2.6. Perceived usefulness

Davis (1989) defines perceived usefulness as the extent to which a user considers that using a particular system will improve his or her work performance. In our context, usefulness refers to the extent to which a consumer believes that AI applications will enhance their shopping experience.

Several factors have been found to influence users' perceptions of usefulness, such as the technology's compatibility with users' needs and values (Venkatesh et al., 2003), social influence (Roca et al., 2006) and user characteristics such as prior experience and expertise (Venkatesh and Morris, 2000).

Similarly to perceived ease of use, many studies have proven that perceived usefulness positively affects consumers' behavioral intention and purchase intention. For example, Amoako-Gyampah showed that perceived usefulness has a positive effect on the behavioral intention to use an ERP system (2007). Also, Ventre and Kolbe demonstrated that the perceived usefulness of online reviews has a positive effect on online purchase intention (2020).

H2a*: Consumers with a higher perceived usefulness of the AI-based application will have a greater behavioral intention to use the application.*

H2b*: Consumers with a higher perceived usefulness of the AI-based application will have a greater purchase intention regarding the recommended products.*

2.7. Behavioral intention

Behavioral intention refers to an individual's conscious decision to perform a specific behavior, and it is a key predictor of actual behavior (IGI Global, n.d.). In our context, the behavioral intention concerns the intention of the consumer to use the AI applications that we are talking about in our thesis.

According to TAM, in the technology field, behavioral intention is driven by user technology acceptance (Venkatesh et al., 2003), which is a result of a user's perceived ease of use and perceived usefulness of the technology (Davis, 1989). Therefore, if consumers perceive that the AI applications are easy to use and useful, they are likely to use them.

Besides, TAM can also explain purchase intention in the context of technology products (Davis, 1989). TAM proposes that user technology acceptance, via perceived usefulness and perceived ease of use, is the key determinant of purchase intention, which means that if consumers perceive the AI technologies as easy to use and useful, they will accept them, which will create a behavioral intention and thus their purchase intention will increase.

H3*: Consumers with a higher behavioral intention to use the AI-based application will have a greater purchase intention regarding the recommended products.*

2.8. Rapidity, enjoyment, innovativeness and trust

Rapidity is defined as the quality of being fast (Cambridge Dictionary, n.d.). In our context, we want to measure the speed of the Artificial Intelligence processes and determine their levels of rapidity.

Venkatesh (2000) defines enjoyment as the extent to which using a specific system is perceived as enjoyable without taking into consideration any performance consequences from the system use. Thus, we aim to determine the degree of enjoyment that users experience when using different kinds of Artificial Intelligence.

Watchravesringkan et al. (2010) define perceived innovativeness as the degree to which consumers find the product as having important innovation attributes such as newness and uniqueness. Here, the focus is no longer on the characteristics of Artificial Intelligence, but on the type of recommended products.

When it comes to a brand, trust is defined as consumers' willingness to rely on the ability of the brand to perform its stated function (Chaudhuri and Holbrook, 2001). In our case, we can transpose this definition to a product and state that product trust is defined as consumers' willingness to rely on the ability of the product to perform its stated function.

Furthermore, the distinction between questionnaire and selfie, which are the two types of skin analysis provided by the AI-enabled applications, can influence the perceived rapidity of the service. Indeed, taking a selfie is quicker than answering the questionnaire. In addition, the type of skin analysis can also influence perceived enjoyment. Using a selfie seems to be more enjoyable as it requires a low cognitive load for instance.

H4a*: A digital service that uses a selfie to analyze the consumer's skin will have a greater consumer's perceived rapidity.*

H4b*: A digital service that uses a selfie to analyze the consumer's skin will have a greater consumer's perceived enjoyment.*

Similarly, it can be relevant to distinguish the type of products that the services recommend, meaning distinguishing whether the recommended products are products already existing from the brand or completely new and personalized products. This distinction can affect perceived innovativeness, and it can influence perceived trust as well. Indeed, completely custom-made products are more likely to be seen as innovative. And consumers are more likely to trust already existing products as they are used by other consumers that can share their experiences and results with the products.

H5a*: A digital service that recommends personalized skincare products to consumers will have a greater consumer's perceived innovativeness.*

H5b*: A digital service that recommends existing skincare products to consumers will have a greater consumer's perceived trust.*

Previous research showed that perceived rapidity and perceived enjoyment have a positive impact on perceived ease of use. When it comes to consumers' behavioral intention to use a mobile commerce – which represents every means that enable a consumer to make a purchase from a mobile phone or tablet –, rapidity and perceived enjoyment are antecedents that positively impact consumers' perceived ease of use (Vărzaru et al., 2021). Also, Ngubelanga and Duffett (2021) established a positive relationship between perceived enjoyment and perceived ease of use in Millennial usage of mobile commerce applications.

H6*: Consumers with a higher perceived rapidity of the AI-based application will have a greater perceived ease of use.*

H7*: Consumers with a higher perceived enjoyment of the AI-based application will have a greater perceived ease of use.*

Besides, a positive relationship between innovation and perceived usefulness has been proven. For example, Kim and Lee (2012) studied how perceived innovation and perceived usefulness of a product can influence customers' adoption of technological innovation. The results of the study showed that perceived innovation has a significant impact on perceived usefulness and adoption of technological innovation, meaning that customers are more likely to adopt a technological innovation if they perceive it as innovative and useful.

H8*: Consumers with a higher perceived innovation of the recommended products will have a greater perceived usefulness.*

Furthermore, several studies established a positive relationship between trust and perceived usefulness. Sun and Chi (2019) reported that American consumers' trust has a positive effect on the perceived usefulness of apparel mobile commerce. Ngubelanga and Duffett (2021) found a positive influence of trust on perceived ease of use in the usage of mobile commerce applications among Millennial users in South Africa.

H9*: Consumers with a higher perceived trust of the recommended products will have a greater perceived usefulness.*

2.9. Technology adoption propensity

As the number of technology-based products and services continues to rapidly increase, technology is playing an increasingly significant role in customer-company interactions. While these advancements have generally been advantageous for customers, there is also mounting evidence that customers are becoming increasingly frustrated with the challenges of navigating technology-based systems (Parasuraman, 2000). Thus, by segmenting and targeting customers based on their propensity to adopt and utilize new technologies, firms can optimize the return on their investments in high-tech products and services, for example by enhancing the effectiveness of marketing expenditures (Ratchford and Barnhart, 2012).

Consumers' chronic predisposition towards adopting new technologies is a significant factor in technology adoption. As individuals exhibit varying degrees of openness to new technologies, it is essential to measure these tendencies accurately to forecast trends and target high-tech products and services effectively (Parasuraman, 2000). Therefore, the more open a consumer is to new technologies in general, the more likely he should be to test or use a new digital service.

H10*: Consumers with a higher technology adoption propensity will have a greater behavioral intention to use the AI-based technology.*

2.10. Involvement into the product category

The level of involvement that a consumer has with a product category is determined by the consumer's lasting beliefs about the significance of the product category, which stem from their inherent needs, values, and interests (De Wulf et al., 2001). Therefore, we have to highlight the fact that the involvement into a product category is consumer-based and not product-based. For example, a consumer A may be highly involved in the cosmetics products category and little involved in the automobile products category while another consumer B may be little involved in the cosmetics products category but highly involved in the automobile products category. The reason why customers engage with a particular product category is due to their alignment with their personal needs and values (Zaichkowsky, 1985).

Customers with a high level of involvement in a product category tend to seek out more information (Mathwick and Rigdon, 2004) and engage in more discussions about the product category compared to those with a lower level of involvement (Wangenheim and Bayón, 2007). Also, customers with high involvement demonstrate greater levels of loyalty (Dick and Basu, 1994), and are thus more likely to buy products from the category.

H11*: Consumers with a higher level of involvement into the skincare products category will have a greater purchase intention regarding the recommended products.*

2.11. Attitude toward the brand

Attitude toward a brand is one of the crucial determinants of a consumer's purchase decision (Kotler et al., 2017).

An attitude is a tendency to react positively or negatively to an object, a person, an institution or an event. It reflects an individual's overall evaluation of the object based on the cognitive, affective, and behavioral information that has been accumulated (Ajzen, 2001). Therefore, attitude is formed over time through personal experiences, information processing, and social influences.

Thus, Keller (1993) defines attitude toward a brand as the consumer’s overall evaluation of the brand in terms of its perceived ability to meet relevant needs and wants. Attitude toward a brand is not only influenced by the brand's functional benefits, but also by its symbolic meaning, image, and personality.

Several factors can influence consumers’ attitudes toward a brand. The first one is brand image, which refers to the overall impression that consumers have about a brand. It includes the brand's perceived quality, reliability, and credibility. A positive brand image can create a favorable attitude toward a brand, while a negative image can lead to a negative attitude (Kim et al., 2013). Secondly, perceived value can influence consumers’ attitudes toward a brand. Perceived value is the consumer's perception of the benefits they receive from a product or service concerning its cost. Consumers are more likely to develop a positive attitude towards a brand if they perceive that it offers good value for money (Lichtenstein et al., 1993). The third factor is brand personality, defined as the set of human characteristics associated with a brand. Consumers may develop a positive attitude towards a brand if they perceive it to have a personality that matches their own (Aaker, 1997). Fourthly, brand loyalty can have an impact on consumers’ attitudes toward a brand. Indeed, brand loyalty is the degree to which a consumer consistently purchases a particular brand over time, and consumers who are loyal to a brand are more likely to have a positive attitude toward it (Wirtz and Chew, 2002). Finally, social influence can impact consumers’ attitudes toward a brand. Social influence refers to the impact that other people have on an individual's attitudes and behavior, and consumers may develop a positive attitude toward a brand if they perceive that it is socially desirable or if their peers have positive attitudes toward it (Bearden and Etzel, 1982).

Besides, a positive attitude towards a brand can lead to brand choice (Keller and Aaker, 1992), loyalty (Oliver, 2010), reduced price sensitivity (Simonson and Rosen, 2014), and positive word-of-mouth (Brown and Reingen, 1987).

All in all, brands need to understand and manage consumer attitudes toward their brand to improve sales and profitability.

H12: Consumers with a more positive attitude toward the brand of the AI-based application will have a greater purchase intention regarding the recommended products.

2.12. Conceptual model

Figure 1 illustrates the proposed model and hypotheses.

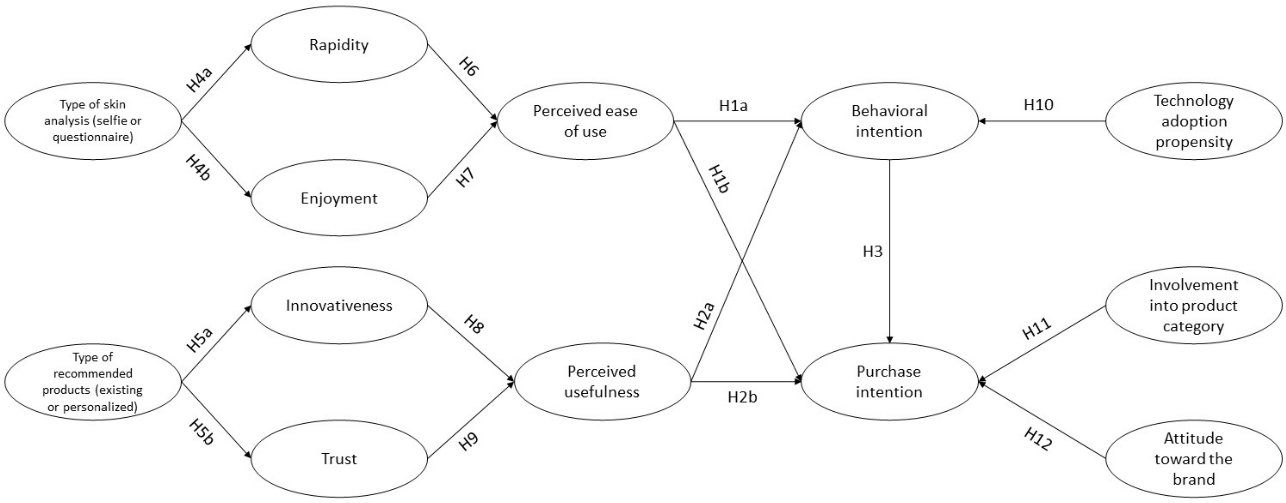

Figure 1. Conceptual model.

3. Methodology

3.1. Survey development

3.1.1. Quantitative research

For this research, quantitative data was gathered through online surveys, using Qualtrics. We developed four different surveys, each introducing a variation of a skincare recommendation system powered by AI. Indeed, to analyze the effect of the type of skin analysis and the effect of the type of recommended products on consumer responses, a manipulation had to be added. Thus, four scenarios were developed and the experiment utilizes a 2 (type of skin analysis: selfie vs. questionnaire) x 2 (type of recommended products: already existing from the brand vs. custom-made to the consumer) between-subjects design.

The surveys are made of four sections. The first section consists in general questions about the respondent's involvement into skincare products and into new technologies. Then, the second section introduces one of the four AI-based technology scenarios, explaining how the service works and its purpose (**Appendix**

1). While describing the AI-based technology, the decision was made not to mention any brand since the effect of the brand will be measured further in the questionnaire. Also, the term “AI” was not used, instead “digital service” was chosen to make it more understandable for participants and to avoid confusion. To be sure that respondents have understood, assimilated and retained the description, three manipulation checks were introduced. The questions were “What do you have to do before the skin analysis?”, “What is the website able to do?” and “What kind of products does the website recommend?”. The third section of the surveys is consecrated to questions about respondent evaluation of the digital service. Finally, the fourth and last section is dedicated to demographic questions. As the study is on the effect of the AI-applications on women only, it was essential to make sure that the respondents were women. This is the reason why a screening question was added in the demographic part of the questionnaires, by asking the respondent’s gender.

3.1.2. In-depth interview

Before developing the questions of our surveys, we decided to start our research with an in-depth interview, to collect unprompted feedback on two digital services that recommend skincare products, already existing on the market.

For this in-depth interview, we chose five participants: five women aged between 21 and 30. The only instruction we gave them was to test the two digital services in question, and give their opinion on them. We did not take part in the debate.

The first digital service offered was the one of PROVEN, which involves answering a multiple choice questionnaire to identify the user’s skin needs and concerns. At the beginning of the questionnaire, the service indicates that it will take 3 minutes to complete. At the end of the questionnaire, the digital service suggests a routine of three products entirely new, personalized and adapted to the user’s skin, indicating the skin concerns that the products address as well as the ingredients used.

The second digital service is Nivea Skin Guide, which asks the user to take a live selfie to analyze her skin. Then, the website evaluates different characteristics of the user’s skin (skin age, firmness, clarity and even tone), on which she can have detailed information. The website also recommends three products adapted to the user’s skin, on which she can have more information. The digital service also offers a skin diary, so the user can follow the evolution of her skin through daily selfies.

All in all, thanks to these two digital services, we were able to cover the two types of skin analysis (questionnaire and selfie) and the two types of recommended products (already existing products and new and personalized products) on which our research focuses.

During this in-depth interview, we collected many interesting remarks, which supported our hypotheses as well as the questions we had in mind, and which also sometimes enabled us to think of new categories and questions to integrate into our surveys.

When we tested the first digital service (PROVEN), we noticed that participants took 6 minutes to complete the questionnaire, rather than the 3 minutes indicated, which was double the time, raising the question of the rapidity of the digital service. Also, while they were answering the questionnaire, we noted remarks such as "How much time a day we spend in sunlight depends on the time of year", "How much time a day we spend in front of screens? 7 to 9 hours?" or "What are retinol-based products?", which raised the question of the difficulty of answering the questionnaire, the cognitive load involved and therefore the level of enjoyment.

Once they had completed their questionnaires, participants had access to their results with the personalized routine recommendation. First of all, participants emphasized the innovative aspect of the products. For example, one said "I think it's good because they create the product, it's not a product that already exists, it's supposed to be really made for you". Then the question of the trust in the products was quickly raised. As the products are totally new and adapted to each consumer, one participant rightly said "We have no proof, we don't know if it has worked on other people". Another added, "What might have been nice is if they had suggested products that already exist and contain the active ingredients that might suit me, because if it's a product that already exists from a brand I already know, it's a bit more reassuring than ingredients they've put together. Because in reality, is putting all these ingredients together going to work?". Nevertheless, another participant qualified her statement by saying "I think it's good that they detail the ingredients". Finally, the attitude toward the brand was also mentioned, with the following comment: "If I use a brand and at the end of a questionnaire like this they suggest products from that brand that are suited to my skin, then I think I'd buy, but I'm not sure I'd test a new brand."

Finally, the participants expressed that they hadn't necessarily developed any purchasing intentions. Two of them said "Honestly, this type of questionnaire is the kind of thing I often do, but I've never bought in the end" and "It's interesting, but I don't know if I'd use it. I'd be interested in reading what the site says, but I'm not sure I'd go through with the consumption stage".

As for the second digital service, given that it's a service from Nivea, a world-famous brand, the trust in their products and the attitude toward the brand were quickly underlined, with comments like "We know Nivea, so I have fewer doubts. I think that if it's a brand you know and use, this digital system can be effective" or "I really liked the experience, but I think it's because it's Nivea, so I'm positively biased". Also, the ease of use compared to the first digital service was highlighted, for example when a participant said "I think the good thing is that it's the artificial intelligence that tells you if you have redness, for example, whereas in the questionnaire it's up to me to judge. I know that from time to time my skin is a little red, but is that considered redness?".

Overall, participants found the digital service enjoyable. They said, for example, "Just thanks to a selfie, that's pretty impressive!".

All in all, all these insights helped us to develop our surveys, through a clearer vision of the perceptions, doubts and expectations of potential cosmetics consumers.

3.2. Measurement

The constructs in the surveys are measured using a 7-point Likert scale, which is largely used in the literature. This scale was used for every construct in order to ensure consistency and to be able to compare them more easily. For each item, participants are asked to indicate their agreement with the statements by choosing between the 7 points: 1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = agree and 7 = strongly agree.

The different constructs that were evaluated in the surveys are *Involvement into the product category*, *Technology adoption propensity*, *Rapidity*, *Enjoyment*, *Perceived ease of use*, *Perceived usefulness*, *Innovativeness*, *Trust*, *Behavioral intention*, *Purchase intention* and *Attitude toward the brand*. In total, each questionnaire was composed of 29 items (**Appendix 2**). All of the items of the above constructs were taken and adapted from existing literature. In order to fit this research question, some of the items and scales had to be adjusted.

Two items used to assess the respondent's involvement into skincare products are adapted from the scale developed by Lastovicka (1979). The aim of this research was to question the existence of an involvement-based product classification system. The wording of the questions was aimed to measure respondents' involvement and familiarity for six different product classes. Thus, the questions were neutral, but they were altered by changing the wording from neutral to more specific by adding "skincare product". The scale used to measure those items was a 5-points Likert scale that was transformed into a 7-points Likert scale for consistency with the other items of the questionnaires. The two following items used for involvement into the product category are adapted from De Wulf et al. (2001). The research measured the effect of product category involvement on consumer's perception of the retailer's relationship investment. Thus, it was necessary to slightly alter the questions by changing "cloth" into "skincare products".

To measure the participant's technology adoption propensity, three items were used from Parasuraman (2000). This research proposes a multiple-item scale to measure people's technology readiness. The wording used was neutral, it was only rephrased slightly to change sentences from the second to the first person singular to fit the other items of the questionnaire. For the first item, the verb "acquire" was altered to "try" to fit the subject as the AI-technology that is being evaluated is a technology consumer can try and use but cannot acquire. In the same way as the previous items, the 5-points Likert scale used was changed to a 7-points Likert scale for consistency.

The two items used to measure rapidity were adapted from Van Dolen et al. (2007). In the research, participants had to assess how they perceived the speed of an online commercial group chat. The wording changed from “chat-based service” to “digital service”.

To measure enjoyment, three items were used from Venkatesh and Bala (2008). The aim of the research was to find determinants of perceived ease of use and perceived usefulness in the TAM. The items were neutral, so “system” was changed into “digital service”.

For the construct perceived ease of use, three items from Davis (1989), Har Lee et al. (2011) and Khare et al. (2012) were used. Davis (1989) developed a scale to measure perceived ease of use and perceived usefulness. The aim of the research from Har Lee et al. (2011) was to analyze the factors that affect consumers online repurchase intentions. Finally, Khare et al. (2012) wanted to understand the effects of normative beliefs, age and gender on consumers’ online shopping behavior. For the three items, the only alteration made was to fit the subject by using “digital service”.

For perceived usefulness, five items were used from the same literature than for perceived ease of use, namely Davis (1989), Har Lee et al. (2011) and Khare et al. (2012). Here again, some adjustments were made in the wording like using “digital service” and “skincare products”.

The construct innovativeness was measured using three items from Watchravesringkan et al. (2010). The aim of their research was to study consumer adoption of technological fashion products. The items were neutral, “recommended products” was specified.

The two items used to measure trust were adapted from Pavlou (2003). In his article he uses the TAM to study consumer acceptance of electronic commerce. The items were altered by changing “web retailer” into “recommended products” since the study measures consumers’ trust in the products recommended by the technology.

To measure behavioral intention, two items from Venkatesh et al. (2003) and Kautish and Sharma (2018) were used. Venkatesh et al. (2003) proposes a model to measure user acceptance of information technology. One of the objectives of Kautish and Sharma (2018) was to determine the behavioral intentions for purchase in the online fashion retail sector. The wording of the question was slightly altered to fit this research.

Purchase intention was measured using two items from Dabholkar and Sheng (2012). Their work investigates the effect of consumer participation in using online recommendation agents on satisfaction, trust and purchase intentions. Once again, a little alteration was made to be coherent with the topic.

Finally, for the construct attitude toward the brand, two items were used from Bobâlcă et al. (2012) and Chen and Chang (2008). Bobâlcă et al. (2012) research focused on developing a scale to assess customer loyalty. Chen and Chang (2008) studied the relationship between brand equity, brand preference and purchase intentions in the field of airline companies. For both items, the wording was altered to be more in line with the thesis.

3.3. Pre-test

Before collecting the data, the questionnaires were pre-tested among a small sample. After looking at the responses and collecting feedback, the order of the questions, the scenario descriptions and the manipulation checks were adjusted to improve comprehension.

3.4. Data collection

To collect answers, the four surveys were distributed to random women on the BI campus or through social media as well as to friends and family.

4. Results

4.1. Data sorting

In total, 150 responses were collected on all four surveys combined. Thanks to the manipulation checks and the gender screening question, answers from respondents who did not understand or pay attention to the scenario, or who were not women were not taken into consideration for the data analysis. Additionally, some respondents did not respond to the entire questionnaire. As a result, only 104 answers were considered for the data analysis.

The data was extracted from Qualtrics and analyzed on SPSS. To measure the different constructs, the mean of the related items was calculated for easier manipulations. The item "This digital service seems to take a long time" was recoded because it was reverse-scored.

Likert-scales were used as rating scales for the different items and are considered to be ordinal data. Thus, the collected data should be analyzed using non-parametric tests (Cohen et al., 2000).

4.2. Respondents' profile

Participants' ages range from 17 to 75 years old, with an average of 29 years old. As presented in **Table 1**, the majority of respondents were between 20 and 29 years old (67%). **Table 2** shows the results of the non-parametric Kruskal-Wallis test that checks if the four participant groups differ in terms of age. The null hypothesis H_0 of this test assumes that there is no difference in age between the four independent groups. And the alternative hypothesis H_a states that at least on group differs from the others in terms of age. In light of the results, it can be concluded that H_0 fails to be rejected because the significance is higher than $\alpha = .05$, meaning that there is no difference in age between the four surveys (H = 3.869, p = .276).

Table 1. Demographic profile.

	Type	Frequency	Percentage
Gender	Female	104	100
Age	Less than 20 years old	2	2
	20-29 years old	70	67
	30-39 years old	7	7
	40-49 years old	3	3
	More than 50 years old	11	11
	Did not answer	11	11

Table 2. Age difference between surveys.

Kruskal-Wallis test results		
Kruskal-Wallis H	**df**	**Asymp. Significance**
3.869	3	.276

Regarding respondents' involvement into skincare products, 3.8% “strongly disagree”, 2.9% “disagree”, 7.7% “somewhat disagree”, 15.4% “neither agree nor disagree”, 29.8% “somewhat agree”, 32.7% “agree” and 7.7% “strongly agree”. On average, their involvement into the product category is 5, meaning they “somewhat agree” being involved into skincare products. Respondents of the tests with the designs selfie x existing products and selfie x personalized products are more involved into skincare products than respondents of the other surveys (respectively, mean = 5.64 and mean = 5.92) (**Table 3**).

For their propensity to accept new technologies, 1.9% “strongly disagree”, 11.6% “disagree”, 22.1% “somewhat disagree”, 37.5% “neither agree nor disagree”, 17.3% “somewhat agree”, 9.6% “agree” and no respondent “strongly agree”. And on average, they rate a 4, meaning that they “neither agree nor disagree” about their tendency to accept technology in general. Respondents with the highest propensity to accept new technologies were in the survey questionnaire x existing products (mean = 4.45) (**Table 3**).

Table 3 gives an overview of the means and standard deviations of each construct across each group, i.e. each survey. Overall, *Rapidity*, *Enjoyment* and *Perceived Ease of Use* have a higher mean for groups 1 and 2, that were facing a selfie analysis scenario. It can also be noted that the construct *Innovativeness* has a higher mean for the groups 2 and 3, which are the groups in a personalized products scenario, whereas the mean of *Trust* is higher for groups facing an existing products scenario. For *Involvement Into the Product Category* and *Attitude Toward the Brand*, there is a higher mean in the groups 1 and 2, corresponding to groups with an AI-based service that uses a selfie for the skin analysis.

Table 3. Descriptive statistics by group.

	1	2	3	4
Constructs	**Mean (Std. dev.)**	**Mean (Std. dev.)**	**Mean (Std. dev.)**	**Mean (Std. dev.)**
RAP	5.52 (1.06)	5.70 (.78)	3.98 (1.44)	3.84 (1.37)
ENJ	5.41 (1.05)	5.37 (1.11)	4.56 (1.04)	4.23 (1.68)
INN	3.10 (1.43)	5.37 (.99)	3.13 (1.32)	5.14 (1.11)
TRUST	4.67 (.99)	4.04 (1.18)	4.32 (1.14)	3.68 (1.08)
PEOU	6.01 (.64)	6.06 (.70)	5.73 (.96)	5.30 (1.04)
PU	5.01 (1.01)	4.98 (1.18)	4.88 (.96)	4.14 (1.40)
BI	4.81 (1.46)	4.80 (1.19)	4.24 (1.68)	4.24 (1.73)
PI	4.59 (1.28)	4.30 (1.51)	4.16 (1.37)	3.84 (1.61)
TAP	3.78 (1.18)	4.21 (1.17)	4.45 (.93)	4.11 (1.44)
IIPC	5.64 (1.08)	5.92 (.80)	4.60 (1.90)	5.01 (1.24)
ATB	5.61 (.92)	5.81 (.79)	4.97 (1.30)	4.84 (1.49)

1 = Selfie x existing products survey, 2 = Selfie x personalized products survey, 3 = Questionnaire x existing products survey, 4 = Questionnaire x personalized products survey.

4.3. Reliability

Before testing the hypothesis, the reliability of the constructs were analyzed. Cronbach's Alpha was used. It is a measure which assesses internal consistency, that is, how closely related are several items (Cronbach, 1951). **Table 4** shows Cronbach's Alpha for the ten variables composed of several items. According to various researches, a Cronbach's Alpha with a value higher than .7 is acceptable (George and Mallery, 2003 ; Hair et al., 2010). After running a reliability test, it was revealed that all Cronbach's Alpha are satisfactory because they are above the .7 acceptable level. As a result, there is an internal consistency among items that measure the same variable.

Table 4. Analysis of reliability.

Reliability test results		
Variables	**Cronbach's Alpha**	**Number of items**
RAP	.846	2
ENJ	.901	3
INN	.933	3
TRUST	.829	2
PEOU	.812	3
PU	.895	4
BI	.915	2
TAP	.723	3
IIPC	.860	4
ATB	.810	2

4.4. The effect of the type of skin analysis and the type of recommended products

To assess the relationships between *Type of skin analysis* and *Rapidity*, *Type of skin analysis* and *Enjoyment*, *Type of recommended products* and *Innovativeness*, and *Type of recommended products* and *Trust*, a first test was run on the dependent variables. A Shapiro-Wilk test of normality was conducted on *Rapidity*, *Enjoyment*, *Innovativeness* and *Trust*. **Table 5** shows the results: the variables are not normally distributed (significance values <.05). As a result, a non-parametric test was used to assess the relationship between the variables. The non-parametric Mann-Whitney U test was chosen. This test assumes the null hypothesis H_0 that the two independent groups are homogeneous and come from the same population. The alternative hypothesis H_1 suggests that the two groups differ from each other (Nachar, 2008).

Table 5. Normality results.

Shapiro-Wilk test results			
Variables	**Statistic**	**df**	**Significance**
RAP	.929	104	<.001
ENJ	.941	104	<.001
INN	.964	104	.007
TRUST	.957	104	.002

Furthermore, Spearman's correlation tests were performed to measure if the variables are related. The results depicted in **Table 6** reveal a negative association between *Rapidity* and *Type of skin analysis* (r = -.543, p <.001) and between *Enjoyment* and *Type of skin analysis* (r = -.404, p = <.001). As in the data set 1 = selfie and 2 = questionnaire for the type of skin analysis, respondents in a selfie scenario ranked *Rapidity* and *Enjoyment* higher than respondents in the questionnaire scenarios. Regarding *Type of recommended products*, the variable has a positive association with *Innovativeness* (r = .672, p = <.001) and a negative association with *Trust* (r = -.303, p = .002). For the type of recommended products, 1 = existing and 2 = personalized. As a result, respondents in the personalized products scenarios ranked *Innovativeness* higher whereas respondents in the existing products scenarios ranked *Trust* higher.

Table 6. Inter-variable correlation analysis.

	RAP	ENJ	Type of skin analysis
RAP	1	.616**	-.543**
ENJ		1	-.404**
Type of skin analysis			1
	INN	**TRUST**	**Type of recom. products**
INN	1	-.027	.672**
TRUST		1	-.303**
Type of recom. products			1

**. Correlation is significant at the 0.01 level (2-tailed).

4.4.1. Rapidity

The first relationship being studied is whether there is an effect of *Type of skin analysis* on *Rapidity*. As **Table 7** shows, the Mann-Whitney U test revealed that the mean rank is higher for the selfie group than for the questionnaire group (68.96 for selfie and 34.72 for questionnaire). As a conclusion, *Rapidity* has higher scores in the selfie scenarios than in the questionnaire scenarios ($U = 461$, $p = <.001$). Thus, an AI-based recommender that uses selfie to analyze the skin is perceived as quicker than a questionnaire one, and ***H4a*** is supported.

Table 7. Mann-Whitney U test results for *Rapidity.*

Mann-Whitney U test Results					
Ranks				**Test Statistics**	
	N	Mean Rank	Sum of Ranks	Mann-Whitney U	461.00
Selfie	54	68.96	3724.00	Wilcoxon W	1736.00
Questionnaire	50	34.72	1736.00	Z	-5.851
Total	100			Asym. Sig. (2-tailed)	<.001

4.4.2. Enjoyment

Table 8 shows the results of the Mann-Whitney U test between *Type of skin analysis* and *Enjoyment*. By looking at the mean ranks, respondents who had the selfie scenarios ranked *Enjoyment* higher than those with the questionnaire scenarios. Thus, an AI-based service that involves a selfie skin analysis is perceived to be more enjoyable than an AI-based service with a questionnaire skin analysis ($U = 704.50$, $p = <.001$). The hypothesis ***H4b*** is supported.

Table 8. Mann-Whitney U test results for *Enjoyment.*

Mann-Whitney U test Results					
Ranks				**Test Statistics**	
	N	Mean Rank	Sum of Ranks	Mann-Whitney U	704.50
Selfie	54	64.45	3480.50	Wilcoxon W	1979.50
Questionnaire	50	39.59	1979.50	Z	-4.225
Total	100			Asym. Sig. (2-tailed)	<.001

4.4.3. Innovativeness

To study the relationship between *Type of recommended products* and *Innovativeness*, another Mann-Whitney U test was run. As **Table 9** shows, the mean rank is higher for personalized products than existing products. Respondents with the scenarios of personalized products had a higher perception of *Innovativeness* compared to respondents with existing products scenarios ($U = 269.50$, $p = <.001$). ***H5a*** is supported.

Table 9. Mann-Whitney U test results for *Innovativeness.*

Mann-Whitney U test Results					
Ranks				**Test Statistics**	
	N	Mean Rank	Sum of Ranks	Mann-Whitney U	269.50
Existing	58	34.61	2007.50	Wilcoxon W	2007.50
Personalized	46	75.05	3452.50	Z	-6.816
Total	100			Asym. Sig. (2-tailed)	<.001

4.4.4. Trust

Table 10 reports the results of the Mann-Whitney U test results for *Type of recommended products* and *Trust*. Existing products have a higher mean rank than personalized products. An AI-based service which recommends existing products has a higher perceived *Trust* than a service that recommends personalized products ($U = 871.50$, $p = .002$). Thus, ***H5b*** is supported.

Table 10. Mann-Whitney U test results for *Trust.*

Mann-Whitney U test Results					
Ranks				**Test Statistics**	
	N	Mean Rank	Sum of Ranks	Mann-Whitney U	871.50
Existing	58	60.47	3507.50	Wilcoxon W	1952.50
Personalized	46	42.45	1952.50	Z	-3.076
Total	100			Asym. Sig. (2-tailed)	.002

4.5. Ordinal regressions

To determine which variables are predictors of the ordinal dependent variables *Perceived Ease of Use*, *Perceived Usefulness*, *Behavioral Intention* and *Purchase Intention*, ordinal logistic regressions were conducted.

4.5.1. Perceived Ease of Use

In order to test the effect of the variables *Rapidity* and *Enjoyment* on *Perceived Ease of Use*, an ordinal regression was used. **Table 11** shows the results of the ordinal regression. There is a positive relationship between *Perceived Ease of Use* and the variables *Rapidity* ($\beta = .731$, $p = <.001$) and *Enjoyment* ($\beta = .467$, $p = .008$), *Rapidity* having the highest impact. Hence, consumers with a higher perceived rapidity and consumers with a higher perceived enjoyment have a higher perceived ease of use and the hypothesis ***H6*** and ***H7*** are supported.

Table 11. Ordinal regression - *Rapidity* and *Enjoyment* on *Perceived Ease of Use*.

Parameter Estimates								
							95% Confidence Interval	
		Estimate	Std. Error	Wald	df.	Sig.	Lower Bound	Upper Bound
Threshold	[PEOU = 3.00]	-.138	1.221	.013	1	.910	-2.532	2.256
	[PEOU = 3.33]	.643	.974	.436	1	.509	-1.266	2.552
	[PEOU = 3.67]	1.591	.830	3.671	1	.055	-.036	3.219
	[PEOU = 4.00]	2.243	.795	7.965	1	.005	.685	3.801
	[PEOU = 4.33]	3.025	.792	14.594	1	<.001	1.473	4.576
	[PEOU = 4.67]	3.629	.806	20.280	1	<.001	2.050	5.209
	[PEOU = 5.00]	4.227	.828	26.077	1	<.001	2.605	5.849
	[PEOU = 5.33]	4.639	.845	30.105	1	<.001	2.982	6.296
	[PEOU = 5.67]	5.133	.869	34.923	1	<.001	3.431	6.836
	[PEOU = 6.00]	6.823	.960	50.532	1	<.001	4.942	8.704
	[PEOU = 6.33]	7.821	1.011	59.865	1	<.001	5.840	9.803
	[PEOU = 6.67]	8.646	1.057	66.935	1	<.001	6.574	10.717
Location	RAP	.731	.167	19.191	1	<.001	.404	1.057
	ENJ	.467	.177	6.942	1	.008	.120	.815

4.5.2. Perceived Usefulness

Table 12 shows the results of the ordinal regression between the variables *Perceived Usefulness* and *Innovativeness* and *Trust*. As a result, *Innovativeness* ($\beta = .362$, $p = <.001$) and *Trust* ($\beta = 1.077$, $p = <.001$) have a positive effect on *Perceived Usefulness*, *Trust* having a higher effect than *Innovativeness*. Thus, consumers with a higher perceived innovativeness and consumers with a higher perceived trust have a higher perceived usefulness. The hypothesis ***H8*** and ***H9*** are supported.

Table 12. Ordinal regression - *Innovativeness* and *Trust* on *Perceived Usefulness*.

Parameter Estimates								
							95% Confidence Interval	
		Estimate	Std. Error	Wald	df.	Sig.	Lower Bound	Upper Bound
Threshold	[PU = 1.50]	.322	1.163	.077	1	.782	-1.958	2.602
	[PU = 1.75]	1.134	.963	1.386	1	.239	-.754	3.021
	[PU = 2.00]	1.619	.899	3.242	1	.072	-.143	3.381
	[PU = 2.25]	1.950	.873	4.992	1	.025	.239	3.660
	[PU = 2.50]	2.230	.859	6.740	1	.009	.546	3.913
	[PU = 2.75]	3.016	.850	12.597	1	<.001	1.350	4.681
	[PU = 3.00]	3.281	.852	14.818	1	<.001	1.611	4.952
	[PU = 3.25]	3.516	.857	16.843	1	<.001	1.837	5.194
	[PU = 3.50]	3.624	.859	17.805	1	<.001	1.941	5.308
	[PU = 3.75]	3.918	.866	20.448	1	<.001	2.220	5.616
	[PU = 4.00]	4.569	.887	26.508	1	<.001	2.830	6.308
	[PU = 4.25]	4.971	.902	30.367	1	<.001	3.203	6.739
	[PU = 4.50]	5.481	.922	35.321	1	<.001	3.674	7.289
	[PU = 4.75]	5.939	.942	39.792	1	<.001	4.094	7.784
	[PU = 5.00]	6.433	.963	44.593	1	<.001	4.545	8.322
	[PU = 5.25]	7.048	.992	50.453	1	<.001	5.103	8.993
	[PU = 5.50]	7.391	1.009	53.662	1	<.001	5.413	9.368
	[PU = 5.75]	8.017	1.041	59.263	1	<.001	5.976	10.059
	[PU = 6.00]	8.935	1.098	66.245	1	<.001	6.784	11.087
	[PU = 6.25]	9.239	1.120	68.003	1	<.001	7.043	11.435
	[PU = 6.50]	10.205	1.221	69.807	1	<.001	7.811	12.599
	[PU = 6.75]	11.445	1.490	59.021	1	<.001	8.525	14.365
Location	INN	.362	.110	10.918	1	<.001	.147	.577
	TRUST	1.077	.176	37.351	1	<.001	.732	1.422

4.5.3. Behavioral Intention

Another ordinal regression was run to assess the relationship between *Behavioral Intention* and the variables *Perceived Ease of Use*, *Perceived Usefulness* and *Technology Adoption Propensity*. **Table 13** reveals that only *Perceived*

Usefulness has a significant effect on *Behavioral Intention* ($\beta = 1.316$, $p = <.001$). Indeed, the effect of the variables *Perceived Ease of Use* and *Technology Adoption Propensity* is not significant at the 5% level (respectively, $p = .186$ and $p = .622$). Consequently, *Perceived Usefulness* has a positive effect on *Behavioral Intention* and ***H2a*** is supported, whereas no conclusion can be drawn on the effects of *Perceived Ease of Use* and *Technology Adoption Propensity* on *Behavioral Intention*. Hence, ***H1a*** and ***H10*** cannot be supported.

Table 13. Ordinal regression - *Perceived Ease of Use*, *Perceived Usefulness* and *Technology Adoption Propensity* on *Behavioral Intention*.

Parameter Estimates								
							95% Confidence Interval	
		Estimate	Std. Error	Wald	df.	Sig.	Lower Bound	Upper Bound
Threshold	[BI = 1.00]	3.838	1.342	8.173	1	.004	1.207	6.468
	[BI = 1.50]	4.833	1.320	13.408	1	<.001	2.246	7.421
	[BI = 2.00]	5.782	1.341	18.588	1	<.001	3.153	8.410
	[BI = 2.50]	6.123	1.353	20.480	1	<.001	3.471	8.775
	[BI = 3.00]	6.514	1.369	22.657	1	<.001	3.832	9.197
	[BI = 3.50]	6.761	1.379	24.030	1	<.001	4.058	9.464
	[BI = 4.00]	7.414	1.410	27.659	1	<.001	4.651	10.177
	[BI = 4.50]	8.175	1.447	31.908	1	<.001	5.339	11.012
	[BI = 5.00]	9.079	1.490	37.127	1	<.001	6.158	11.999
	[BI = 5.50]	10.490	1.549	45.844	1	<.001	7.454	13.527
	[BI = 6.00]	12.377	1.643	56.739	1	<.001	9.157	15.598
	[BI = 6.50]	12.614	1.662	57.636	1	<.001	9.358	15.871
Location	PEOU	.300	.227	1.750	1	.186	-.144	.745
	PU	1.316	.201	42.806	1	<.001	.922	1.710
	TAP	.078	.159	.242	1	.622	-.233	.390

4.5.4. Purchase Intention

Table 14 shows the results from the ordinal regression of *Perceived Ease of Use*, *Perceived Usefulness*, *Behavioral Intention* and *Involvement Into the Product*

Category on *Purchase Intention*. It can be concluded that *Perceived Usefulness* (β = .961, p = <.001) and *Behavioral Intention* (β = .817, p = <.001) have a significant and positive effect on *Purchase Intention*. However, no conclusion can be drawn regarding the effects of *Perceived Ease of Use* and *Involvement Into the Product Category* as the significance p is higher than α = .05 (respectively, p = .110 and p = .356). All in all, ***H2b*** and ***H3*** are supported, whereas ***H1b*** and ***H11*** cannot be supported.

Table 14. Ordinal regression - *Perceived Ease of Use*, *Perceived Usefulness*, *Behavioral Intention* and *Involvement Into the Product Category* on *Purchase Intention*.

Parameter Estimates							95% Confidence Interval	
		Estimate	Std. Error	Wald	df.	Sig.	Lower Bound	Upper Bound
Threshold	[PI = 1.00]	3.179	1.523	4.359	1	.037	.195	6.164
	[PI = 2.00]	6.078	1.617	14.132	1	<.001	2.909	9.247
	[PI = 3.00]	7.026	1.651	18.102	1	<.001	3.789	10.263
	[PI = 4.00]	8.395	1.706	24.222	1	<.001	5.052	11.738
	[PI = 5.00]	11.390	1.854	37.752	1	<.001	7.757	15.023
	[PI = 6.00]	14.688	2.132	47.449	1	<.001	10.509	18.867
Location	PEOU	-.397	.248	2.559	1	.110	-.883	.089
	PU	.961	.253	14.407	1	<.001	.465	1.457
	BI	.817	.197	17.136	1	<.001	.430	1.204
	IIPC	.135	.147	.851	1	.356	-.152	.423

4.6. The effect of Attitude Toward the Brand on Purchase Intention

On the one hand, the item of the construct *Purchase Intention* measured respondents' intention to purchase the recommended products after reading a brandless AI-based service simulation. On the other hand, the items used for *Attitude Toward the Brand* measured respondents' intention to buy the recommended products after knowing that the recommendation came from an AI-based service proposed by their favorite skincare brand. Consequently, a Wilcoxon Signed Ranks Test was performed to compare the two variables. This test is used when the objective is to determine whether two measurements from a single group differ from each other. **Table 15** reports the results. *Attitude Toward the Brand* (mean rank = 42.54) was rated more favorably than *Purchase Intention* (mean rank = 26.20). The observed difference between the two variables is significant (Z = -6.546, p = <.001). Thus, when respondents are exposed to a brand they like, i.e. when they have a positive attitude toward the brand of the AI-based service, they have a higher purchase intention. As a result, ***H12*** is supported.

Table 15. Wilcoxon Signed Ranks Test results.

Ranks				**Test Statistics**	
ATB-PI	N	Mean Rank	Sum of Ranks	Z	-6.546
Negative ranks	10	26.20	262.00	Asym. Sig. (2-tailed)	<.001
Positive ranks	70	42.54	2978.00		
Ties	24				
Total	104				

4.7. Recap of the results

Table 16 summarizes the results we obtained for our 16 hypotheses.

Table 16. Hypothesis results.

Hypothesis	**Path**	**Conclusion**
H1a	PEOU → BI	Not supported
H1b	PEOU → PI	Not supported
H2a	PU → BI	Supported
H2b	PU → PI	Supported
H3	BI → PI	Supported
H4a	Selfie → RAP	Supported
H4b	Selfie → ENJ	Supported
H5a	Personalized → INN	Supported
H5b	Existing → TRUST	Supported
H6	RAP → PEOU	Supported
H7	ENJ → PEOU	Supported
H8	INN → PU	Supported
H9	TRUST → PU	Supported
H10	TAP → BI	Not supported
H11	IIPC → PI	Not supported
H12	ATB → PI	Supported

5. General discussion

Faced with the rise of new technologies, and Artificial Intelligence in particular, companies in all sectors are trying to take advantage of these new tools. Indeed, more and more technological means are being deployed to improve the customer experience and boost sales. These technologies can be found in recommendation systems, ways of trying out or viewing products, payment methods and so on. The cosmetics industry is no exception.

Indeed, some cosmetics companies are using Artificial Intelligence in various forms, such as virtual make-up trials, product recommendations (based on what similar customers have seen, liked or bought, or based on what the consumer has liked or bought previously, but also thanks to questionnaires or skin analysis tools via a photo) or the development of real-time customer service, via a chatbot able to answer consumers' questions. Therefore, the use of Artificial Intelligence is set to expand in all sectors, including cosmetics.

In our study, we have decided to focus on two different types of recommendation systems powered by Artificial Intelligence in the cosmetics industry: via a questionnaire and via a selfie skin analysis. Also, we have decided to analyze two categories of recommended products: products that already exist in a brand's product range, or entirely new and customized products, adapted to each consumer's skin.

Our goal was to determine which combination (type of Artificial Intelligence x type of recommended products) was the most effective, i.e. would lead to the highest purchase intention; but also to understand the underlying mechanics: what motivates users to use the digital service? What drives them to develop a purchase intention?

By developing a framework based on previous research, we have been able to provide a deeper understanding of the effect of Artificial Intelligence and recommended products on purchase intention in the cosmetics field.

First of all, we have determined that *Perceived Usefulness* positively affects *Behavioral Intention* and *Purchase Intention*, which means that if a consumer finds the digital service useful, she will be more likely to use it and also to have the intention to buy the recommended products.

Also, *Behavioral Intention* itself has a positive impact on *Purchase Intention*, which means that if the consumer uses the digital service, she is more likely to intend to buy the recommended products, thus proving that in our situations, Artificial Intelligence has a positive impact on purchase intention. These findings support the Technology Acceptance Model developed by Davis (1989).

However, in the TAM, *Perceived Ease of Use* also has been proven to positively affect *Behavioral Intention* and *Purchase Intention*, but our results do not allow us to validate these relationships in our study.

Furthermore, we wished to determine some factors that drive *Perceived Usefulness* and *Perceived Ease of Use*. *Perceived Usefulness* is driven by factors linked to the type of recommended products, which are *Innovativeness* and *Trust*. Indeed, the more innovative users find the products and the more confidence they have in them, the more useful the digital service will be perceived to be.

Perceived Ease of Use is driven by factors linked to the type of skin analysis, which are *Rapidity* and *Enjoyment*. The more rapid and enjoyable users find the way to analyze their skin, the more easy to use the digital service will be perceived to be.

Besides, we wanted to ascertain which type of skin analysis is perceived as more rapid and which type of skin analysis is perceived as more enjoyable. In the same way, we wanted to determine which type of recommended products is perceived as more innovative and which type of recommended products is perceived as more trustworthy. The results are that both *Rapidity* and *Enjoyment* are higher for the scenarios in which the skin analysis is performed via a selfie, which means that selfie skin analysis is perceived as both more rapid and more enjoyable compared to a questionnaire.

Regarding the type of recommended products, the results are more dispersed: while *Innovativeness* is higher for personalized products, *Trust* is higher for existing products. It means that personalized products are perceived as more innovative compared to existing products whereas existing products are perceived as more trustworthy compared to personalized products.

Finally, we wanted to find out if three factors external to the Artificial Intelligences involved have an impact on *Behavioral Intention* or *Purchase Intention*. More precisely, we wanted to know if *Technology Adoption Propensity* has an impact on *Behavioral Intention* and if *Involvement Into Product Category* and *Attitude Toward the Brand* have an impact on *Purchase Intention*.

Concerning *Technology Adoption Propensity*, the effect on *Behavioral Intention* is not significant, which means that the fact that the user is either very comfortable with new technologies or not at all (in relation to the speed of understanding of new technologies, frequency of use, appreciation of these technologies, etc.) does not affect her *Behavioral Intention*, i.e. if she is going to use the digital service or not.

Regarding *Involvement Into Product Category*, the effect on *Purchase Intention* is not significant either, which means that the fact that the consumer is very used to buying cosmetics and particularly appreciates cosmetics or not at all does not affect her *Purchase Intention* regarding the recommended products.

Finally, about *Attitude Toward the Brand*, the effect on *Purchase Intention* is both significant and positive, which means that if the consumer likes the brand by which the digital service is powered, she is more likely to intend to buy the recommended products.

6. Managerial implications

The current speed of development and adoption of Artificial Intelligence is challenging managers to exploit this transforming technology to enhance the customer experience. Our findings are useful for managers in navigating the outstanding technological opportunities that are developing in today's marketplace.

First of all, we have shown the positive link between *Behavioral Intention* and *Purchase Intention*. Thus, managers should use a digital service powered by Artificial Intelligence to recommend products to customers: when they use this digital service, it will increase their intention to buy the recommended products, and therefore potentially increase sales.

Besides, we have shown that to maximize *Purchase Intention* and *Behavioral Intention*, *Perceived Usefulness* also has to be maximized. Thus, managers should seek to enhance the usefulness that users perceive of their digital service for recommending products. Furthermore, we have shown that *Innovativeness* and *Trust* have a positive effect on *Perceived Usefulness*. Therefore, to improve the usefulness of the digital service that consumers perceive and consequently their intention to use this digital service and buy the products, managers need to maximize the trust that consumers have in the recommended products and the level of product innovation that consumers perceive. Indeed, the more trustworthy and innovative the recommended product is perceived to be, the more useful the digital service will be perceived to be, and therefore the higher the purchase intention will be.

Finally, our research allowed us to determine which type of skin analysis combined with which type of recommended products is the most effective, i.e. leads to the highest purchase intention. Indeed, as shown in **Table 3**, the group for which the mean of *Purchase Intention* is the highest is group 1, which was exposed to the scenario selfie x existing products. Also, group 1 is the group for which the standard deviation of *Purchase Intention* is the lowest. Thus, to maximize consumers' purchase intention and thus potentially lead to more sales, managers should use a selfie to analyze the skin of the users, and recommend products that already exist in their products range.

However, still looking at **Table 3**, we can note that for the construct *Attitude Toward the Brand*, which measures purchase intention considering that the respondent likes the brand that uses the digital service, the mean is the highest and the standard deviation the lowest for group 2, which was exposed to the scenario selfie x personalized products. Thus, if the brand is particularly popular, we advise managers to recommend personalized products rather than existing products.

7. Limitations and suggestions for further research

Our study has some limitations. First of all, the Technology Acceptance Model, developed by Davis in 1989, is not totally supported in our research, since ***H1a***, which hypothesized that *Perceived Ease of Use* had a positive effect on *Behavioral Intention*, is rejected. Indeed, **Table 13** shows that even if the estimate is positive ($\beta = .300$), the effect is not significant because $p > .001$. This inconsistency with Davis' theory, which has been used in many research papers, which undoubtedly highlights the popularity of the model in the field of technology acceptance (Marangunic and Granic, 2015), may be caused by the fact that our sample is too small.

Besides, when developing our thesis and our surveys, we have placed ourselves in a framework where the technology involved works perfectly and identically on all devices. Nevertheless, we are well aware that technology has its share of bugs, and that not everyone is equal when it comes to technology. This was clearly expressed, for example, by the participants in our in-depth interview during the trial of the second digital service, when they had to take a selfie. For one of them, the application did not work on her phone. For another, it took several tries and a specific light before she could take her selfie. One participant added: "Maybe they're basing the selfie analysis on the quality of the photo, so if my phone isn't great, I could look old or too young". As a result , before focusing on the specific attributes of an AI-based service, managers should make sure that the technology they are offering to consumers is high-level. Indeed, the process of using it should be as smooth as possible so that consumers are not negatively biased by the technology performance.

Also, even if we studied the effect of the trust in the recommended products, we did not study the effect of the trust in Artificial Intelligence. Indeed, during the in-depth interview, participants expressed many doubts about the reliability and accuracy of the skin analysis results.

Regarding the first digital service, we collected comments such as "My diagnosis targets eczema, when I don't have any", "I think it's not ultra reliable" or "I still have this doubt of: is it really what I need?".

Concerning the second digital service, they said "They say my skin is only 22 years old, maybe it's a marketing trick to flatter you", "I'm 19. But on what basis are they telling me all this?", "It's not possible that my skin is 20, I find it strange that it's younger than my age when I have fine lines under my eyes. I don't really believe it" or "I wonder how suitable it is for me, or do they give the same recommendation to everyone".

Finally, one of them mentioned the lack of human input: "We still need that human opinion, because AI is cool but it's not enough, it's just a complement".

These observations are in line with the results of various studies, which show that in some cases, consumers can be reluctant to use AI. For example, research showed that for medical decisions people prefer to have a human provider rather than an AI one, even when the AI performance is higher. This resistance was eliminated when the role of the AI provider was limited and was supporting a human provider (Longoni et al., 2019).

Besides, Longoni and Cian (2022) argued that consumers prefer AI recommenders over human ones when the product choice has an utilitarian goal and prefer human recommenders over AI ones when the product choice has an hedonic goal. Also, this effect is eliminated when AI is hybrid, which means that the recommendation system mixes AI recommendation and human viewpoint. Concerning skincare products, the consumption goal seems to be unclear. Indeed, hedonic consumption is linked to experiential, emotional and sensory evaluative dimensions, while utilitarian consumption is linked to factual, rational and logical evaluative dimensions (Botti and McGill, 2011). Thus, it is hard to define the consumption goal of skincare products since it seems to be partly utilitarian (factual, rational and logical tasks like erase or reduce redness, wrinkles, dark circles, pimples or blackheads, make the skin less dry and so on) and partly hedonic (experiential, emotional and sensory tasks like be pleasant to the touch, smell good and so on). Therefore, we cannot really use Longoni and Cian's paper to define if consumers prefer AI or human recommenders in the cosmetics field.

Despite some limitations, we believe this study provides a wider understanding of the effect of recommendations and Artificial Intelligence on purchase intention in the cosmetics industry. As mentioned before, we would suggest that it could be interesting for future research to assess both the effect of the trust in Artificial Intelligence on behavioral intention and purchase intention, and the effect of an hybrid recommendation system (which combines Artificial Intelligence and human thoughts) rather than an AI-based one.

Also, our study focuses only on women, since we considered that women were more concerned by cosmetics than men. However, we are aware that men are using more and more cosmetics, and it could be interesting to extend the research to men, to compare the results and see the other factors that come to play a part in their decision journey.

Besides, during the in-depth interview, participants mentioned the possibility of combining the analysis of a selfie with a questionnaire to obtain a more complete analysis and more reliable results. Thus, it could be interesting to explore this option and compare the results with the analysis based on a selfie only and that based on a questionnaire only.

Finally, future research could focus on other types of Artificial Intelligence applications in the cosmetics field. For example, some brands have developed or are willing to develop a real-time customer service, via a chatbot able to answer consumers' questions; and it could be interesting to explore the effect of this type of Artificial Intelligence in the customer experience. Also, our study focused on skincare products, but one of the most famous application of Artificial Intelligence in the cosmetics industry lies in the makeup virtual try-on: rather than going into a shop to try on products, or buying blind without having tried them on, many brands have developed a digital service that allows users to try on make-up virtually by taking a selfie. It would be interesting to know the effect of this kind of Artificial Intelligence on purchase intention, using the Technology Acceptance Model (via perceived ease of use, perceived usefulness and behavioral intention).

Appendix

Appendix 1. Four different survey scenario descriptions

A. **Selfie x personalized products**

Imagine the following situation:

You decide to go on a cosmetics brand website in order to buy skincare products. You see that the brand is now offering a digital service that will create your own personalized skincare products that best fit your personal needs.

You decide to try this new digital service.
It is written that you only have to take a selfie. Then, a few seconds later, thanks to the selfie analysis, the website gives you ratings and information on different characteristics of your skin (skin age, firmness, clarity and even tone).

Finally, the service recommends you an entire skincare routine composed of three completely new and unique products with personalized formulas that are adapted to your skin.
You cannot read any customer review to know if the recommended products work since they are new and especially created for you.

At the end, you can decide if you want to buy the entire routine or a selection of the products.

B. **Selfie x existing products**

Imagine the following situation:

You decide to go on a cosmetics brand website in order to buy skincare products. You see that the brand is now offering a digital service that will help you to find the skincare products that best fit your personal needs.

You decide to try this new digital service.

It is written that you only have to take a selfie. Then, a few seconds later, thanks to the selfie analysis, the website gives you ratings and information on different characteristics of your skin (skin age, firmness, clarity and even tone).

Finally, the service recommends you three products adapted to your skin among the brand's product range. Those products are well-known from the brand and you can read reviews of customers who are satisfied with the products.

At the end, you can decide to buy all or part of the products.

C. Questionnaire x personalized products

Imagine the following situation:

You decide to go on a cosmetics brand website in order to buy skincare products. You see that the brand is now offering a digital service that will create your own personalized skincare products that best fit your personal needs.

You decide to try this new digital service.
It is written that you have to answer a three-minute multiple choice questionnaire to formulate your custom skincare.
The questionnaire asks you several questions such as "What are your main skin concerns?" or more specific ones that require some thoughts such as "How often do you experience facial redness?".
You realize that it actually took you ten minutes to complete the questionnaire.

Finally, after having completed the questionnaire, the service recommends you an entire skincare routine composed of three completely new and unique products with personalized formulas that are adapted to your skin.
You cannot read any customer review to know if the recommended products work since they are new and especially created for you.

At the end, you can decide to buy the entire routine or a selection of the products.

D. Questionnaire x existing products

Imagine the following situation:

You decide to go on a cosmetics brand website in order to buy skincare products. You see that the brand is now offering a digital service that will help you to find the skincare products that best fit your personal needs.

You decide to try this new digital service.
It is written that you have to answer a three-minute multiple choice questionnaire to formulate your custom skincare.
The questionnaire asks you several questions such as "What are your main skin concerns?" or more specific ones that require some thoughts such as "How often do you experience facial redness?".
You realize that it actually took you ten minutes to complete the questionnaire.

Finally, after having completed the questionnaire, the service recommends you three products adapted to your skin among the brand's product range. Those products are well-known from the brand and you can read reviews of customers who are satisfied with the products.

At the end, you can decide to buy all or part of the products.

Appendix 2. Survey development and sources.

Constructs	Items	References
Involvement into the product category (IPC)	***IPC-1***: I rate skincare products as being of the highest importance to me personally.	Lastovicka (1979)
	IPC-2: I can remember having purchased a skincare product in the last month.	
	IPC-3: Generally, I am someone who finds it important what skincare products I buy.	De Wulf et al. (2001)
	IPC-4: Generally, I am someone who is interested in the kind of skincare products I buy.	
Technology adoption propensity (TAP)	***TAP-1***: In general, I am among the first in my circle of friends to try new technology when it appears.	Parasuraman (2000)
	TAP-2: I can usually figure out new high-tech products and services without help from others.	
	TAP-3: I am always open to learning about new and different technologies.	

Rapidity (RAP)	***RAP-1***: This digital service is time efficient. ***RAP-2***: This digital service takes a long time.	Van Dolen et al. (2007)
Enjoyment (ENJOY)	***ENJOY-1***: I find using the digital service to be enjoyable. ***ENJOY-2***: The actual process of using the digital service seems pleasant. ***ENJOY-3***: I would have fun using this digital service.	Venkatesh and Bala (2008)
Perceived ease of use (PEOU)	***PEOU-1***: I would find this digital service is easy to use. ***PEOU-2***: I believe that using this digital service does not require a lot of mental effort. ***PEOU-3***: I think that I would find it easy to learn how to use this digital service.	Davis (1989) Har Lee et al. (2011) Khare et al. (2012)
Perceived usefulness (PU)	***PU-1***: I believe that using this digital service would make it easier to find the best skincare products. ***PU-2***: I believe that using this digital service would enable me to find the best skincare products more quickly. ***PU-3***: I would find this digital service useful in finding skincare products that fit my needs. ***PU-4***: I find shopping with this digital service more convenient compared with shopping without it.	Davis (1989) Har Lee et al. (2011)
Innovativeness (INN)	***INN-1***: The recommended products are unique. ***INN-2***: The recommended products are new. ***INN-3***: The recommended products are innovative.	Watchravesringkan et al. (2010)
Trust (TRUST)	***TRUST-1***: I think that the recommended products are trustworthy. ***TRUST-2***: I think that the recommended products keep promises and commitments.	Pavlou (2003)
Behavioral intention (BI)	***BI-1***: I would definitely like to visit this digital service in future purchases. ***BI-2***: I predict I will use this digital service in the future.	Venkatesh et al. (2003) Kautish and Sharma (2018)

Purchase intention (PI)	***PI-1***: I would most probably purchase the recommended products.	Dabholkar and Sheng (2012)
Attitude toward the brand (ATB)	***ATB-1***: I would buy the products recommended by this brand because I really like it. ***ATB-2***: If I was to buy a recommended product, I would prefer the digital service to be from this skincare brand if everything else was equal.	Bobâlcă et al. (2012) Chen and Chang (2008)

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