# Smart Digital Signage with facial recognition as in-store personalization enhancer: a study on Italian consumers' perceptions and elasticity to be recognized during the shopping experience

Alice D'Uonno

Dissertation written under the supervision of Cristina Mendonça

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**Abstract**

**Title:** Smart Digital Signage with facial recognition as in-store personalization enhancer: a study on Italian consumers' perceptions and elasticity to be recognized during the shopping experience
**Author:** Alice D'Uonno

In today's rapidly evolving retail landscape, driven by consumers demand for extreme levels of personalization, smart Digital Signage stands out as a game changer for enhancing in-store consumer experience. In this context, recent technological advancements are empowering the next generation of brick-and-mortar stores to leverage consumer-facing smart technologies that, integrated to smart Digital Signage, would allow to offer unparalleled personalization levels to their customer base.

As smart Digital Signage with facial recognition has never been studied, this thesis aims to fill this substantial gap through a comprehensive approach that combines qualitative and quantitative analyses. Consumers' associations towards the technology and their elasticity to be recognized were investigated, and the existence of strong generational differences have been highlighted. In particular, younger consumers had more positive associations towards the technology and were more willing to be recognized in stores. Then, when studying the incentives that would positively affect consumers' elasticity to be recognized, the results showed how they do not have enough power to motivate those consumers who showed reluctancy towards the technology. Lastly, the conjoint analysis outlined the best-case scenario for introducing the technology in stores, while the cluster analysis identified distinct consumer clusters within the Italian market highlighting the existence of a specific cluster ready to embrace this innovation.

This thesis can be considered the starting point of a new wave of research on smart Digital Signage with facial recognition, essential to be prepared for a retail future that will be shaped by technologies and extreme personalization standards.

**Keywords:** smart Digital Signage, facial recognition, smart retail, personalization-privacy paradox, personalization

**Sumário**

**Título:** Sinalética digital inteligente com reconhecimento facial como fator de personalização na loja: um estudo sobre as percepções e a elasticidade dos consumidores italianos para serem reconhecidos durante a experiência de compra
**Autor:** Alice D'Uonno

No atual cenário de retalho em rápida evolução, conduzido pela exigência dos consumidores de níveis extremos de personalização, a Sinalização Digital inteligente destaca-se como um fator de mudança para melhorar a experiência do consumidores. Neste contexto, os recentes avanços tecnológicos estão a permitir que a próxima geração de lojas aproveite as tecnologias inteligentes viradas para o consumidor que, integradas na Sinalética Digital Inteligente, permitem oferecer níveis de personalização sem paralelo.
Dado que a Sinalética Digital inteligente com reconhecimento facial nunca foi estudada, esta dissertação preenche esta lacuna através de uma metodologia que combina análises qualitativas e quantitativas. Foi investigada a associação dos consumidores à tecnologia e a sua elasticidade para serem reconhecidos, evidenciando a existência de fortes diferenças geracionais. Em particular, os consumidores mais jovens tinham associações mais positivas e estavam mais dispostos a ser reconhecidos nas lojas. Depois, ao estudar os incentivos que afectariam a elasticidade dos consumidores para serem reconhecidos, os resultados mostraram que estes não têm poder suficiente para motivar os consumidores que mostraram relutância em relação à tecnologia. Por último, a análise conjunta delineou o melhor cenário para a introdução da tecnologia, enquanto a análise de grupos identificou grupos de consumidores distintos no mercado italiano, destacando a existência de um grupo pronto para adotar esta inovação.
Esta dissertação pode ser considerada o ponto de partida de uma vaga de investigação sobre Sinalética Digital inteligente com reconhecimento facial, essencial para estar preparado para um futuro do retalho que será moldado por tecnologias e elevados requisitos de personalização.

**Palavras-chave:** Sinalética Digital inteligente, reconhecimento facial, retalho inteligente, paradoxo personalização-privacidade, personalização

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## 1. Introduction

To date, we are witnessing an unprecedent technological retail revolution (Grewal et al., 2020). The adoption of digital technologies in physical stores is rapidly increasing due to the ongoing technological advances and consumers' expectations for new technologies (Pantano & Vannucci, 2019). Indeed, with reference to the latter, the results of research conducted by Cite Research showed that 81% of consumers expect to use digital technologies in physical stores by 2030 (Tan, 2019). All this has contributed to the development of the so-called smart retail (Pantano & Dennis, 2019), a new retail environment that engages consumers in increasingly efficient and satisfying shopping experiences using technology. In the current scenario, Digital Signage (DS) can be considered one of the main elements that enhance the digitalization of the physical store. DS refers to an electronic display that exhibits various forms of multimedia content, including audio, video, images, and text, for various objectives. As it is the third most adopted technology across retailers (Pantano & Vannucci, 2019), DS systems are widely diffused, and its adoption has grown over the years: in 2022, the global DS market was valued at approximately USD 25.1 billion, and it is projected to grow at a compound annual growth rate of 7.7% to 2032 (Market.us, 2023).

DS provides numerous advantages to retailers, including increased consumer attention and engagement (Magner, 2020), improved recall rates of brand and advertising (Meadows, 2016), and the potential to enhance in-store traffic, customer satisfaction, and sales (Burke, 2009; Dennis et al., 2010). However, there are also some disadvantages to consider, such as the potential for display blindness (Müller et al., 2009), which happens when consumers ignore displays when content is too generic, and the high initial investment required for installing DS systems (Stan, 2021). The integration of advanced technologies (e.g., sensors, the internet of things, and Artificial Intelligence) that makes DS become smart helps overcome the challenges of traditional DS: As smart DS is a type of Technology-Enabled Personalization (TEP), it allows the reduction of display blindness risks by displaying hyper-personalized content based on real-time audience detection and targeting (Garaus et al., 2021). Display blindness is also reduced by enabling consumers to interact with the display via interactive features (Bauer et al., 2011). Lastly, the initial investment is amortized and justified by the possibility of remote control of content that allows real-time flexibility (Bauer et al., 2011) and of data collection to improve content personalization and enhance data-driven decision making (Raydiant, 2022). To summarize, DS has significant benefits for retailers while smart DS technologies offer even greater advantages by addressing the limitations of traditional DS systems.

The present study focuses on smart DS and, in particular, on smart DS with facial recognition systems and its (potential) application in Italy. This technology allows retailers to offer a certain personalization that could not be offered with standard DS systems, while keeping consumers' attention high and better engaging with them. At the same time, as this study will center on the Italian landscape, the collection and processing of consumer data must be compliant with the General Data Protection Regulation (GDPR). Because of this, smart DS's full potential is not being exploited today by retailers and content is not as personalized as it could be. Indeed, the few European retailers that currently apply facial recognition technologies to their DS are generally using systems that only detect facial features instead of identifying individuals. In other words, the current smart DS systems are estimating demographic features such as gender and age (to display content accordingly), instead of recognizing the precise identity of the viewer (Hoh, 2021). If it would be possible to actually recognize, under consent, the identity of the consumer entering the store, the content shown by the digital display could be tailored to a specific viewer, offering high levels of personalization. Personalization that, in a way, has been happening for a long time in the online environment (e.g., targeted ads based on cookie tracking) and to which consumers are used to. In the offline world, though, privacy concerns seem to still be high. All of this embodies what the literature has defined as the personalization-privacy paradox. Indeed, if on one hand there might be privacy fears, on the other hand consumers today want more personalization: A recent McKinsey study (Arora et al., 2021) showed that more than 71% of consumers expect companies to deliver personalized interactions in store, associating personalization with positive experiences and a feeling of being important. Also, this research found that consumers expect the companies they buy from to "recognize them as individuals and know their interests" (p. 4).

While many studies have been conducted on traditional DS, only a few studies have investigated consumers' attitudes towards smart DS with facial recognition technology. At the same time, we are living in a context where technologies are advancing at an unprecedented speed and authors are calling for more research in the smart DS area.

## 1.1 Problem Statement

The objective of this thesis is to investigate consumers' perceptions and attitudes towards the possibility of being recognized as individuals to receive greater in-store personalization via smart DS solutions. The focus of this thesis will be on the consumer side, as without their involvement, retailers could never exploit the opportunities that this technology can provide in terms of enhanced consumer experience and sales.

Given this objective, the thesis will aim at answering the following research problem: What is Italian consumers' elasticity to be recognized in a retail context to receive personalized communications and interactions?

Under this problem, the research will aim at providing an answer to the following research questions:
RQ1: What are consumers' perceptions towards smart DS with facial recognition?
RQ2: What type of incentives could motivate consumers to identify themselves in a store, thus overcoming the personalization-privacy paradox?
RQ3: What would be the optimal and most appreciated scenario to start introducing the technology in terms of retailer typology, content type, display medium, and recognition modality?
RQ4: Are there specific segments in the Italian population more willing to be recognized in-store through facial recognition to receive personalized services via smart DS?

To investigate these research questions, this thesis employs a mixed-methods approach. Firstly, I conducted a qualitative analysis with two focus groups and six in-depth interviews, involving both males and females belonging to four generational cohorts (Baby Boomers, Generation X, Millennials, and Generation Z). The insights obtained from this phase of the research served, in combination with the literature review, as the basis for the quantitative research. The quantitative analysis was then conducted through a questionnaire administered to Italian consumers. The data gathered through the online questionnaire were analyzed through SPSS.

### 1.2 Academic and managerial relevance

The purpose of this thesis is to fill a large literature gap. Despite an increased use of TEP in retail, academic research on these technologies and on their effects on consumers has been surprisingly limited (Riegger et al., 2021). In fact, Foroudi and colleagues (2018) have stressed the need to explore more deeply consumers' acceptance of smart displays, among the smart retail technologies (Foroudi et al., 2018). Also, personalization topics in physical places have been much less researched than in online environments (Bauer et al., 2018). For example, Pizzi and Scarpi (2020) have highlighted how, while privacy concerns in the online environment have received significant attention from scholars, the same level of focus in the offline environment has been lacking (Pizzi & Scarpi, 2020). This situation is consequently reflected also on smart DS with facial recognition. Lee and Choo (2019) have indeed highlighted how even if smart DS advertising is experiencing an accelerated growth – that is predicted to continue – academic research on this topic is not following the same trend. Similarly, in analyzing consumers' perceptions towards facial recognition technologies, Seng and colleagues (2021) have emphasized how they are expected to change in response to technological advancements, alterations in privacy and security regulations, and emerging narratives surrounding facial recognition, and that new studies are needed to capture these possible changes (Seng et al., 2021). Lastly, apart from one study conducted by Pantano and colleagues (Pantano et al., 2022), all the research that have been reviewed for this thesis does not focus on the Italian consumers and landscape, even if the Italian retail market is a significant one worldwide. Moreover, Pantano and colleagues' study only gives a first overview on consumers' attitudes towards facial recognition technologies in smart retail in general, without investigating their application to smart DS systems.

Regarding the managerial relevance, this study will provide retailers with a first overview of the attitudes of Italian consumers towards smart DS with facial recognition. With the growing importance of data-driven marketing and personalized customer experiences, understanding the factors that influence Italian consumers' acceptance of in-store facial recognition can provide retailers with a great competitive edge. Also, this thesis aims at identifying a segment of Italian consumers more willing to accept smart DS with facial recognition while defining the type of content that retailers should show on display, the incentives they should provide to consumers, and the way they should "sell" facial recognition. All of this will support retailers in making informed decisions regarding the adoption and implementation of this technology in their stores.

### 1.3 Structure

Subsequent to this introduction, the thesis is organized as follows: Chapter 2 presents the literature review. First, an overview of what smart DS is and how facial recognition can be applied to it is given. Second, the personalization topic in smart retail with focus on the personalization privacy paradox is presented. Third, the technology acceptance model is followed by an analysis of consumers' acceptance of TEP and then, more specifically, their attitudes towards facial recognition technologies.

Chapter 3 and 4 respectively go through the qualitative and quantitative analysis conducted to provide answers to the research questions. Chapter 5 presents the discussion by summarizing the analyses' results also in relation to existing literature, deriving managerial implications, and highlighting the limitations of this thesis. Finally, Chapter 6 offers a brief conclusion.

## 2. Literature Review

### 2.1 From Digital Signage to smart Digital Signage

According to Lafitte (2019), DS refers to the usage of digital display technologies, such as LCD, LED, or projection screens, to convey information, advertisements, or messages to a targeted audience in several settings such as public spaces, retail stores, corporate environments, transportation hubs, or other locations where people gather. DS's three main components are the hardware, the software, and the content management system (Lafitte, 2019). Starting from the modern age, all the three components have embraced a constant and strong evolution (Lafitte, 2019). The hardware includes the physical equipment used to display content, which typically consists of displays, such as LCD or LED screens, video walls, interactive kiosks, or projection systems (Lafitte, 2019). These devices are designed to showcase high-quality visuals and can be installed in various sizes and formats (Lafitte, 2019). DS software provides the tools and capabilities to manage and control the content displayed on the hardware, and it enables users to create, schedule, and distribute content across one or multiple displays (Lafitte, 2019). Lastly, the content management system serves as the central platform for content creation, organization, and distribution (Lafitte, 2019). It enables users to upload media assets, design templates, arrange content playlists, schedule playback times, and target specific screens or groups of screens (Lafitte, 2019).

Digital signs are part of our everyday life as they have several functions: They can be placed inside or outside stores to advert products sold by the retailer, they can have an informational function, giving product-related information to consumers, or even an interactive function, by making the consumers interact with the display to order, pay, or even play games. To give a concrete example, Esselunga, an Italian supermarket chain, has implemented a DS system inside its stores giving the DS multiple functions (Visconti, 2017): Some displays were placed next to the cashiers to entertain consumers with advertising while waiting in line. Others, like the "virtual sommelier", were placed in the aisles, allowing consumers to discover product information. Lastly, consumers could also order and pay for their ready meals from interactive touchscreen totems.

DS has been widely demonstrated to provide numerous advantages to retailers. One of the primary benefits of DS is its ability to engage consumers. As DS captures 400% more views than paper displays (Magner, 2020), it is a powerful tool for attracting consumers' attention. Additionally, DS has been shown to have a positive impact on consumers' brand and advertising recall rates (Meadows, 2016). DS can also be used to increase in-store traffic, customer satisfaction, and sales. In particular, research by Burke (2009) and Dennis and collaborators (2010) has shown that DS technology can increase both customer traffic and time spent at the point of sale, leading to potential sales opportunities. Moreover, DS has been classified as an in-store experience provider, and studies have demonstrated how it can be successfully used to evoke sensory experiences to positively influence consumers' purchasing intentions (Dennis et al., 2010). For instance, DS with affective content that enhances positive emotions seems to increase impulsive purchases and store loyalty (Garaus et al., 2017). Garaus and Wagner (2019) have also studied how DS positively influences store satisfaction and store experience through a reduction of the perceived waiting time.

Despite the prevalence of advantages, there are also some disadvantages that should be considered when dealing with DS. Firstly, installing DS systems may require a high initial investment due to hardware and software costs (Stan, 2021). Secondly, and most importantly, as displayed content might be generic, it is possible that a so-called display blindness emerges (Müller et al., 2009): Indeed, displays for which users expect irrelevant content are often ignored. Moreover, retailers are recognizing that customers have become accustomed to encountering digital content within stores, making it more challenging to draw their attention (Hoh, 2021) and not overwhelm them with irrelevant information (van de Sanden et al., 2020). Yet, the integration and combination of more advanced technologies – that make DS become smart – can help overcome these issues.

Smart DS is a DS solution that, incorporating sensors and integrating the internet of things and Artificial Intelligence, enhances the overall user experience and effectiveness of the DS system (Vozza, 2022).

For what concerns the initial investment incurred by retailers for the installation of DS systems, smart DS technologies contribute to amortize it by enabling businesses to collect valuable data and real-time insights that can be used to optimize and personalize the content being displayed while making data-driven decisions for their strategies. For example, retailers can measure audience composition or campaign performance in terms of views, impression, and attention time and adjust their strategies accordingly (Raydiant, 2022).

Regarding display blindness, smart DS technologies allow the reduction of this risk in two ways: enabling consumer interaction with the display (Pavlou & Stewart, 2000) and allowing the deployment of hyper-personalized content to every viewer (Lee & Cho, 2019). Interactivity is one of the key features of smart DS which enables consumers to actively engage with the content on the display, providing feedback, asking questions, or making purchases (Lafitte, 2019). Previous studies have already emphasized the value of the interaction with the digital screen, as it positively influences consumer engagement (Bauer et al., 2011), while enhancing their attitudes towards the advertising and increasing their purchases intentions (Lee & Cho, 2019). Touchscreen technologies are among the most obvious interactive solutions and, as consumers are currently very familiar with using smartphones with an interactive touch interface, they are very comfortable and used to interact with touch displays at the point of sales (Want & Schilit, 2012). Still, interactivity does not only refer to touchscreens, as technological advances, and the internet-of-things era, have expanded the level of possible interactions with DS. The beyond-touch interactive technologies include: RFID (Radio Frequency Identification), in which products embedded whit RFID tags can interact with DS (e.g., placing them near the screen allows the display of product information; (van de Sanden et al., 2020); beacons (micro-location-based technologies that use Bluetooth) that allow stores to identify the presence of shoppers who have installed the store's app on their smartphone to have a personalized interaction (e.g., displaying contents on nearby screens that may be determined by the person's purchase history, demographics, or other factors; Skinner, 2014); QR codes that can be scanned to connect consumers with online resources (e.g., to encourage social media follows or app downloads; Speed Pro, 2021); and cameras connected to the displays, which make it possible to recognize, in real time, shoppers' gestures (that are converted into commands that can control the display) or individual characteristics (e.g., demographics, emotions, and attention span; (van de Sanden et al., 2020).

The use of cameras in combination with facial recognition systems and AI allows the detection and targeting of audiences in real time in order to deploy hyper-personalized and variable contents, the second way to reduce display blindness. Indeed, as AI is making micro-segmentation possible (Grewal et al., 2020), the digital screen can display personalized content based on consumers' demographic (e.g., age, gender) or behavioral (e.g., viewers' mood, facial expression) characteristics (Garaus et al., 2021). This can then be subsequentially correlated with other contextual information, such as date, time, or weather (Bauer & Spiekermann, 2011). As it is also the focus of this study, a deeper understanding of consumer facing smart technologies applied to DS will follow.

### 2.2 Facial recognition and Digital Signage

The US Government Accountability Office has defined facial recognition technologies as computer programs that: 1) detect the presence of human faces in an image or video; 2) predict

certain demographic traits of the person such as age, gender, and race; 3) authenticate the claimed identity of a person by either granting or denying access; and 4) recognize an individual by comparing their image with a pre-existing database of known individuals (U.S. Government Accountability Office, 2013).
The main steps of facial recognition systems that allow for the recognition of consumers' identities are face detection, face alignment, feature extraction, and face matching. This last step allows the software to identify a person, by matching their face to a pre-existing database of known faces (Qinjun et al., 2023). Nevertheless, facial recognition systems can also be used to recognize psychological states or sociodemographic characteristics without actually determining the identity of the consumer. In these cases, as data can be anonymized, retailers might prevent privacy issues from arising. For this reason, this is the solution that seems to be mainly considered by retailers to personalize the communications and the interactions with consumers in store, as shown by the analysis done by Hess and colleagues (2020).

In the literature, several studies have used the term "facial recognition" even when the studies do not involve the recognition of the participants' identities but just the recognition of other characteristics, such as gender and age. Given that the purpose of this thesis is to study the perceptions and attitudes of consumers towards the possibility to be recognized as individuals to receive greater in-store personalization, it is worth to state internal definitions to better distinguish the different applications of facial recognition systems. From now onwards, the term face analysis will refer to technological solutions that enable the detection of individual characteristics without identifying the individual (in alignment with Valenti et al., 2008). Facial recognition will instead refer to the technology that enables the actual identification of consumers as individuals.

Facial recognition and face analysis systems are some of the recent technology developments in smart DS that are facilitating two-way communication and interaction with consumers (Lee & Cho, 2019). Video analytics technologies make possible the generation of human profiles that can then be linked to targeted contents displayed via digital screens (Bauer et al., 2012). As of today, the performance of facial recognition and face analysis models has been greatly enhanced by recent advancements in deep learning techniques (Sun et al., 2018), allowing the next generation of brick-and-mortar stores to have greater access to consumer-facing smart technologies (Inman & Nikolova, 2017).

Few retailers and chains around the world have introduced facial recognition technologies applied to smart DS in their stores. As a first example, CP Lotus, a Chinese hypermarket chain, has built its first intelligent stores installing several screens that display targeted content or recommendations based on the recognition of consumers (Kankan AI, 2019). Similarly, 7-Eleven, a convenience store chain, has introduced, in its 11,000 stores in Thailand, facial recognition and AI technologies that identify loyalty members and provide tailored recommendations suggesting them ad hoc products (Chan, 2018). As a third example, CaliBurger, a Californian restaurant chain, has integrated facial recognition technology with their loyalty program. At the ordering kiosks, it identifies registered members as they are near the kiosk, activates their loyalty accounts, and, based on their past purchases, can show their preferred meals or suggest additional options (RetailWire, 2018).

In the Italian retail landscape, smart DS solutions are limited in numbers. In terms of facial analysis, some companies are developing pilot projects for retailers in which DS is integrated with facial analysis. Among these projects, Alkemy S.p.a. and Samsung's recent partnership project is worth mentioning: it is a smart DS solution where an installed camera, after detecting viewers' demographic characteristics and integrating them with context information (weather, day of the week, and season), plays recommended content for 15 seconds. In terms of facial recognition, cases of smart DS integrated with it are still absent, but they might arise at some point in the future due to the faster technological developments and hyper-personalized shopping experiences trends we are witnessing, especially in the smart retail.

### 2.3 Personalization in smart retail

The main advantage of smart DS solutions with face analysis or facial recognition is to make consumers undergo a more personalized experience in the retail setting. When considering what personalization is, there is no unique definition. Still, it is associated with the effort of companies in offering relevant and tailored content or products of interest to customers as solutions to their needs (Riegger et al., 2021). Relevance can be, in this context, very important, as it implies delivering "the right content to the right person at the right time" (Tam & Ho, 2006, p. 867).

As the online revolution has made consumers encounter extraordinary levels of personalization, consumers are now requesting a similar experience in the offline environment (Arora et al., 2021). In fact, we are witnessing an increasing demand of a seamless experience between online, mobile, and in-store shopping (Barthel et al., 2015). A study conducted by McKinsey in 2021 highlighted how consumers expect brands to "demonstrate they know them on a

personal level" (p. 4). In particular, the study's results revealed how important it is for consumers that companies "know their tastes" and "offer something just for them" (p. 4), and nearly 80% of consumers get frustrated when this does not happen. Indeed, today, consumers see personalization as the default standard for a more engaging experience (Shankar et al., 2011). Offering personalization benefits not only consumers but also brands. For example, and with reference to advertising, personalization has been shown to greatly increase consumers' involvement while positively influencing their purchase decisions (Pavlou & Stewart, 2000).
All of this is making retailers search for smart technologies that can enhance personalization and customer experience (Riegger et al., 2021) and consequently satisfy consumers' desires. This is perhaps why some researchers argue that smart retail technologies are designed explicitly to enable personalization (Roy et al., 2017).
In this context, Riegger and colleagues (2021) have defined Technology-Enabled Personalization (TEP) as the "integration of physical and digital personalization dimensions at the point of sale to provide individual customers with relevant, context-specific information, according to historic and real-time data in combination" (Riegger et al., 2021, p. 142). With TEP, it is possible to link the gap between the conventional in-store personalization through sales assistants and the algorithm-based personalization characteristic of the online environment.

Smart DS has emerged as a critical enabler for organizations seeking to achieve personalization at scale. By leveraging data-driven insights and integrating them with DS, organizations can transcend the limits of static content and offer highly personalized and interactive experiences across various screens (Digital Signage Today, 2022). By using face analysis or facial recognition technologies, smart DS can dynamically display tailored content based on consumers' preferences, past interactions, or just their demographics or behaviors. Personalized content, then, is more likely to resonate and will likely increase consumers' satisfaction and engagement (Venkatesan et al., 2017).
As personalization via smart DS with facial recognition or face analysis is possible only through the collection of data, the personalization-privacy paradox is one of the main challenges that retailers should consider when introducing these solutions in their stores. In fact, a widely held belief is that personalization is a "double-edged sword", as it has both positive and negative effects on consumers (Tucker, 2012). While customers increasingly expect personalized experiences and interactions that are relevant to their needs, there is also a growing concern about their privacy (Aguirre et al., 2016). Indeed, literature has shown how personalization can

both enhance or diminish consumers' level of engagement towards the firm (Aguirre et al., 2016), according to their feelings and thoughts. In particular, it has been found that, when consumers perceive a high level of control over the collection and use of their personal information, personalized advertisements are more effective in terms of generating positive attitudes and purchase intentions (Aguirre et al., 2016). Personalization can indeed induce consumers' satisfaction and enjoyment through self-associations, matches with preferences, and provision of relevant information (Vesanen, 2007). However, when consumers perceive a low level of control, personalized advertisements are perceived as intrusive, resulting in negative attitudes and reduced effectiveness (Aguirre et al., 2016). As consumers might feel a sense of vulnerability, personalization can irritate and distance customers from the retailer, negatively impacting their purchases decisions and satisfaction (Aguirre et al., 2015). In the retail context, and with specific regards to facial recognition technologies, consumers' concerns might result in their lack of knowledge regarding how the captured footage is being processed (e.g., which algorithms are being utilized and for what purposes) and how the data is being used (e.g., with whom it is being shared, for how long it is being stored) (Zhang et al., 2021).

When deciding whether to disclose personal information, consumers engage in a decision-making process called privacy calculus (Dinev & Hart, 2006). In this process, consumers' decisions regarding the disclosure of their personal information are based on how they balance the potential risks and benefits associated with such disclosures (Dinev & Hart, 2006). Pantano and colleagues (2022) aimed to research the attitudes of four different generational cohorts towards facial recognition technology and explored the drivers of consumers' willingness to disclose their data. The literature that Pantano and colleagues' study reviewed mainly focuses on online environments (e-commerce and social networks), with no study on smart DS with facial recognition technology. Still, Pantano's review of facial recognition technology is one of the most comprehensive available. Also, as the boundaries between the online and offline environment are nowadays blurred, the findings of their study may be informative. Pantano and colleagues identified six factors that influence consumers' elasticity to reveal their personal information: 1) the nature of the information being requested, 2) the circumstances surrounding the request for personal information, 3) the type of relationship that exists between the consumer and the company, 4) the perceived warmth or care demonstrated by the retailer, 5) the advantages and benefits that may result, and 6) the individual characteristics of the consumers who are being asked to disclose the information (Pantano et al., 2022).

As follows from factors three and four, retailers themselves can enhance consumers' elasticity of sharing their personal information by being perceived as trustworthy and respectful of consumers' privacy. The more positive associations consumers have towards retailers, the more they might be willing to share their personal information with them (Rodríguez-Priego et al., 2022). For this reason, trust-building strategies, such as transparent privacy policies and data security assurance, can highly mitigate privacy concerns (Aguirre et al., 2016). Indeed, it has been proven that, in the online environment, the presence of privacy statements and virtual assurances, such as privacy seals, provides consumers with a sense of confidence and reassurance while reducing their privacy concerns (Aguirre et al., 2016; Karimov & Brengman, 2011). Moreover, the fifth factor confirms the theory that consumers are willing to expose themselves to the risk of privacy loss only when they actually receive real benefits in return (Lee et al., 2008). Finally, the last factor stresses that consumers' diversity, also in terms of personality traits, influences their elasticity in sharing their personal data. For example, Iannou and colleagues (2021) have demonstrated a relationship between the personality trait of mindfulness and consumers' privacy concerns: the more mindful consumers are, the more likely they are to share their personal information, interpreting privacy violations as less threatening (Ioannou et al., 2021).

To disclose their personal information, consumers may need to first accept the technology itself and show a propensity to use it and take advantage of it. For this reason, a review of the Technology Acceptance Model (TAM) will follow, as marketing literature has traditionally explained consumers' acceptance of in-store technologies through this model.

## 2.4 Technology acceptance model

The TAM is a popular theoretical model used since its first appearance to understand consumers' acceptance or rejection of technology. Over the years, the model has undergone several revisions and extensions to encompass different technological contexts and user populations.

The first version of TAM was proposed by Davis in 1985 and suggested that perceived usefulness and perceived ease of use affect consumers' attitudes towards technology, which consequently influences their intention to use it. Perceived usefulness refers to the degree to which individuals believe that using a particular technology will enhance their performance or productivity, while perceived ease of use relates to the extent to which individuals believe that using the technology will be effortless and free of complexity (Davis, 1985). As additional findings of research done by Davis and colleagues (1989) questioned the mediating role of

attitudes, they eliminated this variable while proposing that consumers might form strong intentions to use a certain technology even without having formed any attitudes towards it. After some years, Davis and Venkatesh (1996) demonstrated that some external variables influence the perceived usefulness and consequently the intention to use the technology: 1) the influence of other people (subjective norm), 2) the tendency to hold a positive reputation or social status within their social group (image), 3) the degree of the technology's applicability (job relevance), and 4) the achievement of tangible results through the technology (result demonstrability). In 2004, Davis and colleagues also suggested that perceived enjoyment, the extent to which the usage of the technology is perceived enjoyable, also influences the intention to use a certain technology. Over time, scholars have introduced new factors that influence the acceptance or rejection of a technology, enhancing and sophisticating the TAM. A comprehensive literature review done by Marangunić and Granić (2014) summarized these advancements in four major categories: 1) additional factors that influence the perceived usefulness and perceived ease of use, such as technology anxiety, prior usage and experience, self-efficiency, and confidence in technology (external predictors); 2) factors that influence the intention to use, such as expectations, user participation, risk, and trust (factors from other theories beyond the TAM); 3) factors that have moderating effects on the entire model, such as gender and culture (contextual factors); and 4) factors directly affecting the actual usage of the technology, such as usage perception and attitudes towards technology (usage measures).
With regard to the retail environment, several studies have applied the TAM to investigate consumers' adoption or rejection of smart in-store technologies. Kim and colleagues (2016) have demonstrated that the influence that the revised TAM's three variables (perceived usefulness, perceived ease of use, and perceived enjoyment) have on the intention to adopt certain technology vary according to the in-store technology itself. For this reason, it is important to verify the impact of these factors in consumers' acceptance of the novel technology of smart DS with facial recognition technology. At the same time the TAM can be considered a general model of technology acceptance and technologies vary in their specific characteristics. For these reasons, as this thesis centers on smart DS with facial recognition – an example of TEP – the focus will now shift to more tailored models that address consumer acceptance specific to TEP.

### 2.5 Consumer acceptance of technology enabled personalization

Research on consumer acceptance of TEP has mostly focused on drivers and barriers of use, the impact of devices used, and on the role of social presence and impression management.

Concerning the drivers and barriers of use, Riegger and colleagues (2021) identified five drivers and four barriers that determine the success and consumer acceptance of TEP (Riegger et al., 2021). In terms of drivers, they are of the following: 1) consumers' belief that TEP allows them to save time by showing them products that match their preferences and helping them find products faster (utilitarian). This driver is highly linked to perceived usefulness, the technology's ability to help customers complete their shopping more efficiently and effectively (Davis, 1985), a main determinant of consumers' acceptance and adoption of smart retail technologies in general (Kim et al., 2017); 2) consumers' perception that TEP gives them suggestions on products that are not part of their habitual purchases (hedonic); 3) consumers' perceived control over TEP, as they are the only ones who decide whether retailers can identify them (control); 4) the possibility of consumers to interact with TEP devices (interaction); and, lastly, 5) consumers' feeling that personalization is based on their purchase history (integration). In turn, the barriers are: 1) consumer fears that stem from the retailer's ability to personalize pricing and reduce consumer autonomy, potentially resulting in consumers being subject to manipulation (exploitation); 2) perceived incongruence between consumers' previous personal experiences in retail settings, such as interacting with store employees (interaction misfit); 3) consumers' perceptions that retailers are invading their privacy through "identity disclosures, irresponsible data sharing, or monitoring" (p. 47), instead of protecting their data (privacy); and 4) consumers' limited trust and belief in the convenience and capabilities of a new technology (lack of confidence). This might happen when consumers see the technology as complicated or inconvenient or when they still do not trust it.
Riegger and colleagues' (2021) drivers and barriers are very generic, as they are not directly related to any specific TEP, such as DS with facial recognition or face analysis. Still, they provide useful insights on the type of variables that should be investigated to better understand how consumers can be positively influenced to accept facial recognition to receive greater levels of in-store personalization.

Regarding the impact of devices used, another study conducted by Riegger and colleagues (2022) took into consideration that retailers can offer personalization through both customer- (e.g., smartphones) and retailer-owned devices (e.g., DS) and that the devices used to provide personalization might influence shoppers' attitudes and reaction towards TEP. These authors discovered that personalized messages are more accepted when they appear on customer-owned devices, as these devices are perceived as part of customers' extended self. In contrast, when it comes to more standardized messages, they affect more positively the shopping behavior when they are displayed on retailer-owned devices (Riegger et al., 2022).

This impact of device type can be related to the two variables studied by Hess and colleagues (2020) that influence consumers' acceptance of personalized advertising: social presence and impression management (Hess et al., 2020). As personalized advertising is displayed in public, other people can judge the targeted viewer based on the displayed contents. This can consequently raise impression management concerns in the viewer, as people attempt to create the best possible impression of themselves in public (Leary et al., 1986). What Hess and colleagues (2020) demonstrated is that, with social presence, consumers have positive attitudes towards the personalized ads and the retailer only when the advertising matched consumers' self-concept and highlighted positive aspects of the self. This happens because, with this type of advertising, consumers can meet their goal of making a positive impression in public. However, when there is a mismatch between the advertising and consumers' self-concept or when the advertising highlights a negative aspect of consumer's self-concept, consumers' attitudes and behavioral intentions towards the retailer are negative as they feel a sense of embarrassment. In this case, as proposed by Bauer and colleagues (2018), consumers might interpret person-related content as invasive or even inappropriate, thus reacting with anger and denial (Bauer et al., 2018). In the experiment conducted by Hess and colleagues (2020), both ads that highlight a negative aspect of the viewer (threatening ads) and ads that highlight a positive aspect of the viewer (bolstering ads) were included. The ads were displayed on a computer screen during a survey, as the study was a laboratory experiment. The products shown were products that held personal significance and contributed to the expression and reinforcement of one's self-identity (clothes and dental health products). Also, the advertising personalization was based only on physical characteristics, such as gender, body shape, and color of teeth. Because of this, the authors considered that it should be appropriate to investigate consumers' attitudes basing the personalized ads also on other variables beyond demographic ones, such as consumers' history purchases. Moreover, as also indicated by the authors, other product categories apart from clothes and dental health products should be examined to better identify when and how consumers would be more willing to accept this type of personalization. At the same time, it is worth mentioning that these results provide useful insights on how displaying content that enhances people's feeling of making a good impression to others could be an optimal way to enhance consumers' acceptance of facial recognition personalization.

In conclusion, the existing research on consumers acceptance for TEP has provided two important insights. First, the drivers and barriers that determine consumer acceptance and perceptions of these technologies have been identified with details. Second, studies have explored the impact of devices used for personalization, indicating that personalized messages are more accepted on customer-owned devices compared to retailer-owned devices. When ads are shown on retailer-owned devices, social presence and impression management have been demonstrated to be important influential factors. In fact, when in public, consumers' attitudes are affected by the match or mismatch between the personalized ads and their self-concept and by what personal aspects the ads are highlighting.

The aforementioned literature provides valuable insights into consumer perceptions and acceptance of TEP, even if there is still room for deepening the literature's findings. Moreover, there is also a need to explore specific attitudes towards facial recognition technology, which is the topic of this thesis' study. Facial recognition holds great potential for personalized experiences but also raises concerns related to privacy and ethical implications as involving the collection and usage of personal data. For this reason, it is essential to explore consumers' attitudes towards facial recognition to understand how consumers can eventually be positively influenced to embrace this technology as a means of receiving personalized in-store experiences.

### 2.6 Attitudes towards facial recognition

As of today, face analysis and facial recognition technologies are starting to be used in several contexts in our everyday life. At the same time, as these technologies are new and still not very widespread (Marlow & Wiese, 2017), researchers have not analyzed with depth consumers' attitudes in all the possible contexts of application. Indeed, the literature mainly focuses on facial recognition technologies applied to security (Smith, 2019), surveillance (Stark et al., 2020), or smart payments (Moriuchi, 2021).

A notable exception is the recent study conducted by Pantano and colleagues (2022), which analyzed, through 80 semi-structured interviews, the attitudes of four different generations of Italian consumers towards facial recognition in the retail setting (Pantano et al., 2022). This study found that four generational cohorts (Baby Boomers, Generation X, Millennials, and Generation Z) have different attitudes towards facial recognition technology and highlighted a certain variance in the cohorts' reluctance to provide consent to data collection. However, this reluctance could be compensated through certain types of gratifications. Indeed, the results of the research reflected the fact that there might be consumers triggers, such as benefits and rewards, that could make consumers much more inclined to accept being recognized in store, thus aligning with Lee's study on consumers' propensity of exposure to the risk of privacy loss (Lee et al., 2008). As the current thesis' study will also involve generational cohorts, the results of each cohort are reported in detail next.

According to Pantano and collaborators' (2022) study, Baby Boomers have limited knowledge of facial recognition and perceive it as an intrusive tool that makes them vulnerable towards retailers. For this reason, they are reluctant to accept the idea of giving their consent to be recognized, preferring to share only less intrusive data, such as their name or age. Similarly, even if Generation X is more familiar with the technology, they are still skeptical about the idea of making retailers collect more data than the ones they already have, as they feel vulnerable too. At the same time, both of these generational cohorts would be more inclined to give their consent when getting economic advantages (e.g., discounts and customized offers) or utilitarian benefits (e.g., personalized assistance, customized product recommendations, or product assortments that match their preferences) in exchange.

As for Millennials and Generation Z, Pantano and collaborators' (2022) study found that both have extensive knowledge of facial recognition and are aware that sharing information with retailers is needed to receive particular services. At the same time, due to their knowledge, the study found they are much more conscious about the risk of the possible misuse that retailers can make of their data (e.g., disclosure and sale to third parties). For this reason, they would like retailers to be transparent and inform them about the specific purposes of data collection, usage, and storage. Also, the study found these two generations could be more incentivized by receiving utilitarian gratifications (e.g., faster purchases, reduced waiting times, personalized information of relevant products) that results in a greater personalized experience.

Even if it has not specifically been correlated with the elasticity to accept being recognized in store, Pantano and colleagues' (2022) study showed how different generations have a different level of familiarity towards the technology. Familiarity can be considered another variable that could influence consumers' attitudes towards facial recognition as, in general, customers who are technology ready are more inclined to overlook negative aspects and enthusiastically embrace the opportunity to engage with technological innovations (Grewal et al., 2020). In their study, Sens and colleagues (2021) have discovered that the more familiar consumers were with facial recognition technologies, the higher their comfort level and perceived usefulness of the technology. As the authors have analyzed a gas station and a library to gather this insight, it should be examined whether it holds when considering a retail setting. However, a study conducted by Shore (2022) demonstrated that familiarity does not have an influence on privacy concerns when dealing with facial recognition technologies (Shore, 2022). Still, Shore stressed that research should keep investigating whether the relationship between familiarity and perceptions towards facial recognition technology exists or not.

It is also important to consider that consumers' perceptions and attitudes can always be influenced by external factors. Firstly, how the scenario – the possibility to be recognized in store – is framed is important, since framing affects people's perceptions (Dobson & Poels, 2020). For this reason, and as highlighted by Garaus and colleagues (2021), retailers should consider "educating customers on the benefits of targeting practices at the Point Of Sale" (Garaus et al., 2021, p. 758). Secondly, when consumers are members of a network with strong ties, the network itself can influence the understanding of new situations. Indeed, when encountering novel in-store technologies, consumers may initially hesitate to engage with them or even accept them (Grewal et al., 2020). However, positive information about these technologies coming from strong ties can encourage and enhance immersion and engagement (Grewal et al., 2020). Also, consumers are more willing to disclosure their personal data – that in the case of this study would be their faces – to companies when they perceive that other people are also doing so (Acquisti et al., 2012).

In conclusion, the literature on attitudes towards facial recognition technology in the retail setting is still limited but growing. Recent research has highlighted generational differences, with Baby Boomers and Generation X exhibiting skepticism and reluctance, while Millennials and Generation Z are more open to sharing data for personalized benefits. Moreover, familiarity with technology shows mixed effects on attitudes, and external factors such as framing and social networks could influence consumer perceptions and attitudes.

### 2.7 Hypothesis development

Following the literature review, I propose some hypotheses that will be tested in order to give a more complete answer to the thesis' research questions.

Pantano and colleagues' study (2020) highlighted the presence of differences among generational cohorts with regards to their perceptions towards facial recognition technology and their propensity to adopt the technology. It is then reasonable to believe that the results apply also to the specific application of facial recognition to smart DS. Also, as indicated in

Pantano and collaborators' study's future research suggestions, gender might act as driver of differences too. For this reason, the following hypothesis were derived:

> **H1:** Perceptions towards smart DS with facial recognition vary according to demographic characteristics (i.e., gender and age).
>
> **H2:** The elasticity to be recognized varies according to demographic characteristics (i.e., gender and age).

As the TAM and TEP drivers and barriers model were never applied to DS or smart DS technology, it was reasonable to believe that the variables analyzed in the models also have an impact on the elasticity to be recognized. For this reason, I elaborated the following hypothesis:

> **H3:** Perceived usefulness, perceived ease of use, and perceived enjoyment (TAM variables) together with TEP drivers have a positive impact on the elasticity to be recognized. Conversely TEP barriers have a negative impact on the elasticity to be recognized.

Lastly, as demonstrated in Pantano and colleagues' study (2022), incentives can positively influence consumers' decision to accept facial recognition technology. The following hypothesis was then proposed:

> **H4**: Consumers with low elasticity to be recognized show high appreciation towards the incentive to be recognized.

## 3. Study 1

### 3.1 Method

For Study 1, qualitative analyses were conducted to gather insights as a first exploration of the phenomenon of analysis and to better design the questionnaire for the quantitative analysis. To this end, two focus groups and six in-depth interviews were conducted. The informants involved in the analysis included men ($n$ = 9) and women ($n$ = 9), belonging to the generational cohorts of Baby Boomers (1946-1964, $n$ = 4), Generation X (1965-1980, $n$ = 5), Millennials (1981-1994, $n$ = 4), and Generation Z (1995-2010, $n$ = 5). The reason why informants of different ages were involved was to verify whether there are any differences among different generational cohorts, as in Pantano and collaborators' (2022) study.

For the focus groups, the four generations were divided in two groups, one of adults (Baby Boomers and Generation X) and one of young people (Millennials and Generation Z). The phenomena investigated through the two focus groups were the same and the following: First, participants were asked to describe their perceptions towards in-store personalization and towards the technologies that can contribute to greater personalized experiences; Second, participants shared their experience towards traditional DS; Third, participants were presented with face analysis and facial recognition scenarios applied to DS aimed at making the in-store experience even more personalized and were asked for their views and opinions. The objective was to identify their perceptions towards this technology, their willingness to be analyzed or recognized, and their fears towards it. In addition, incentives to be recognized and potential differences among retailers using these technologies were explored.

For the in-depth interviews, the phenomena investigated were the same as in the focus groups, except for four topics not directly addressed in the focus groups (but which emerged during them) but which were explored during the interviews. First, after participants shared their views and opinions towards smart DS with facial analysis or face recognition I asked them to indicate the types of personalized content that they would like to see on displays; Second, after the questions on facial recognition applied to smart DS, I investigated the impacts that the social component could have on participants' propensity to be recognized in store; then I asked questions on the type of device on which participants would prefer to see personalized communications (customer-owned vs retailer-owned) and on the ways in which participants would like to be recognized (always when entering the store vs. on occasion by scanning a QR code or a card).

### 3.2 Results

#### 3.2.1 In-store personalization: associations, importance, and connections with technologies

When talking about in-store personalization, during the focus groups, both adults and young participants associated it with the interactions with sales assistants and with the possibility to receive discounts based on their preferences and purchase history. While having a personalized shopping experience was very important for all the young participants, for half of the adults it was considered irrelevant. All those who appreciated in-store personalization valued the feeling of being treated as important that comes from it ("I really like the idea that the store knows me and my tastes" – P1, Generation Z, "I really value the feeling of being important that comes from personalization. Not as if I were just some random customer" – P2, Baby Boomer*)*.
Technology was not immediately associated with in-store personalization, especially – and surprisingly – by young participants. Still the majority of both groups were able to mention some in-store technologies, such as interactive displays, tablets, virtual mirrors, Bluetooth technologies, and informative QR codes, thus showing a certain familiarity with the topic. Even if all participants believed that the future of physical stores will be marked by more technologies, not all of them had positive feelings about it. Indeed, half of the adults feared that technologies could manipulate and monitor them too much, thus reducing their individual freedom ("I think all these technologies can over direct to certain products, being manipulative" – P3, Baby Boomer). The other half of adults – the same ones who valued the personalized experiences – and all the young participants believed, instead, that technologies will be more a help than a barrier, as they would enhance the personalized shopping experience while reducing the time spent at the point of sales ("I think they will allow us to save a lot of time." – P4, Generation X, "I believe that, thanks to the technology, we will have a much better shopping experience." – P5, Millennial).

#### 3.2.2 Traditional DS: familiarity and attractiveness

All participants of both focus groups were familiar with traditional DS but what they associated with it varied. Except for one adult who reported being always attracted to DS due to the attractive images, all the remaining adults considered traditional DS unhelpful and unattractive and, for this reason, they reported tending to ignore them. Those participants said they would pay more attention if the content showed on displays would be more informative and inspirational (composition of products, how to use products, etc.) rather than promotional ("I would be prompted to look at them if they gave more useful information about the products" – P6, Generation X). Differently, all the young participants declared that they always tend to look at the displays, not only for the attractiveness of the images but mainly because they believe that they can receive a sort of help, such as learning about deals and promotions of the day or the novelties of the moment ("In some cases I purposefully search for them, because I know they show the promotions of the day" – P1, Generation Z). Still, the young acknowledged the fact that, as they are exposed to a lot of digital screens, they do not always look at the content with the same attention. For them, their attention and attraction towards DS would increase if they were able to interact with the display.

Results from the in-depth interviews partially confirm and expand the focus groups'. In this case, all the interviewees, independently from the generation they belonged to, said they tended to look at DS and not ignore them. Except for one young interviewee, who reported looking at DS to search for promotions and more product-related information, all other interviewees (adult and young) cited the attractive images and videos as their main driver. Also, it emerged that, not only for the young but also for the adults, the attention is not always high when looking at the display, and all interviewees considered they would be more attentive if displays were interactive ("Instead of just watching the images scrolling passively, it would be nice to be able to actively interact with the display" – P7, Generation X). In particular, the majority would appreciate the possibility to explore product information such as discounts or how to use them ("I'd like to find out things I don't know about products like what's new or special discounts" – P8, Generation Z).

### 3.2.3 DS with face analysis: perceptions, attitudes, and preferences

When confronted with face analysis applied to DS, opinions in both focus groups were not unanimous. On one hand, the majority of young people and half of the adults viewed face analysis applied to DS positively, seeing it as a very helpful way to improve efficiency (e.g., less wasted time) and relevance in communication ("I find it more useful than looking at men's products I am not interested in" – P9, Baby Boomer; "I think it is useful to save time" – P5, Millennial). As a result, these participants would accept facial analysis without any fear, as they considered the anonymity of their data as reassuring. Moreover, for two young participants, the presence of this technology would make the stores even more attractive. On the other hand, one young participant and the other half of adults (the same ones who did not value in-store personalization) feared facial analysis mainly due to privacy concerns: as they did not trust the data to be anonymized, they would be worried about companies collecting and reselling their data. Also, they associated this technology with a feeling of manipulation and a threat to their freedom. For these reasons, these participants would not accept facial analysis and would find retailers with this technology less attractive and untrustworthy to the extent of potentially avoiding them ("I would not be comfortable knowing that there are cameras that do these analyses, I would stop going to these stores" – P10, Generation X).

Results from the in-depth interviews slightly differ from the focus-group ones. All the young interviewees and one out of three adults had positive associations towards facial analysis: they too associated it with the possibility of encountering more relevant communication and saving time while shopping. These participants would be willing to be analyzed as they value personalization and speed in the shopping experience and stores with these technologies would be more attractive to them. Still, the young interviewees were not fearless: they slightly feared that their privacy may be violated and that retailers may misuse their data. For this reason, they would like to receive more information and guarantees from them ("I would like the retailer to make available documents where they guarantee compliance with the regulations" – P11, Millennial). No adults were against or afraid of this technology: the other two adults were mainly indifferent. Indeed, they did not find neither positive nor negative aspects to associate with this technology and they would keep going to the same stores, with or without the introduction of this technology ("There is nothing in particular neither holding me back nor exciting me about this technology [...] it would not change the stores I frequent." – P12, Generation X).

During the interviews, a topic that had not been explored during the focus group was investigated: the types of content one would like to see on the display. Interviewees' preferred content can be divided into three categories: discounts and promotions, inspirational content (e.g., tutorials on how to use/match products, news and trends, etc.), and informational content (e.g., product composition, provenance, environmental impact, etc.). While, for apparel and beauty retailers, the preferred category was inspirational content, discounts and promotions and informational content were the preferred in supermarkets.

### 3.2.4 DS with facial recognition: perceptions, attitudes, and preferences

When moving to the topic of facial recognition applied to DS, in both focus groups, associations were both positive and negative. Regarding the positive associations, it is worth mentioning that they emerged even from those adults initially averse to facial analysis. Both adults and young believed that this technology would be an optimal way to save time. Only the young also believed that this technology would give them a hyper-personalized shopping experience, like what happens in the online world ("I think it could give me extremely accurate advice, like when I surf online" – P1, Generation Z). Few young participants had negative associations and they mainly revolved around a fear of being judged by other consumers in the store ("If I always buy short skirts and advice related to this comes out in front of everyone, I would feel embarrassed" – P13, Generation Z). They indicated that this last-mentioned fear would be reduced if personalized communication were displayed on their smartphones rather than on big displays. In contrast, the negative associations of the adults revolved around a feeling of being controlled and privacy concerns: they felt a sense of discomfort in thinking that someone would know where they were, and they were very afraid of what might happen to their data ("I would be afraid that all the data about me, also related to my face, would be sold" – P2, Baby Boomer). Even if the young did not have big privacy concerns, they noted they would still carefully read the terms and conditions on the processing of personal data before possibly giving their consent. Overall, only half of young participants and two adults would be willing to be recognized, but only by retailers they trust. For the other half of young participants, the possibility to scan a QR code or use a card to actively choose when and whether to be recognized conveys them a greater sense of control and may incentivize them to accept this recognition. In contrast, this option does not change the perceptions of the other adults and those contrary to the recognition would stop visiting the stores using this technology. All participants agreed that they could be persuaded if they could receive something in return. While for all the adults the incentives should be economic in nature, for the young, playing interactive games to receive gifts, being able to explore new products, receiving personalized recommendations, or being able to observe live reviews would be valuable incentives too.

The positive associations towards DS with facial recognition that emerged from the in-depth interviews coincide with those of the focus groups: while for the adults this technology would be a great way to save time simplifying the decision-making process, for young people it would also be an effective mean to have a 100% personalized experience. In contrast, negative associations were different. On one hand, two out of three adults had no negative associations towards this technology ("I can't associate anything negative to this technology" – P14, Baby Boomer) and the only one who had them were related to a feeling of being manipulated and not to privacy concerns. On the other hand, for young people, privacy concerns were more predominant: the idea that their identity would be fully recognized led them to think that there might be risks of privacy violations (e.g., selling their data to third parties). Despite this, they would be willing to be recognized by retailers they trust if they were assured that their data would be protected by the company ("In this case it would be known exactly what kind of face I have and that would scare me [...] it's important to me that the company gives me protection" – P15, Millennial). The same is also true for the two (out of three) adults who were willing to be recognized. Supermarkets were the preferred retailer category in which to be recognized, followed by beauty and apparel stores, and interviewees noted these retailers would be perceived as more attractive if they introduced facial recognition technology. The interviewees who would be willing to be recognized had different opinions regarding the possibility to scan a QR code or a card to decide when to be recognized: two young people and one adult appreciated it and saw it as a fair compromise to keep having a high level of control over their data ("It would be perfect, as in this case I would be the one who decide when to be supported" – P14, Baby Boomer), while the remaining ones saw it as a waste of time. Regarding the types of content interviewees would like to see on the display, the categories remained the same as in the facial analysis scenario: discount and promotions, inspirational content, and informative content. Also in this case, the inspirational content was the preferred category for beauty and apparel stores, while discounts and promotions and informational content for supermarkets. It is worth mentioning that during the interviews no one feared the idea that personalized content would be seen also by other people and for this reason everyone preferred seeing this content on the retailer-owned displays. Lastly, all the interviewees cited gifts and ad hoc discounts as the incentives that should be provided by retailers. Only the young believed that having the possibility to interact with the display would also be a great incentive for them.

### 3.3 Discussion

Comparing the qualitative analysis' results with the existing literature, areas of alignment as well as discrepancies emerged. First of all, it is worth mentioning that what McKinsey's (2021) study showed has been confirmed also by the qualitative analysis: the majority of participants (75%) actually believed that having a personalized in-store experience is something extremely important for them.

Moving on to facial recognition applied to DS, not all participants were willing to accept this technology and to be recognized, showing different attitudes and perceptions. Differently from existing literature (Pantano et al., 2022), not all Baby Boomers felt vulnerable towards the facial recognition technology and not all Generation X participants were skeptical about the rationale behind it. Instead, similarly to Pantano and collaborators' results, Millennials and Generation Z participants were more familiar with this technology and more aware that sharing personal information is necessary to receive personalized services by retailers. This finding concurs also with Sens and colleagues' (2021): the perceived usefulness of facial recognition technology is higher the more consumers are familiar with it.

The participants of both generations who were willing to be recognized associated to this technology the possibility to save time simplifying the decision-making process. This association is in line with the "utilitarian" driver identified by the literature (Riegger et al., 2021) that determines consumers' acceptance of TEP. Another positive association with this technology was having the possibility to be exposed to more relevant communication, enhancing personalization in the shopping experience. Even if this factor is not part of Riegger and collaborator's drivers, it can be related to the advantages that results from the technology that, according to Pantano and collaborators (2022), positively influence consumers' elasticity to share their personal data.

Regarding the negative associations, especially the adults associated this technology with a feeling of being subject to manipulation and to a privacy invasion from the retailer. Both associations reflect two barriers identified by Riegger and collaborators (2021) that negatively affect consumer acceptance of TEP: exploitation and privacy. Moreover, the adults that felt high level of manipulation and loss of control would stop frequenting the retailers that introduce facial recognition. This result extends the findings presented in the literature – consumers who feel vulnerable to personalized ads tend to distance themselves from retailers (Auguirre et al., 2015) – to DS with facial recognition.

While the young do not have any manipulation fears, they have some privacy concerns too. However, they would be willing to be recognized at the point of sales if retailers would reassure them about the protection of their data. In particular, the young would like to receive from retailers clear and easy-to-read terms and conditions, thus confirming that transparent privacy policies could actually mitigate privacy concerns (Aguirre et al., 2016; Pantano et al., 2022). This validates and extends to DS with facial recognition one of the factors that positively influence consumers' elasticity to share their personal information that have been defined by the literature: perceived warmth or care demonstrated by the retailer (Pantano, 2022). During the focus groups it emerged that some young participants would also fear a sense of embarrassment thinking that other people would see their personalized communication on the retailers' screens, and, because of that, they would be more likely to accept personalized advertising on their smartphones, as also demonstrated by the literature (Riegger et al., 2022). However, this result was not confirmed by the in-depth interviews where all participants who would accept facial recognition would like to keep seeing the communication on retailer-owned devices, as they would not feel judged by the social presence, differently from what Hess and colleagues (2020) demonstrated. The differences observed between the focus groups and the in-depth interviews might be justified because of a group effect observed during the focus group: once a participant expressed a preference for smartphone-based communication, several other participants agreed with that view.

Another important result is that the majority of consumers who would be willing to be recognized and the young participants that were more skeptical saw in the possibility to scan a QR code or a card (to actually determine when to be recognized) a perfect option that would allow them to feel much more in control. In fact, consumers' perceived control over the technology has been included by Riegger and colleagues (2021) among the drivers that positively influence consumers' acceptance of TEP.

Considering the typologies of retailers, all the participants who were willing to be recognized at the point of sales declared that they would do it only in retailers they trust, supporting that that the type of relationship with retailers actually affects the elasticity to reveal personal information (Pantano, 2022).

Lastly, results of the qualitative analysis concur with existing literature (Lee et al., 2008; Pantano et al., 2022) on the fact that valued incentives would make consumers more willing to be recognized. Differently from what was demonstrated by Pantano and colleagues (2022), economic advantages such as gifts or discounts were seen as a great incentive not only by adult participants but also by the younger ones. The latter would also appreciate, in line with Pantano and colleagues' results, other utilitarian gratifications, such as the possibility to interact with the display, thus confirming the positive influence that interactivity has on consumer engagement (Bauer et al., 2011).

## 4. Study 2

### 4.1 Method

#### 4.1.1 Research approach and questionnaire design

For Study 2, a quantitative analysis was conducted to reach a relevant sample of Italian consumers and give statistical relevance to the research.

The questionnaire was designed taking into account variables that have already been investigated in previous literature and topics that emerged during the qualitative analysis. The survey was set up on the Qualtrics platform and included 13 questions with qualitative and quantitative variables and nominal, ordinal, and scale measures. For the scale questions, 10-point Likert scales were chosen to powerfully capture respondents' point of view while offering a high degree of measurement precision (Wittink et al., 1994).

The quantitative questionnaire consisted of 11 questions, divided into six different blocks.

The first block consisted of preliminary questions aimed at investigating respondents' shopping behaviors. Respondents were asked to answer three single-choice questions indicating, for each of the three retailers presented (supermarkets, apparel stores, and beauty stores), their frequency of visit (once a day vs. once a week vs. once every two weeks vs. once a month or less).

In the transition between the first and second block, participants were presented with an accurate explanation of what smart DS with facial recognition technology is, including also concrete examples of its in-store applications aimed at making participants answer the subsequent questions with more precision.

The second block measured positive and negative associations towards smart DS with facial recognition. The associations were evaluated asking respondents to rate, through a 10-point Likert scale, their level of agreement or disagreement towards 12 statements. Regarding the positive associations, based on the TAM model of Davis and colleagues (2004), the TEP drivers of Riegger and colleagues (2021) that have been cited during the qualitative analyses, and the insights from the qualitative analyses, the six statements were: 1) "I find the technology easy to use" to evaluate the perceived ease-of-use in the TAM model; 2) "The technology would simplify the shopping experience" to evaluate the perceived usefulness in the TAM model; 3) "I find the technology fun to use", to evaluate the perceived enjoyment in the TAM model; 4) "The technology would allow me to save time while shopping" refers to one of the TEP drivers, namely utilitarian; 5) "The technology would allow me to explore new products" refers to one of the TEP drivers, namely hedonic; and 6) "The technology would enhance the shopping experience" from one of the qualitative analyses' insights. Regarding the negative associations, the six statements were elaborated taking into account the TEP barriers of Riegger and colleagues (2021) that have been cited during the qualitative analyses, Hess and colleagues' (2020) study, and the insights from the qualitative analyses: 1) "The technology would make me feel manipulated" refers to one of the TEP barriers, namely exploitation; 2) "The technology would make me feel controlled by the companies" refers to one of the TEP barriers, namely privacy; 3) "I would be scared of data misusage by companies" refers to one of the TEP barriers, namely privacy; 4) "I would feel ashamed if other people would see my personalized communication" has been elaborated from Hess and colleagues' study on social presence's influence on consumers' acceptance of personalized advertising; 5) "It scares me to think that someone can associate my face to my name" and 6) "I would not feel to have control over the technology", both from two qualitative analyses' insights.

The third block measured the elasticity to be recognized in store via facial recognition technology, using a 10-point Likert scale. The question that was asked was: "How much would you be willing to be recognized in-store via facial recognition to receive personalized services from smart DS?". Then, respondents were asked to express, through a single-choice question, their recognition preferences (in all retailers vs. in trusted retailers vs. never). This question was adapted from one of the factors that influence consumers' elasticity to reveal their personal information identified by Pantano and colleagues (2022).

In the fourth block, respondents were presented with six incentives and were asked to express, on a 10-point Likert scale, how much they might motivate them to accept in-store facial recognition. "Exclusive discounts" and "information on the personal data treatment" incentives were adapted from Pantano and colleagues (2022) study. The other incentives, "periodic gifts", "display interaction", "virtual mirrors", and "possibility to see reviews", emerged from qualitative analyses.

In the fifth block, respondents had to evaluate, on a 10-point Likert scale, the level of attractiveness of nine scenarios that were presented to them. The scenarios were determined through an orthogonal design performed on SPSS and the attributes and levels used were: 1) retailer typologies (supermarkets vs. apparel stores vs. beauty stores), 2) content typologies (discounts and promotions vs. informative vs. inspirational; with levels emerged from the in-depth interviews), 3) display medium (totem vs. smartphone; with levels elaborated from Riegger and colleagues' study, 2022), and 4) recognition modality (always vs. QR code scanning; with levels emerged from the qualitative analyses' insights).

The sixth block measured participants' demographic variables. Four demographic questions were presented at the end of the questionnaire, asking information regarding age, gender, education level, and occupation. Except for age, measured with an open-ended question, all other variables were measured through single-choice questions.
A complete transcript of the questionnaire can be consulted in the Appendix (Appendix 1).

### 4.1.2 Questionnaire distribution

After development, to ensure clarity and comprehensibility, the questionnaire was pretested with 10 people aged between 18- and 75-years old. No adjustments were required, and these answers were not included in the analysis. Then, the questionnaire was distributed in Italian to Italian consumers through messaging apps (e.g., WhatsApp) and social media (e.g., Instagram). Also, respondents were asked to spread the survey in their own networks in order to reach other groups of people. All the participants involved in this study were volunteers and no rewards were offered.

### 4.1.3 Participants

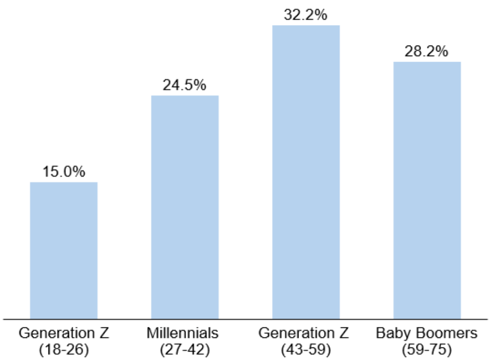
The questionnaire reached 368 respondents, out of which 281 (76%) provided responses to all questions. To assess respondents' attentiveness and ensure data integrity, one of the best performing attention checks from Curran and Hauser's (2019) study, "I have never used a computer", was included. Among the respondents, eight failed the attention check and were excluded from the dataset to uphold the quality and accuracy of the collected data. As the methodological choice was to consider only the completed and valid questionnaires, the final number of respondents was 273.
Before initiating the analysis, an assessment of the sample representativeness was done on gender and age comparing the sample results with official statistics provided by ISTAT (2023) on the Italian population. The sample was considered representative as the majority of deviations from the official statistics were no higher than 2%. Table 1 shows the comparison between the sample observations and the ISTAT official statistics.

**Table 1.** Comparison between sample observation and ISTAT data.

| | Gender | | | |
|---|---|---|---|---|
| | Male | | Female | |
| | Sample | Population | Sample | Population |
| Age Classes | | | | |
| 18-26 | 7.7% | 6.3% | 7.3% | 5.8% |
| 27-42 | 12.4% | 12.5% | 12.1% | 12.2% |
| 43-58 | 15.0% | 17.0% | 17.2% | 17.4% |
| 59-75 | 13.6% | 13.8% | 14.7% | 15.1% |

Participants were 140 women (51.3%) and 133 men (48.7%) aged between 18 and 75 years old (*M* = 45.41, *SD* = 15.51). Ages were divided into four classes, taking into account the four generational cohorts that were considered also for the qualitative analysis: Baby Boomers (1946-1964), Generation X (1965-1980), Millennials (1981-1994) and Generation Z (1995-2010). As shown in Figure 1*,* the majority of participants were concentrated in the 43-58 and 59-75 age classes, in line with the actual distribution of the Italian population, according to ISTAT data.

**Figure 1.** Sample frequency by age cohort.




Considering the educational level, the majority of participants indicated their educational level as master's degree (*n* = 118, 43.2%) and High School degree (*n* = 116, 42.5%), followed by bachelor's degree (*n* = 39, 14.3%). Finally, as for the occupation status, the majority of participants were employees (*n* = 232, 85%). The remaining minority was divided between students (*n* = 24, 8.8%) and unemployed (*n* = 17, 6,2%). These results can be considered quite in line with the official statistics provided by ISTAT for the age range 18-75 years old, with the only more relevant difference detected in the employment rate (85% vs. 62% actual percentage).

Among participants, supermarkets were the most frequently visited retailers. Specifically, 23.1% (*n* = 63) of participants reported visiting supermarkets once a day, while 57.1% (*n* =

156) reported visiting them once a week. Apparel and beauty stores were less frequented, and the majority of respondents indicated they visit them once per month or even less, 67.8% (*n* = 185) of participants for apparel stores and 85.7% (*n* = 234) of participants for beauty stores, respectively. Table 2 summarizes the overall results for the three retailer categories.

**Table 2.** Frequency of visit split by retailer category.

| | Frequency | | | |
|---|---|---|---|---|
| | Once a day | Once a week | Once every two weeks | Once a month or less |
| Retailer | | | | |
| Supermarkets | 23.1% | 57.1% | 11.7% | 8.1% |
| Apparel Stores | 1.1% | 9.9% | 21.2% | 67.8% |
| Beauty Stores | 0% | 4.4% | 9.9% | 85.7% |

Some differences of retailer visit depending on gender and age class were observed. Women visited supermarkets, apparel stores, and beauty stores more frequently than men and, as age increased, the frequency of visits to the supermarket increased too (see Appendix 2 for details).

## 4.2 Results

### 4.2.1 Descriptive Statistics

In this study, participants were asked positive and negative associations towards smart DS with facial recognition. Concerning the positive associations, the statement participants agreed with the most referred to the ease of use of the technology (*M* = 6.65, *SD* = 2.55*)*. For the other statements, the means revolved around 6.0 and the *SD* was higher than 2.70. Table 3 summarizes the main statistics concerning the positive associations.

**Table 3.** Statistics on positive associations towards smart DS with facial recognition

| | Ease of use | Simplify the shopping experience | Perceived enjoyment | Save time | Enhance the shopping experience | Explore products |
|---|---|---|---|---|---|---|
| *M* | 6.65 | 6.08 | 5.88 | 6.36 | 6.1 | 6.03 |
| *SD* | 2.55 | 2.70 | 2.78 | 2.85 | 2.72 | 2.77 |

Concerning the negative associations, participants showed the highest level of agreement with the statement concerning the fear of data misuse (*M* = 6.83, *SD* = 2.79). Following closely, the feeling of being overcontrolled by companies received a relatively high level of agreement too (*M* = 6.71, *SD* = 2.95). Conversely, the statement that received the most disagreement was related to the sense of shame caused by the idea that others could see personal communications ($M$ = 5.30, $SD$ = 2.94). Regarding the other perceptions, participants' sentiments were more neutral, with mean values hovering around 6.0 and $SD$ around 2.90. Table 4 summarizes the main statistics concerning the negative associations.

**Table 4.** Statistics on negative associations towards smart DS with facial recognition

| | Lack of control | Under control feeling | Data misuse | Fear of face-name association | Shame feeling | Manipulation feeling |
|---|---|---|---|---|---|---|
| *M* | 6.29 | 6.71 | 6.83 | 6.09 | 5.30 | 6.10 |
| *SD* | 2.92 | 2.95 | 2.79 | 2.99 | 2.94 | 3.09 |

Participants were also asked questions aimed at measuring the elasticity to be recognized ($M$ = 4.93, $SD$ = 2.87, $n$ = 273, min = 1, max = 10).

Moving to the recognition preferences, the analysis of frequencies showed that 53% ($n$ = 145) of participants would be willing to be recognized only by retailers they trust, while 12% ($n$ = 33) of participants would be willing to be recognized by all retailers they visit regardless of the degree of trust. The remaining 35% ($n$ = 95) were those participants who would never be willing to be recognized by any retailer.

Finally, participants were asked about the incentives that could motivate them to overcome negative associations or fears. Among the listed incentives, discounts emerged as the favorite ($M$ = 6.26, $SD$ = 3.03). In contrast, the least favored incentive was the interaction with the display ($M$ = 4.53, $SD$ = 2.76). For the other incentives, the mean values were around 5.70 and $SD$ was higher than 2.80. Detailed results are shown in Table 5.

**Table 5.** Statistics on Incentives to be recognized

| | Discounts and Promotions | Special Gifts | Interaction with the display | Virtual Mirrors | Information on data processing and protection | See other consumers' reviews |
|---|---|---|---|---|---|---|
| *M* | 6.26 | 5.74 | 4.51 | 5.07 | 5.71 | 5.63 |
| *SD* | 3.03 | 3.04 | 2.77 | 2.90 | 3.11 | 2.84 |

### 4.2.2 Hypothesis Testing

To test this thesis' four hypotheses, different statistical analyses were conducted on SPSS according to the type of variables that were used, which are presented next, divided according to the hypothesis.

#### 4.2.2.1 Gender and age and their relationship with positive and negative DS associations

H1 stated that: "Perceptions towards smart DS with facial recognition vary according to demographic characteristics (i.e., gender and age)."

To test the hypothesis, ANOVAs were conducted with the positive and negative perceptions as dependent variable and gender or age classes as (separate) predictors. The categories of gender variables were "male" and "female", while the categories of the age classes were the four generational cohorts.

When considering gender, significant relationships ($p < .05$) were found with only two positive perceptions: 1) the technology would simplify the shopping experience, $F$(1, 271 = 4.64, $p$ = .032, $\eta$ = .13, and 2) the technology would allow me to save time, $F(1, 271) = 7.27$, $p = .007$, $\eta$ = .16. In both cases, male participants exhibited higher agreement with these statements compared to female participants. However, these relationships were relatively weak, as the $\eta$ values were small (i.e., below 0.2; Adams et al., 2014). Regarding all the other statements, no significant relationships emerged ($p > .05$), indicating that there were no apparent differences in perceptions based on gender (see Appendix 3 for details).

Regarding age, significant relationships were found only with positive perceptions. Indeed, as shown in Table 6, each positive perception statement had $p < .001$ and $\eta > 0.2$. As age increased, a general decreasing trend in the means of positive perceptions was observed. Younger participants (Generation Z and Millennials) exhibited more favorable perceptions towards DS with face recognition, while older participants (Generation X and Baby Boomers) showed lower levels of positive perceptions, thus suggesting the presence of generational differences in individuals' positive perceptions towards the technology (details in Table 7). As stated, age was not related to any of the negative perceptions, all $p$s < .05(see Appendix 4 for details).

**Table 6.** ANOVA positive associations and age classes

| | *SS* | *df* | *F* | *p* | η |
|---|---|---|---|---|---|
| Ease of use * Age classes | 256.93 | 3 | 15.18 | <.001 | .38 |
| Simplify the shopping experience * Age classes | 345.89 | 3 | 18.87 | <.001 | .42 |
| Perceived enjoyment * Age classes | 285.38 | 3 | 14.05 | <.001 | .37 |
| Save time * Age classes | 280.57 | 3 | 13.03 | <.001 | .36 |
| Enhance the shopping experience * Age classes | 352.40 | 3 | 19.12 | <.001 | .42 |
| Explore products * Age classes | 292.81 | 3 | 14.58 | <.001 | .37 |

**Table 7.** *M*, *SD*, and *N* for each positive association statement, by age class

| Age Classes | | Ease of use | Simplify the shopping experience | Perceived enjoyment | Save time | Enhance the shopping experience | Explore products |
|---|---|---|---|---|---|---|---|
| 18-26 | *M* | 7.41 | 7.44 | 7.15 | 7.20 | 7.15 | 7.58 |
| | *N* | 41 | 41 | 41 | 41 | 41 | 41 |
| | *SD* | 2.25 | 2.39 | 2.47 | 2.58 | 2.55 | 2.19 |
| 27-42 | *M* | 7.91 | 7.39 | 7.03 | 7.60 | 7.45 | 6.93 |
| | *N* | 67 | 67 | 67 | 67 | 67 | 67 |
| | *SD* | 1.77 | 1.79 | 2.19 | 2.06 | 1.82 | 2.42 |
| 43-58 | *M* | 6.43 | 5.64 | 5.51 | 6.23 | 5.92 | 5.81 |
| | *N* | 88 | 88 | 88 | 88 | 88 | 88 |
| | *SD* | 2.61 | 2.85 | 2.78 | 3.10 | 2.81 | 2.74 |
| 59-75 | *M* | 5.39 | 4.74 | 4.64 | 4.97 | 4.56 | 4.69 |
| | *N* | 77 | 77 | 77 | 77 | 77 | 77 |
| | *SD* | 2.61 | 2.55 | 2.78 | 2.68 | 2.54 | 2.74 |

According to these results, H1 was only partially supported. Gender played a relevant role only in shaping two positive perceptions; age did it but only with regards to the positive perceptions.

#### 4.2.2.2 Gender and age and their relationship with elasticity to be recognized

H2 stated that "The elasticity to be recognized varies according to demographic characteristics (i.e., gender and age)". To test this hypothesis, an ANOVA was conducted relating elasticity to be recognized with gender. Then a correlation analysis was conducted to relate elasticity to be recognized with age as continuous variable, as well as an ANOVA relating elasticity to be recognized with the generational cohorts.

The ANOVA test examining the relationship between elasticity to be recognized and gender revealed that there was no statistically significant difference in the elasticity among gender

groups ($p$ = .480). The lack of statistical significance suggests that gender may not be a significant factor influencing individuals' willingness to be recognized in stores.
Age, in turn, was strongly correlated with elasticity to be recognized ($p < .001$, $r = -.35$): as age increased, elasticity to be recognized decreased. To deepen the analysis and measure the average willingness to be recognized in each generational cohort, another ANOVA was conducted. The overall ANOVA result was significant, $F$ (3, 269) = 11.23, $p < .001$, with Generation Z (18-26 years old) reporting the highest average score ($M$ = 6.30) and average willingness appearing to decrease gradually with advancing age, evidenced by the average scores of 5.85 for Millennials (27-42 years old), 4.65 for Generation X (43-58 years old), and 3.74 for Baby Boomers (59-75 years old). These findings confirmed that younger individuals were more open to being recognized in stores, whereas older individuals exhibited a reduced willingness for such recognition (see Appendix 5 for the complete ANOVA results).
Based on the results, H2 was also only partially supported. The elasticity to be recognized varied only according to the age.

#### 4.2.2.3 TAM and TEP drivers and barrier and their relationship with elasticity to be recognized

H3 stated that: "Perceived usefulness, perceived ease of use and perceived enjoyment (TAM), together with TEP drivers, have a positive impact on the elasticity to be recognized. Conversely TEP barriers have a negative impact on the elasticity to be recognized".
To test the hypothesis, a multiple regression analysis was conducted.
In the first trial, the elasticity to be recognized was the outcome variable while the predictors were: perceived usefulness, perceived ease of use, perceived enjoyment, hedonic (explore products), utilitarian (save time), privacy (data misuse), privacy (control feeling), exploitation (manipulation feeling). In this trial, all the outcome variables were included for the regression. The model was significant and able to explain 48% of the variability ($p < .001$). However, half of the variables (4 out of 8) were not significant ($p > .05$). The four predictors that were significant were: perceived enjoyment, utilitarian, hedonic and privacy (control feeling). The VIFs were analyzed and suggested a potential problem of multicollinearity (see Appendix 6 for regression first trial). This result was likely predictable since, in the correlation table between the TAM and TEP variables, most variables were correlated with each other ($p < .001$, $| r | > .30$; see Appendix 7 for correlation table). To solve this issue, a factor analysis was performed. The dimension reduction suggested the extraction of only two factors, one referring to TAM and TEP drivers and the other referring to TEP barriers (see Appendix 8 for the factor analysis).

This result was not considered satisfactory as, with these two factors, the TAM and TEP models would have been merged, and, thus, the impact of the models on the elasticity in the regression could not have been assessed properly.

For the second trial, the regression analysis was performed using the stepwise method. The model that was selected was the second one proposed by the method (see Appendix 9 for the stepwise method). It was significant and able to explain 43% of the variability ($p < .001$, $R^2 = .43$). The reason for choosing this model was that it was the only one that solved the multicollinearity issue, as the two variables had a VIF equal to 1.2.

The regression was built using the standardized coefficients and was the following:

$$y = 0.47x_1 - 0.32x_2 + \varepsilon$$

Where y = elasticity to be recognized, $x_1$ = TAM perceived enjoyment, $x_2$ = TEP privacy.

While perceiving that the technology is funny increased the elasticity to be recognized, feeling controlled by companies through the technology decreased it.

Due to the multicollinearity issue that arose among the variables, what the regression model was able to highlight were the variables which had the strongest impact on the elasticity of being recognized in-store. For this reason, I could only partially accept H3 as the model excluded six variables (in particular two variables belonging to the TAM and six variables belonging to the TEP) to solve the multicollinearity issue, preventing from assessing their impact on the elasticity to be recognized and make a comparison between the two models.

#### 4.2.2.4 Incentives to be recognized and their relationship with elasticity to be recognized

H4 stated that: "Consumers with low elasticity to be recognized show high appreciation towards the incentive to be recognized via smart DS with facial recognition".

To test the hypothesis a correlation analysis was conducted.

All six incentives were correlated with the elasticity to be recognized ($p < .001$). However, the correlation was strongly positive ($r > .30$), not negative, meaning that the more participants were willing to be recognized, the more they found all the incentives to be motivating (Table 8).

**Table 8.** Correlation between elasticity to be recognized and incentives to be recognized

**Correlations**

| | | Discounts and Promotions | Special Gifts | Interaction with the display | Virtual Mirrors | Information on data processing | See other consumers' reviews | Elasticity to be recognized |
|---|---|---|---|---|---|---|---|---|
| Elasticity to be recognized | Pearson Correlation | .59 | .64 | .62 | .60 | .54 | .61 | 1 |
| | Sig. (2-tailed) | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | |
| | N | 273 | 273 | 273 | 273 | 273 | 273 | 273 |

Given these results, I could not accept H4, as what emerged was exactly the opposite of what I hypothesized. These findings highlight the possibility that consumers who were very restrained in accepting the technology also reported not being persuaded by incentives, while those who were more convinced could be convinced even more through them.

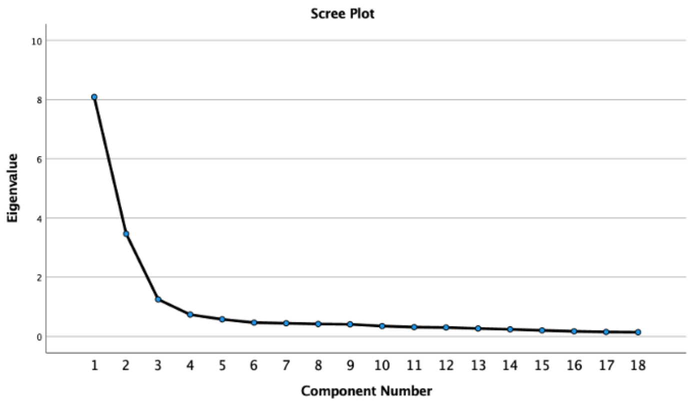
### 4.2.3 Demand segmentation

To proceed with the behavioral segmentation of the target population, a conventional analytical protocol involving the integration of factor analysis and cluster analysis was employed. This phase of analysis aimed at answering the RQ4: Are there specific segments in the Italian population more willing to be recognized in-store through facial recognition to receive personalized services via smart DS?

To perform the factor analysis, 18 input variables belonging to three groups of questions were considered: 1) positive associations toward DS with facial recognition (Q5_1-Q5_6), 2) negative associations toward DS with facial recognition (Q7_1-Q7_6), and 3) incentives to be recognized by retailers (Q11_1-Q11_6). These variables were chosen as they were deemed most suitable for describing consumers based on their perceptions and level of influenceability.

To determine the appropriate number of factors, the eigenvalue-greater-than-one rule of Kaiser (1960) was used together with the explained variance criterion and the scree plot analysis. The first criterion suggested three factors, as only the first three components had eigenvalues higher than one. The second criterion, based on the percentage of explained variance (according to which the components should explain at least the 60% of variance), suggested three factors, which together accounted for 70% of the variability (see Appendix 10 for eigenvalues and explained variance table). Lastly, the scree plot analysis also supported the three-factor solution as the most suitable (Figure 2).

**Figure 2.** Scree Plot (18 factors)




Following the extraction of the three factors, a communalities analysis was conducted to verify whether all variables were adequately explained by the chosen factors (see Table 9). All communalities were found to be higher than the threshold of 0.40, except for one variable related to feeling ashamed about personalized communications, which had a value of 0.38. However, since this variable was not considered the most critical in the analysis, the three-factor solution remained optimal.

**Table 9.** Communalities (Extraction method: Principal Components Analysis)

**Communalities**

| | Initial | Extraction |
|---|---|---|
| The technology is easy to use | 1.00 | .56 |
| The technology would simplify the shopping experience | 1.00 | .86 |
| The technology is funny to use | 1.00 | .77 |
| The technology would allow me to save time | 1.00 | .78 |
| The technology would enhance the shopping experience | 1.00 | .83 |
| The technology would alow me to explore products I could like | 1.00 | .65 |
| The technology would make me feel manipulated | 1.00 | .77 |
| I would not feel I have control over the technology | 1.00 | .67 |
| The technology would make me feel controlled by companies | 1.00 | .79 |
| I would be afraid that companies misuse my personal data | 1.00 | .69 |
| It scares me that someone could associate my name with my face | 1.00 | .67 |
| I would be ashamed if other clients could see my personalized communications | 1.00 | .38 |
| Discounts and Promotions | 1.00 | .77 |
| Special Gifts | 1.00 | .76 |
| Interaction with the display | 1.00 | .69 |
| Virtual Mirrors | 1.00 | .76 |
| Information on data processing and protection | 1.00 | .71 |
| See other consumers' reviews | 1.00 | .71 |

Subsequently, to enhance interpretability, the component matrix was rotated using the Varimax method (Table 10).

**Table 10.** Rotated component matrix (Varimax method)

**Rotated Component Matrix**

| | 1 | 2 | 3 |
|---|---|---|---|
| Virtual Mirrors | .81 | | |
| Discounts and Promotions | .79 | | |
| Special Gifts | .79 | | |
| Interaction with the display | .77 | | |
| Information on data processing and protection | .78 | | |
| See other consumers' reviews | .77 | | |
| The technology would simplify the shopping experience | | .86 | |
| The technology would enhance the shopping experience | | .82 | |
| The technology would allow me to save time | | .81 | |
| The technology is funny to use | | .79 | |
| The technology would allow me to explore products I could like | | .72 | |
| The technology is easy to use | | .69 | |
| The technology would make me feel manipulated | | | .86 |
| The technology would make me feel controlled by companies | | | .85 |
| I would be afraid that companies misuse my personal data | | | .83 |
| It scares me that someone could associate my name with my face | | | .82 |
| I would not feel I have control over the technology | | | .81 |
| I would be ashamed if other clients could see my personalized communications | | | .61 |

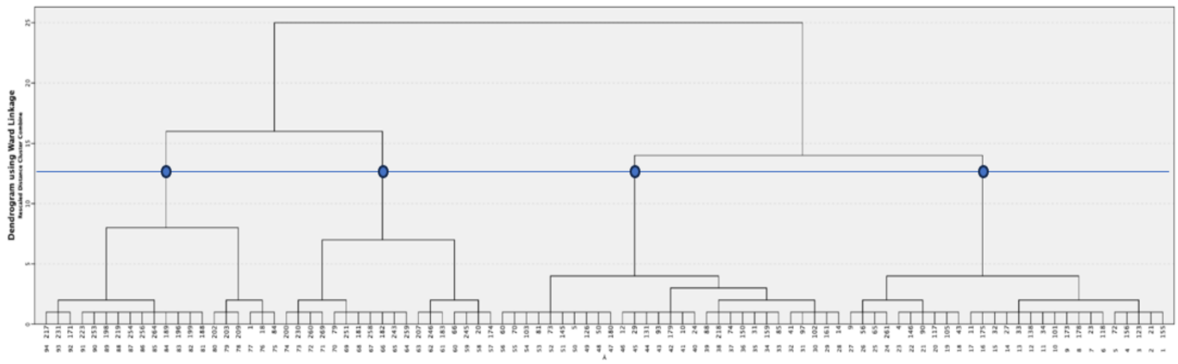
Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 4 iterations.

The three identified factors follow the same division of the three groups of questions to which the variables used to perform the factor analysis belonged to. Firstly, "Incentives to be recognized" (Factor 1) refers to the appreciation of a set of external incentives that could positively influence consumers' acceptance and willingness to be recognized in store by retailers. Secondly, "Positive associations" (Factor 2), meaning the extent to which DS with facial recognition technology is positively perceived as a powerful and easy enabler that ameliorates the whole in-store shopping experience. Thirdly, "Negative associations" (Factor 3) summarizes all the negative associations connected to the implementation of DS with facial recognition technology that would cause consumers a sense of vulnerability and discomfort.

The three factors identified through the factor analysis were used as input for conducting the cluster analysis, applied to determine customer segments. These segments represent groups of consumers characterized by internal homogeneity and external heterogeneity. The segmentation research aimed to identify consumer groups that share certain characteristics in order to analyze the object of study of this thesis in more detail and support subsequent managerial implications.

The cluster analysis was first conducted using the Ward method, a hierarchical method used to evaluate the valid potential number of clusters. The hierarchical cluster analysis was performed on 30% of participants randomly selected from the sample. Analyzing the dendrogram, the optimal number of clusters was identified as four (Figure 3).

**Figure 3.** Dendogram Ward method, cluster analysis




An ANOVA was then performed to identify the initial centers, functional to the second method used for the cluster analysis (K-means method). To run the ANOVA test, the cluster membership was used as dependent variable while the three factors of the factor analysis were used as independent ones. The initial centers have been saved in a separate SPSS file and used to run the cluster analysis with the K-means method that was applied to the entire dataset (100% of participants), using as number of clusters the one identified through the Ward method (four). Then, the significance of the factors was verified through an ANOVA test. The significance in all cases was lower than the threshold of .05, thus assessing the goodness of the clusterization (see Table 11).

**Table 11.** ANOVA K-means method, Cluster Analysis

| ANOVA | Cluster | | Error | | F | Sig |
|---|---|---|---|---|---|---|
| | Mean Square | df | Mean Square | df | | |
| Incentives to be recognized | 58.67 | 3 | .36 | 269 | 164.38 | <.001 |
| Positive associations | 51.48 | 3 | .44 | 269 | 117.77 | <.001 |
| Negative associations | 40.09 | 3 | .56 | 269 | 71.08 | <.001 |

Lastly, the validity of the division of the participants was analyzed by looking at the distribution of respondents into clusters. All clusters had a number of respondents higher than 5% and lower than 50%-60%. Moreover, as shown in Table 12, the clusters were fairly balanced with the smallest representing 17% of participants ($n$ = 46) and the largest representing 32% of participants ($n$ = 87).

**Table 12**. Number of Cases in each cluster K-means method, Cluster Analysis

Number of Cases in each Cluster

| 1 | 2 | 3 | 4 |
|---|---|---|---|
| 69 | 71 | 87 | 46 |

The final cluster centers were then identified and used to describe each cluster based on the three identified factors. To facilitate the interpretation, as shown in Table 13, a color coding was applied to the table using a threshold of approximately 0.4 in absolute terms (considering the distance from the overall mean equal to 0).

**Table 13.** Final Cluster Centers K-means method, Cluster Analysis

Final Cluster Centers

| | Cluster | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Incentives to be recognized | -0.59 | 0.56 | 0.73 | -1.35 |
| Positive associations | -1.22 | 0.38 | 0.17 | 0.92 |
| Negative associations | -0.12 | -0.98 | 0.73 | 0.31 |

The four identified clusters were the following: 1) Cluster 1, the unconvinced and disinterested. Representing 25% of the sample, this cluster comprises those consumers with extremely low positive associations towards DS with facial recognition technology. This characteristic does not stem from a fear of the technology, as the cluster's negative associations are average, but rather from a perception that the technology would not offer significant enhancements to their shopping experience. In fact, the fact that the external incentives are not highly appreciated demonstrated that this cluster would not change their opinion towards the technology; 2) Cluster 2, the incentive-driven explorers. Representing 26% of the sample, this cluster comprises those consumers with the lowest negative associations compared to the average sample. As they do not feel any sense of discomfort or vulnerability, this cluster perceives DS with facial recognition as a powerful and convenient tool that would enhance their shopping experience. Moreover, the cluster could be further motivated to accept in-store facial recognition by incentives as they are highly appreciated; 3) Cluster 3, the convertibles. Representing 32% of the sample, this cluster comprises those consumers who exhibit substantial negative associations towards DS with facial recognition technology. However, what sets this cluster apart is their high appreciation for incentives. The possibility of receiving appealing incentives might convince them to overcome their fears and move from being scared to being willing to embrace an innovative way of shopping; 4) Cluster 4, the uninfluenceable ambivalents. Representing 17% of the sample, this cluster comprises those consumers who held both positive and negative associations towards smart DS with facial recognition technologies. On the one hand, they recognize the potential benefits and advantages of the technology. On the other hand, the fact that they possess negative associations, too, reveals their concerns about the potential drawbacks of facial recognition applied to DS. Incentives to be recognized are not appreciated at all and might not be what would make positive associations prevail over the negative ones.

To enhance the description of the clusters, cross-analyses were conducted involving other variables. Considering the demographic variables, the results of the analysis revealed a noteworthy correlation between the clusters and the variables of gender, age, and education level ($p < 0.05$, Cramer's V > 0.2). Cluster 1, the unconvinced disinterested, consists of 58% women and 42% men, primarily from the Generation X and Baby Boomers age groups, with a majority holding a High School Diploma. Cluster 2, the incentive-driven explorers, comprises 52% women and 48% men, spanning all age categories, but with a notable presence of Millennials. The majority of individuals in this cluster possess a master's degree. Cluster 3, the convertibles, comprises 56% women and 44% men, covering all age groups, with a pronounced representation from the Millennials and Generation X categories. Participants in this cluster possess either a diploma or a master's degree. Cluster 4, The uninfluenceable ambivalents, includes 30% women and 70% men, primarily from adult age groups, with a majority holding a High School Diploma. No statistically significant differences were observed in terms of occupation across the clusters, and each cluster predominantly consists of individuals who are employed.

Considering the frequency of visits, no statistically significant differences were observed: Across all clusters, participants predominantly engage in weekly visits to supermarkets, whereas their visits to apparel and beauty stores occur mainly once a month or less.

Moving on to the elasticity to be recognized, a significant relationship with the clusters was observed, $F(3, 269) = 56.32$, $p < .001$, $\eta = .62$. The unconvinced disinterested (Cluster 1) showed the lowest willingness to be recognized in store with an average of 2.74 out of 10 ($SD$ = 2.10). In contrast, the incentive-driven explorers (Cluster 2), showed the highest willingness to be recognized with an average score of 7.39 out of 10 ($SD$ = 1.96). For the convertibles (Cluster 3), a more neutral sentiment was observed, reflected in an average score of 5.37 out of 10 ($SD$ = 2.37). The uninfluenceable ambivalents (Cluster 4) showed instead no willingness to be recognized, with an average score of 3.58 out of 10 ($SD$ = 2.65).

Lastly, another significant relationship has been observed between the clusters and the recognition preferences ($p < .001$, Cramer's V = 0.39). Consistently aligning with prior findings, 66% of the individuals in the unconvinced disinterested cluster (Cluster 1) and 57% of those in the uninfluenceable ambivalents cluster (Cluster 4) expressed no inclination towards recognition in any retailer. With regards to the incentive-driven explorers (Cluster 2), 24% showed willingness to be recognized across all retailers, while 73% were open to recognition solely within retailers they trust. Lastly, for the convertibles (Cluster 3), although 24% exhibited hesitancy towards in-store recognition, the remaining 76% were willing to be recognized, but principally in trusted retailers (Table 14).

**Table 14.** Count Cluster Number of Case * Recognition preferences

**Cluster Number of Case * Recognition preferences**

| | | Recognition preferences | | | |
|---|---|---|---|---|---|
| | | In all retailers | In retailers I trust | Never | Total |
| Cluster Number of Case | 1 | 3 | 20 | 46 | 69 |
| | 2 | 17 | 52 | 2 | 71 |
| | 3 | 9 | 57 | 21 | 87 |
| | 4 | 4 | 16 | 26 | 46 |
| Total | | 33 | 145 | 95 | 273 |

Table 15 summarizes the insights obtained from the Cluster Analysis, with the objective of presenting a comprehensive overview of the four distinct clusters that have been identified.

**Table 15.** Summary of clustering analysis

| | **The unconvinced disinterested** | **The incentive-driven explorers** | **The convertibles** | **The uninfluenceable ambivalents** |
|---|---|---|---|---|
| Sample % | 25% | 26% | 32% | 17% |
| Gender | F: 58%; M: 42% | F: 52%; M: 48% | F:56%; M:44% | F:30%; M:70% |
| Age | Generation Z: 9%<br>Millennials: 0%<br>Generation X: 36%<br>Baby Boomers: 55% | Generation Z: 20%<br>Millennials: 38%<br>Generation X: 28%<br>Baby Boomers: 14% | Generation Z: 23%<br>Millennials: 30%<br>Generation X: 32%<br>Baby Boomers: 15% | Generation Z: 2%<br>Millennials: 30%<br>Generation X: 33%<br>Baby Boomers: 35% |
| Occupation | Mainly workers (81%) | Mainly workers (85%) | Mainly workers (85%) | Mainly workers (91%) |
| Education level | High School Diploma predominance (60%) | Master's Degree predominance (56%) | Distributed between High School Diploma and Master's Degree | High School Diploma predominance (55%) |
| Smart DS associations | Low positive associations<br>On average negative associations | High positive associations<br>Low negative associations | On average positive associations<br>High negative associations | High positive and negative associations |
| Recognition elasticity | Low: 2.7/10 | High: 7.4/10 | Neutral: 5.4/10 | Low: 3.6/10 |
| Recognition preferences | Nowhere (67%) | All retailers (24%)<br>Trusted retailers (73%) | All retailers (10%)<br>Trusted retailers (65%) | Nowhere (57%) |
| Incentives to be recognized | Not motivating | Motivating: discounts and promotion best preference | Motivating: discounts and promotion best preference | Not motivating |

The cluster analysis highlighted the existence of differences in the Italian population and the presence of clusters that might be more ready for the introduction of smart DS in Italian retailers. Indeed, the incentive-driven explorers (Cluster 2) emerged as the most suitable cluster for the adoption of this novel in-store technology. This is not only due to their high elasticity to be recognized but also due to their exclusively positive attitudes and perception towards this technology. The convertibles (Cluster 3) also showed interesting characteristics that could render them potential targets once the technology starts to spread. In fact, as they might progressively verify the tangible benefits of the technology, their fears might be reduced. Also, the strategic use of incentives could highly work on them, moving their elasticity to be recognized from a neutral stance to a positive one.

### 4.2.4 Conjoint analysis

With the aim of identifying the most effective combination of elements that would facilitate the successful integration of smart DS with facial recognition in stores, a conjoint analysis was performed. The analysis aimed at answering at RQ3: What would be the optimal and most appreciated scenario to start introducing the technology in terms of retailer typology, content type, display medium, and recognition modality?

The attributes and related levels considered were identified through the literature review and the qualitative research's insights and consisted of the following: 1) Retailer Typology: This attribute encompassed three levels, namely supermarkets, apparel stores, and beauty stores, representing the different retail environments where smart DS with facial recognition technology would be employed; 2) Recognition Modality: The third attribute consisted of two levels, recognition upon store entrance and recognition through QR code scanning, representing different modalities through which customers would engage with the facial recognition system; 3) Display Medium: This attribute comprised two levels, totem and smartphone, which represented the diverse display through which personalized content could be presented to customers; and 4) Content Type: The fourth attribute involved three levels, discounts and promotions, informative contents, and inspirational contents, representing the typologies of personalized contents that could be displayed to customers. The different scenarios that were evaluated by the respondents in the questionnaire were obtained through SPSS' orthogonal design function, which made it possible to identify nine different combinations.

The importance values table measured the value that consumers have placed on the individual attributes that could characterize smart DS with facial recognition. The most important attribute was the Recognition Modality with an importance value of 55.5, followed by the Retailer Typology (25.5), the Content Type (17.2), and the Display Medium (1.6).

The Utilities table allowed to analyze the utility of each single level for each attribute. The utilities suggested that the best-case scenario would be being recognized in apparel stores by scanning a QR code to see, on the personal smartphone, personalized discounts and promotions (see Table 16). This result highlighted two important considerations: First, consumers might prefer to decide when to be recognize and have more control over the technology; Second, even if it was not one of the most agreed statements among the perceptions toward the technology, consumers might still prefer to avoid that other people could see their own personalized communications, thus preferring their smartphone as display medium.

**Table 16.** Conjoint, Utilities (all respondents)

| Utilities | | | |
|---|---|---|---|
| | | Utility Estimate | Std. Error |
| Content Type | Discounts and Promotions | 0.16 | 0.05 |
| | Inspirational | -0.05 | 0.05 |
| | Informative | -0.11 | 0.05 |
| Retailer Typology | Supermarket | 0.04 | 0.05 |
| | Beauty Store | -0.23 | 0.05 |
| | Apparel Store | 0.18 | 0.05 |
| Recognition Modality | Always | -0.44 | 0.04 |
| | QR Code Scanning | 0.44 | 0.04 |
| Display Medium | Totem | -0.01 | 0.04 |
| | Smartphone | 0.01 | 0.04 |
| (Constant) | | 5.98 | 0.04 |

To determine whether the preferences toward the different scenarios varied according to respondents' socio-demographic characteristics, additional analyses were conducted by dividing the sample by gender and age classes.

When considering the gender, the most important attribute remained the Recognition Modality (women = 63.5, men = 44.7). Among women, in contrast to the overall results, the second attribute for importance was the Content Type with an importance value of 24.6. Conversely, for men, aligning with the overall results, the Retailer Typology took precedence with an importance value of 38.2. The attribute of least importance, consistent with the overall results, was the Display Medium, with comparable importance values between genders (1.6 for women and 1.4 for men; see Table 17). A detailed analysis of the utilities underscored that the best-case scenario was the same for both genders and remained consistent with the best-case scenario emerged from the overall analysis: being recognized in apparel stores by scanning a QR code to see, on the personal smartphone, personalized discounts and promotions (Appendix 11).

**Table 17.** Conjoint, Importance Values (split by Gender)

| Importance Values | | |
|---|---|---|
| Male | Content Type | 15.52 |
| | Retailer Typology | 38.27 |
| | Recognition Modality | 44.77 |
| | Display Medium | 1.44 |
| Female | Content Type | 24.63 |
| | Retailer Typology | 10.17 |
| | Recognition Modality | 63.54 |
| | Display Medium | 1.66 |

Averaged Importance Score

Moving to the split by age classes, the importance scale remained the same as in the overall analysis (Recognition Modality, Retailer Typology, Content Type and Display Medium) for Generation Z respondents, Millennials, and Generation X respondents. In contrast, for Baby Boomers, even if the most important attribute remained the Recognition Modality, this time was followed by the Content Type (see Table 18).

**Table 18.** Conjoint, Importance Values (split by Age Classes)

| Importance Values | | |
|---|---|---|
| 18-26 | Content Type | 12.28 |
| | Retailer Typology | 19.80 |
| | Recognition Modality | 61.58 |
| | Display Medium | 6.34 |
| 27-42 | Content Type | 7.15 |
| | Retailer Typology | 26.90 |
| | Recognition Modality | 61.52 |
| | Display Medium | 4.44 |
| 43-58 | Content Type | 24.54 |
| | Retailer Typology | 31.85 |
| | Recognition Modality | 43.34 |
| | Display Medium | .26 |
| 59-75 | Content Type | 28.29 |
| | Retailer Typology | 27.30 |
| | Recognition Modality | 39.31 |
| | Display Medium | 5.10 |

Averaged Importance Score

Even the best-case scenario was aligned with the one emerged from the overall analysis for Generation Z and Generation X respondents: being recognized in apparel stores by scanning a QR Code to see, on the personal smartphone, personalized discounts and promotions. Instead, both Millennials and Baby Boomers preferred the totem over the personal smartphone as Display Medium, while only Baby Boomers preferred the supermarkets over the apparel stores as Retailer Typology (Appendix 12).

The last analysis aimed at identifying eventual differences among the four clusters in terms of preferences and verifying whether the utilities schemes varied according to the clusters. For all the four clusters, the attributes ranking remained consistent with the overall results: Recognition Modality, Retailer Typology, Content Type and Display Medium (Table 19).

**Table 19.** Conjoint, Importance Values (split by Clusters)

| Importance Values | | |
|---|---|---|
| The unconvinced disinterested | Content Type | 14.99 |
| | Retailer Typology | 27.61 |
| | Recognition Modality | 47.93 |
| | Display Medium | 9.47 |
| The incentive-driven explorers | Content Type | 22.96 |
| | Retailer Typology | 30.35 |
| | Recognition Modality | 37.35 |
| | Display Medium | 9.34 |
| The convertibles | Content Type | 11.79 |
| | Retailer Typology | 16.51 |
| | Recognition Modality | 57.88 |
| | Display Medium | 13.83 |
| The uninfluenceable ambivalents | Content Type | 25.46 |
| | Retailer Typology | 29.18 |
| | Recognition Modality | 45.36 |
| | Display Medium | .00 |

Averaged Importance Score

Focusing on the utilities of the two main clusters of interest, namely the incentive-driven explorers (Cluster 2) and the convertibles (Cluster 3), they both preferred personalized discounts and promotions as Content Type and apparel stores as Retail Typology. In contrast, while the incentive-driven explorers preferred to be always recognized and see the personalized content on the store displays, the convertibles manifested a preference in scanning a QR code to determine when to be recognized and see the personalized content on their smartphones (see Table 20).

**Table 20.** Conjoint, Utilities (split by Clusters, focus on Cluster 2 and Cluster 3)

| Utilities | | | | |
|---|---|---|---|---|
| | | | Utility Est | Std. Error |
| The incentive-driven explorers | Content Type | Discounts and Promotions | 0.16 | .13 |
| | | Inspirational | -0.04 | .13 |
| | | Informative | -0.14 | .13 |
| | Retailer Typology | Supermarket | -0.05 | .13 |
| | | Beauty Store | -0.18 | .13 |
| | | Apparel Store | 0.23 | .13 |
| | Recognition Modality | Always | 0.25 | .10 |
| | | QR Code Scanning | -0.25 | .10 |
| | Display Medium | Totem | 0.06 | .10 |
| | | Smartphone | -0.06 | .10 |
| | (Constant) | | 7.101 | .10 |
| The convertibles | Content Type | Discounts and Promotions | 0.15 | .04 |
| | | Inspirational | -0.04 | .04 |
| | | Informative | -0.11 | .04 |
| | Retailer Typology | Supermarket | -0.04 | .04 |
| | | Beauty Store | -0.11 | .04 |
| | | Apparel Store | 0.20 | .04 |
| | Recognition Modality | Always | -0.62 | .03 |
| | | QR Code Scanning | 0.62 | .03 |
| | Display Medium | Totem | -0.15 | .03 |
| | | Smartphone | 0.15 | .03 |
| | (Constant) | | 6.930 | .03 |

### 4.3 Discussion

The results of the quantitative analysis were compared with both the literature and the qualitative analysis' results. Starting from the associations towards the technology, one of the statements participants agreed the most was that the technology would allow them to save time. This is what Riegger and colleagues (2021) defined as the "utilitarian" driver and what emerged to be the main positive association also in the qualitative analyses. Areas of alignment were identified also considering the negative associations. The main negative associations, as emerged also from the qualitative insights, referred to the fear of data misuse, what Riegger and colleagues (2021) defined as the "privacy" barrier.

Pantano and colleagues' (2022) study suggested the existence of generational differences when it comes to associations towards facial recognition, and the outcomes derived from this thesis' qualitative and quantitative studies confirmed the existence of these differences also in the case of smart DS; however, they were not aligned between the two studies. The main differences identified by the qualitative analysis pertained to negative perceptions; in particular, that adults would experience a significantly stronger sense of manipulation compared to the younger. This result was not confirmed by the quantitative analysis, wherein it appeared that belonging to different generational cohorts did not influence the intensity of negative associations. Conversely, the quantitative analysis highlighted generational differences concerning positive perceptions. Specifically, the younger associated more positive aspects with smart DS with facial recognition technology.

When moving to the elasticity to be recognized, the quantitative study showed that there was a good proportion of participants who would still be reluctant to accept facial recognition, in contrast to the interviews' evidence. The quantitative analysis also confirmed the existence of generational differences, as suggested by Pantano (2022), in the elasticity to be recognized, as it reduced the more the age increased. In particular, Generation Z reported the highest elasticity among generational cohorts. The elasticity to be recognized was correlated with the associations towards the technology: Reasonably, those who had more positive associations had a higher elasticity to be recognized while those who had negative associations were less willing to be recognized. These results were in line with Riegger's (2021) drivers and barriers that influence the acceptance of TEP.

Another finding that was in line with previous literature and with the qualitative analyses' results was the importance of trust in shaping participants' recognition preferences. Indeed, also the quantitative results confirmed that the majority of participants would be willing to be recognized only by trusted retailers.

Regarding the incentives to be recognized, they were appreciated only by those participants that already showed a good elasticity to be recognized and did not change the perceptions of those who showed reluctancy towards the technology. These results contrasted with what was found in Pantano's (2022) study, according to which everyone would be more incentivized to accept facial recognition through some gratifications. As emerged also in the qualitative analysis, the most appreciated incentives were discounts and promotions, appreciated by all generational cohorts and not just by adults as indicated in Pantano's study. The least appreciated incentive was the possibility to interact with the display, in misalignment with the literature and the in-depth interviews' results.

Finally, the conjoint analysis highlighted two interesting aspects. The first was that most participants preferred to scan a QR code and decide when to be recognized rather than be recognized every time they entered the stores. This result confirmed what was stated by some participants of the qualitative analyses and supports Riegger's (2021) vision, according to which perceiving a sense of control over the technology positively contributes to its acceptance. The second referred to the participants' preference of seeing the personalized display on their smartphones, in line with the focus group's results but not with the interviews' ones. This result was coherent with previous literature, in particular with what emerged in Riegger's (2022) study and might be justified in terms of social presence and impression management, as highlighted in Hess and colleagues' (2021) study. Lastly, the conjoint analysis showed that participants would prefer to see discounts and promotions and the preferred stores to be recognized were the apparel ones. This result slightly differed from what emerged in the in-depth interviews, where content related to discounts and promotions were seen more appropriate for supermarkets.

## 5. General discussion

### 5.1 Summary of results

The main findings of the thesis were the following: First, smart DS with facial recognition was mainly associated, on one hand, with the possibility to save time in the qualitative analyses and with the perceived ease of use in the quantitative analysis and, on the other hand, with a fear of data misuse by companies in both analyses. Both associations coincide with one driver and one barrier that influence the acceptance of TEP identified by Riegger (2021). The regression in the quantitative analysis allowed to demonstrate that the fear of data misuse, together with the perceived enjoyment coming from the TAM, were the variables with the strongest impact on the elasticity to be recognized. Second, the only demographic variable that was correlated with smart DS with facial recognition technology, also in line with Pantano's study (2022), was age. Indeed, young consumers showed more positive and less negative associations towards the technology while showing higher elasticity to be recognized if compared to the adult generations. Third, in line with one of the factors that influence consumers to share personal information (Pantano, 2022), both of this thesis' studies underlined the importance of trust, as consumers were mainly willing to be recognized in trusted retailers. Lastly, concerning the incentives to be recognized, the quantitative analysis did not confirm the results gathered from the qualitative analysis, which were instead in line with previous literature according to which incentives positively influence the willingness to be recognized in store. The quantitative analysis highlighted that incentives seemed not to be enough to convert reluctant consumers; however, they seemed to be an optimal way to enhance the enthusiasm of those already willing to be recognized.

### 5.2 Implications

This thesis and its findings offer some contributions to the academic and managerial context. On the academic side, very little research was done on facial recognition technology and no studies were done on its applications to smart DS for personalization and commercial purposes. Apart from studying, for the first time, consumers' perceptions and attitudes towards smart DS with facial recognition in the Italian landscape, this thesis also aimed to fill several gaps highlighted by previous scholars. In particular, Lee and Choo's (2019) call for more research on DS advertising and Foroudi and colleagues' (2018) suggestions for more research on consumers' acceptance of smart displays. Moreover, this thesis tried to extend Pantano and colleagues' (2022) qualitative study on facial recognition to the case of its application to smart

DS using also a quantitative methodology and mainly confirming that generational differences do exist. Overall, I believe that this thesis has opened a window to future research, considering also that smart in-store technologies will dominate the retail market with their several applications.

On the managerial side, this thesis has offered managers the possibility to understand consumers' perceptions and attitudes towards an in-store TEP. In particular, the thesis has highlighted that younger consumers have more positive associations towards smart DS with facial recognition and would be more willing to accept it in stores to receive greater personalization, something highly positive considering that they are the consumers of the future and that probably the first application of smart DS with facial recognition will be done by youth brands as they are usually more innovative. Also, as this thesis has demonstrated that having positive associations towards the technology positively influences its acceptance, managers should develop strategies aimed at communicating the advantages that this technology would bring to consumers' shopping experience. Moreover, as this thesis has stressed the role that trust has in shaping consumers' recognition preferences, managers should consider the introduction of more trust-building strategies in their agenda. Lastly, through the conjoint analysis, this thesis has offered managers some insights on how the technology could be introduced in the market: making consumers scan a QR code to be recognized and displaying the personalized content on their smartphones.

### 5.3 Limitations and future studies

Despite the interesting findings of this thesis, some limitations have been identified, together with possible ways to overcome them through future studies.

The first limitation refers to the sample used for the quantitative study. Due to financial and time constraints, I used a convenience sample extended through snowball sampling. For this reason, it can be hard to make meaningful generalizations. Moreover, the sample was unbalanced on the educational level, as the majority of participants had a bachelor's or master's degree. Future research should use larger and more representative samples, using, for example, paid services like Prolific for participant recruitment.

Another limitation lies in the fact that I tested a hypothetical scenario, as smart DS with facial recognition technology is not currently adopted by any retailers in Italy. Participants' answers were based only on how I described the technology application and functionalities. Participants might have found it difficult to assess their opinions and behaviors towards something they have never experienced and so their responses might have been biased. For these reasons, future studies should make participants experiment with the technology itself, even if in a laboratory setting, to make them be more conscious while answering the questionnaires and provide more accurate answers.

The third limitation refers to the broad scope of this thesis. Indeed, to provide a comprehensive overview, I have covered many aspects related to the technology: perceptions towards the technology, incentives to be recognized, retailer typologies in which to be recognized, type of preferred content that should be displayed on the screen and preferred display medium to see the personalized communication. Future studies can focus only on one aspect and analyze it with more depth, including, for example, more variables estimated using more items, moderators, and mediators.

Moreover, the regression model that I used only included two variables (perceived enjoyment from TAM and privacy barrier from TEP model) to explain the elasticity to be recognized. I ended up not knowing the exact impact that all the other variables of the model had on the elasticity to be recognized as they were excluded from the regression not because of a problem of significance but because of a multicollinearity issue. However, as all these variables are correlated with the elasticity to be recognized, future studies should use more items for each variable to better study the TAM and TEP drivers and barriers model when applied to smart DS with facial recognition.

Lastly, I encountered difficulties in finding previous studies on facial recognition technologies, in particular quantitative ones. As smart DS is going to be better known in the future, I find it reasonable that more accurate and specific literature will emerge, and more hypotheses will be tested.

## 6. Conclusion

Smart DS has become a commonly used technology in the retail sector. One of its applications, even if not yet widely spread, is to deliver customers targeted communications thanks to facial recognition technology. The results of this thesis can be considered the first layer for understanding consumers' attitudes and perceptions towards smart DS with facial recognition. Indeed, this thesis' results provided a comprehensive overview covering several aspects concerning this technology. It started with identifying the main consumers' positive and negative associations towards the technology, moving to their willingness to be recognized, recognition preferences and incentives to be recognized, and it ended with the identification of clusters within the Italian population together with the identification of the best-case scenario for introducing the technology. I hope this thesis was just the starting point and that more research will be done to better understand consumers when confronted with this new type of smart DS in order to be prepared to a retail future that will be shaped by technologies and extreme personalization standards.

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## 8. Appendix

**Appendix 1:** Questionnaire

Ciao, mi chiamo Alice e sono una studentessa double degree dell'Università Bocconi e Universidade Catolica Portuguesa. Sto conducendo una ricerca quantitativa per la mia tesi di laurea magistrale sullo smart digital signage. Ti chiedo gentilmente di rispondere a 13 domande, per una durata di circa 5 minuti. Il tuo contributo è prezioso per la mia laurea e per l'avanzamento della conoscenza!

Tutte le informazioni e i dati raccolti durante questo studio saranno anonimi e mantenuti riservati e saranno utilizzati solo a scopo di ricerca. Hai il diritto di rifiutarti a partecipare e ritirarti dalla ricerca ora o in qualsiasi momento una volta iniziata. Per ogni domanda o per conoscere i risultati, per favore invia una mail a s-aduonno@ucp.pt

Grazie per il tuo tempo e per la partecipazione a questo studio.

Q1 Quante volte frequenti i seguenti retailer in un mese?

| | Una volta al giorno (1) | Una volta a settimana (2) | Una volta ogni due settimane (3) | Una volta al mese o meno (4) |
|---|---|---|---|---|
| Supermercati (4) | ○ | ○ | ○ | ○ |
| Negozi di abbigliamento (5) | ○ | ○ | ○ | ○ |
| Negozi di beauty (6) | ○ | ○ | ○ | ○ |

La **tecnologia di riconoscimento facciale** applicata alla segnaletica digitale all'interno dei punti vendita permette di mostrare sui display/totem del negozio **comunicazioni estremamente personalizzate**. Queste ultime, infatti, si basano sulle caratteristiche di chi entra in negozio, sul suo storico acquisti e sulle sue preferenze.

Di seguito tre brevi esempi per aiutarti a immaginare al meglio questo scenario:

*- Maria è una cliente di Zara amante dei* ***colori sgargianti*** *e delle* ***gonne****. Entrata in negozio vede pubblicizzate sul display le* ***gonne colorate*** *della nuova collezione adatte al suo fisico e consigli su* ***come abbinarle****. Quando invece Marco, amante del* ***nero*** *e delle* ***t-shirt****, entrerà in punto vendita, vedrà sul display gli* ***sconti della settimana sui capi scuri****.*

*- Maria è una cliente di Sephora amante di* ***make-up****. Entrata in negozio vede sul display un* ***tutorial di make-up*** *con i suoi prodotti preferiti. Quando invece Marco, amante di* ***skin-care,*** *entrerà in punto vendita, vedrà sul display le* ***composizioni di creme da giorno****.*

*- Maria è una cliente di Esselunga amante dei* ***dolci****. Entrata al supermercato vede pubblicizzati sul display i prodotti per cucinare una* ***ricetta a base di Nutella****. Quando invece Marco, amante del* ***tonno****, entrerà in punto vendita vedrà sul display digitale tutti gli* ***sconti della settimana sui brand di tonno****.*

**NB: sia Maria che Marco hanno acconsentito a farsi riconoscere in punto vendita**

Q2 Per favore, rispondi alle seguenti domande pensando alla tecnologia appena descritta.
Su una scala da 1 (**per nulla d'accordo**) a 10 (**estremamente d'accordo**), quanto sei d'accordo con le seguenti affermazioni:

- Trovo che la tecnologia sia facile da usare
- Questa tecnologia semplificherebbe l'esperienza di acquisto in negozi fisici
- Questa tecnologia è divertente da utilizzare
- Questa tecnologia mi aiuterebbe a risparmiare tempo durante gli acquisti
- Questa tecnologia migliorerebbe l'esperienza di acquisto in negozi fisici
- Questa tecnologia mi permetterebbe di esplorare prodotti mai acquistati che potrebbero piacermi

Q3 Per favore, rispondi alle seguenti domande pensando alla tecnologia appena descritta. Su una scala da 1 (**per nulla d’accordo**) a 10 (**estremamente d’accordo**), quanto sei d’accordo con le seguenti affermazioni:

- Questa tecnologia mi farebbe sentire manipolato
- Non mi sentirei di avere il controllo su questa tecnologia
- Questa tecnologia mi farebbe sentire controllato dalle aziende
- Avrei paura che le aziende possano usare i miei dati in modo sbagliato
- Mi spaventa pensare che qualcuno possa associare il mio nome al mio volto
- Mi vergognerei se anche altri clienti possano vedere le comunicazioni personalizzate su di me

Q4 Su una scala da 1 (**per nulla disposto**) a 10 (**decisamente disposto**), quanto saresti disposto a essere riconosciuto in store per ricevere più servizi di personalizzazione tramite smart Digital Signage?



Q5 Sarei più propenso a farmi riconoscere:

- In tutti i negozi in cui faccio i miei acquisti
- Nei negozi di cui mi fido
- Mai

Q6  Per favore, valuta i seguenti scenari su una scala da 1 (per nulla attraente) a 10 (estremamente attraente).

Nota:
- Per contenuti ispirazionali si intendono tutorial, come usare il prodotto, ricette, outfit etc
- Per contenuti informativi si intendono informazioni sulla composizione dei prodotti, provenienza, impatto ambientale etc
- Immagina negozi (supermercati, di abbigliamento, di beauty) che frequenti

- In un negozio di beauty, essere riconosciuto sempre e vedere sul totem contenuti personalizzati informativi

- In un negozio di abbigliamento, essere riconosciuto sempre e vedere sul proprio smartphone contenuti personalizzati informativi
- In un supermercato, essere riconosciuto sempre e vedere sul proprio smartphone contenuti personalizzati ispirazionali
- In un negozio di abbigliamento, essere riconosciuto solo se viene scannerizzato un QR Code e vedere sul totem contenuti personalizzati ispirazionali
- In un negozio di beauty, essere riconosciuto sempre e vedere sul totem contenuti personalizzati ispirazionali
- In un negozio di abbigliamento, essere riconosciuto sempre e vedere sul totem sconti e promozioni personalizzate
- In un supermercato, essere riconosciuto sempre e vedere sul totem sconti e promozioni personalizzate
- In un supermercato, essere riconosciuto solo se viene scannerizzato un QR Code e vedere sul totem contenuti personalizzati informativi
- In un negozio di beauty, essere riconosciuto solo se viene scannerizzato un QR Code e vedere sul proprio smarphone sconti e promozioni personalizzate

Q7 Non ho mai usato un computer.

- Vero
- Falso

Q8 Quanti anni hai?

____________________________________________________________

Q9 In che genere di identifichi?

- Uomo
- Donna
- Preferisco non rispondere

Q10 Quale è il tuo livello di istruzione?

- Diploma
- Laurea Triennale
- Laurea Magistrale / Master / Phd

Q11 Quale è la tua occupazione?

- Studente
- Lavoratore
- Disoccupato

**Appendix 2:** Relationship between Frequency of visits and demographic variables (i.e. gender, age classes, occupation and educational level).

Gender was connected with the frequency of visits. Regarding supermarkets, women visited them more frequently than men (30% of women visited once a day vs. 15% of men), $X^2$ (3, 273) = 9.61, $p$ = .022. However, as the Cramer's V was equal to 0.19, the connection was considered weak[1]. Similar results emerged with regards to apparel stores where a higher percentage of women stated to visit them once every two weeks compared to men (27% vs. 15%), $X^2$ (3, 273) = 9.67, $p$ = .022. Even in this case the connection was weak as the Cramer's V was equal to 0.19. Differently, a moderate connection was observed between gender and beauty stores' frequency of visit as the Cramer's V was equal to 0.25, 17% of women stated to visit beauty stores once every two weeks, while only 2% of men stated to do the same, $X^2$ (2, 273) = 17.59, $p$ < .001. Age classes were related only to supermarket's frequency of visit, $X^2$ (9, 273) = 25.45, $p$ = .003. As age increased, the frequency of visits increased too. However, with a Cramer's V of 0.18, the connection was considered weak. Lastly, neither the occupation nor the education level emerged to be significantly connected with any of the retailers' frequencies of visit, $p$ < .05.

1) Relationship between supermarket frequency of visits and gender

**Chi-Square Tests**

| | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Square | 9.614a | 3 | .022 |
| N of Valid Cases | 273 | | |

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 10.72.

**Symmetric Measures**

| | | Value | Asymptotic Significance |
|---|---|---|---|
| Nominal by Nominal | Phi | .19 | .022 |
| | Cramer's V | .19 | .022 |
| N of Valid Cases | | 273 | |

[1] The evaluation of the Cramer's V has been based on Le Quéau et al. (2017) thresholds: V < 0.1: very weak, 0.1 ≤ V < 0.2: weak, 0.2≤ V <0.3: moderate, V ≥0.3: strong.

**Crosstab**

| | | Gender | | |
|---|---|---|---|---|
| | | Male | Female | Total |
| Frequency Supermarkets | Once a day | 21 | 42 | 63 |
| | Once a week | 79 | 77 | 156 |
| | Once every two weeks | 19 | 13 | 32 |
| | Once a month or less | 14 | 8 | 22 |
| Total | | 133 | 140 | 273 |

2) Relationship between apparel stores frequency of visits and gender

**Chi-Square Tests**

| | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson Chi- | 9.666a | 3 | .022 |
| N of Valid Cases | 273 | | |

a. 2 cells (25.0%) have expected count less than 5. The minimum expected count is 1.46.

**Symmetric Measures**

| | | Value | Asymptotic Significance |
|---|---|---|---|
| Nominal by Nominal | Phi | .19 | .022 |
| | Cramer's V | .19 | .022 |
| N of Valid Cases | | 273 | |

**Crosstab**

| | | Gender | | |
|---|---|---|---|---|
| | | Male | Female | Total |
| Frequency Apparel Stores | Once a day | 0 | 3 | 3 |
| | Once a week | 13 | 14 | 27 |
| | Once every two weeks | 20 | 38 | 58 |
| | Once a month or less | 100 | 85 | 185 |
| Total | | 133 | 140 | 273 |

3) Relationship between beauty stores frequency of visits and gender

**Chi-Square Tests**

| | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson Chi- | 17.593a | 2 | <.001 |
| N of Valid Cases | 273 | | |

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 5.85.

**Symmetric Measures**

| | | Value | Asymptotic Significance |
|---|---|---|---|
| Nominal by Nominal | Phi | .25 | <.001 |
| | Cramer's V | .25 | <.001 |
| N of Valid Cases | | 273 | |

**Crosstab**

| | | Gender | | |
|---|---|---|---|---|
| | | Male | Female | Total |
| Frequency Beauty Stores | Once a day | 0 | 0 | 0 |
| | Once a week | 5 | 7 | 12 |
| | Once every two weeks | 3 | 24 | 27 |
| | Once a month or less | 125 | 109 | 234 |
| Total | | 133 | 140 | 273 |

4) Relationship between supermarkets frequency of visits and age classes

**Chi-Square Tests**

| | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson Chi- | 25.405a | 9 | .003 |
| N of Valid Cases | 273 | | |

a. 2 cells (12.5%) have expected count less than 5. The minimum expected count is 3.3.

**Symmetric Measures**

| | | Value | Asymptotic Significance |
|---|---|---|---|
| Nominal by Nominal | Phi | .31 | .003 |
| | Cramer's | .18 | .003 |
| N of Valid Cases | | 273 | |

| Crosstab | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Age Classes | | | | | |
| | | 18-26 | 27-42 | 43-58 | 59-75 | Total |
| Frequency Supermarkets | Once a day | 2 | 12 | 34 | 15 | 63 |
| | Once a week | 26 | 43 | 41 | 46 | 156 |
| | Once every two weeks | 6 | 8 | 9 | 9 | 32 |
| | Once a month or less | 7 | 4 | 4 | 7 | 22 |
| Total | | 41 | 67 | 88 | 77 | 273 |

**Appendix 3:** ANOVA Associations and gender; *M*, *SD*, and *N* for significant association statement, by gender

**ANOVA Table**

| | Sum of Squares | df | F | Sig. | Eta |
|---|---|---|---|---|---|
| Ease of use * Gender | 18.76 | 1 | 2.90 | 0.90 | .10 |
| Simplify the shopping experience * Gender | 33.49 | 1 | 4.64 | .032 | .13 |
| Perceived enjoyment * Gender | 10.37 | 1 | 1.34 | .248 | .07 |
| Save time * Gender | 57.72 | 1 | 7.23 | .007 | .16 |
| Enhance the shopping experience * Gender | 28.82 | 1 | 3.95 | .048 | .12 |
| Explore products I could like * Gender | 15.11 | 1 | 1.97 | .162 | .09 |
| Lack of control feeling * Gender | .53 | 1 | .06 | .804 | .02 |
| Under control feeling * Gender | 1.20 | 1 | .14 | .711 | .02 |
| Data misuse * Gender | .01 | 1 | .01 | .969 | .00 |
| Fear of face-name association * Gender | 2.41 | 1 | .27 | .605 | .03 |
| Shame feeling * Gender | 4.47 | 1 | .52 | .472 | .04 |
| Manipulation feeling * Gender | .42 | 1 | .04 | .835 | .01 |

**Report**

| Gender | | Simplify the shopping experience | Save time |
|---|---|---|---|
| Male | Mean | 6.44 | 6.83 |
| | N | 133 | 133 |
| | Std. Deviation | 2.560 | 2.68 |
| Female | Mean | 5.74 | 5.91 |
| | N | 140 | 140 |
| | Std. Deviation | 2.80 | 2.95 |

**Appendix 4:** ANOVA Negative associations and age classes

**ANOVA Table**

| | Sum of Squares | df | F | Sig. | Eta |
|---|---|---|---|---|---|
| Lack of control feeling * Age Classes | 34.91 | 3 | 1.37 | .253 | .12 |
| Under control feeling * Age Classes | 60.21 | 3 | 2.35 | .073 | .16 |
| Data misuse * Age Classes | 1.99 | 3 | .08 | .969 | .03 |
| Fear of face-name association * Age Classes | 5.35 | 3 | .19 | .898 | .05 |
| Feeling of shame * Age Classes | 14.09 | 3 | .54 | .654 | .08 |
| Manipulation feeling * Age Classes | 15.49 | 3 | .54 | .657 | .08 |

**Appendix 5:** ANOVA Elasticity to be recognized and age classes; *M*, *SD*, and *N* for elasticity to be recognized, by gender

**ANOVA Table**

| | Sum of Squares | df | F | Sig. | Eta |
|---|---|---|---|---|---|
| Elasticity to be recognized * Age Classes | 248.93 | 3 | 11.23 | <.001 | .33 |

**Report**

Elasticity to be recognized

| Age Classes | Mean | N | Std. Deviation |
|---|---|---|---|
| 18-26 | 6.29 | 41 | 231.56 |
| 27-42 | 5.85 | 67 | 249.39 |
| 43-58 | 4.65 | 88 | 301.35 |
| 59-75 | 3.74 | 77 | 274.53 |

**Appendix 6:** Regression first trial

**ANOVA[a]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 1082.86 | 8 | 135.36 | 30.97 | <.001[b] |
| | Residual | 1153.96 | 264 | 4.37 | | |
| | Total | 2236.82 | 272 | | | |

a. Dependent Variable: Elasticity to be recognized
b. Predictors: (Constant). I would be afraid that companies might use my data wrongly. The technology would simplify the shopping experience. The technology is easy to use. The technology would allow me to explore product I could like. The technology would make me feel manipulated. The technology is funny to use. The technology would make me feel controlled by companies. The technology would allow me to save time

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .69[a] | .48 | .47 | 2.09 |

a. Predictors: (Constant). I would be afraid that companies might use my data wrongly. The technology would simplify the shopping experience. The technology is easy to use. The technology would allow me to explore product I could like. The technology would make me feel manipulated. The technology is funny to use. The technology would make me feel controlled by companies. The technology would allow me to save time

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. | Collinearity Statistics Tolerance | Collinearity Statistics VIF |
|---|---|---|---|---|---|---|---|---|
| 1 | (Constant) | 3.08 | .59 | | 5.25 | <.001 | | |
| | Ease of use | .03 | .07 | .03 | .49 | .628 | .54 | 1.85 |
| | Simplify the shopping experience | .09 | .10 | .08 | .86 | .391 | .21 | 4.69 |
| | Perceived enjoyment | .17 | .08 | .16 | 2.21 | .028 | .35 | 2.86 |
| | Save time | .18 | .08 | .18 | 2.23 | .026 | .29 | 3.39 |
| | Explore product I could like | .15 | .07 | .14 | 2.19 | .029 | .47 | 2.15 |
| | Manipulation feeling | -.07 | .07 | -.08 | -1.08 | .283 | .36 | 2.81 |
| | Under control feeling | -.26 | .07 | -.27 | -3.59 | <.001 | .35 | 2.87 |
| | Data misuse | .04 | .07 | .04 | .56 | .577 | .45 | 2.23 |

a. Dependent Variable: Elasticity to be recognized

## **Appendix 7:** Correlations between perceptions

**Correlations**

| | | Ease of use | Simplify the shopping experience | Perceived enjoyment | Save time | Explore products | Under control feeling | Data misuse | Manipulation feeling |
|---|---|---|---|---|---|---|---|---|---|
| Ease of use | Pearson Correlation | 1 | .67 | .56 | .55 | .50 | -.19 | -.09 | -.19 |
| | Sig. (2-tailed) | | <.001 | <.001 | <.001 | <.001 | .002 | .152 | .002 |
| Simplify the shopping experience | Pearson Correlation | .67 | 1 | .74 | .82 | .68 | -.24 | -.04 | -.19 |
| | Sig. (2-tailed) | <.001 | | <.001 | <.001 | <.001 | <.001 | .511 | .001 |
| Perceived enjoyment | Pearson Correlation | .56 | .74 | 1 | .70 | .68 | -.36 | -.21 | -.33 |
| | Sig. (2-tailed) | <.001 | <.001 | | <.001 | <.001 | <.001 | <.001 | <.001 |
| Save time | Pearson Correlation | .55 | .82 | .70 | 1 | .62 | -.33 | -.12 | -.26 |
| | Sig. (2-tailed) | <.001 | <.001 | <.001 | | <.001 | <.001 | .054 | <.001 |
| Explore products | Pearson Correlation | .50 | .68 | .68 | .62 | 1 | -.25 | -.07 | -.19 |
| | Sig. (2-tailed) | <.001 | <.001 | <.001 | <.001 | | <.001 | .227 | .001 |
| Under control feeling | Pearson Correlation | -19 | -.24 | -.36 | -.33 | -.25 | 1 | .68 | .76 |
| | Sig. (2-tailed) | .002 | <.001 | <.001 | <.001 | <.001 | | <.001 | <.001 |
| Data misuse | Pearson Correlation | -.09 | -.04 | -.21 | -.12 | -.07 | .68 | 1 | .69 |
| | Sig. (2-tailed) | .152 | .511 | <.001 | .054 | .227 | <.001 | | <.001 |
| Manipulation feeling | Pearson Correlation | -.19 | -.19 | -.33 | -.26 | -.19 | .76 | .69 | 1 |
| | Sig. (2-tailed) | .002 | .001 | <.001 | <.001 | .001 | <.001 | <.001 | |

## **Appendix 8:** Factor Analysis

**Total Variance Explained**

| | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| Component | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 4.04 | 50.50 | 50.50 | 4.04 | 50.50 | 50.50 | 3.63 | 45.32 | 45.32 |
| 2 | 2.05 | 25.61 | 76.11 | 2.05 | 25.62 | 76.11 | 2.46 | 30.79 | 76.11 |
| 3 | .53 | 6.59 | 82.70 | | | | | | |
| 4 | .40 | 5.05 | 87.75 | | | | | | |
| 5 | .33 | 4.08 | 91.83 | | | | | | |
| 6 | .28 | 3.47 | 95.29 | | | | | | |
| 7 | .23 | 2.83 | 98.12 | | | | | | |
| 8 | .15 | 1.88 | 100.00 | | | | | | |

Extraction Method: Principal Component Analysis.

**Communalities**

| | Initial | Extraction |
|---|---|---|
| Ease of use | 1.000 | .58 |
| Simplify the shopping experience | 1.000 | .87 |
| Perceived enjoyment | 1.000 | .76 |
| Save time | 1.000 | .77 |
| Explore product | 1.000 | .67 |
| Manipulation feeling | 1.000 | .83 |
| Under control feeling | 1.000 | .82 |
| Data misuse | 1.000 | .79 |

Extraction Method: Principal Component Analysis.

**Rotated Component Matrix[a]**

| | Component 1 | Component 2 |
|---|---|---|
| Ease of use | .76 | -.06 |
| Simplify the shopping experience | .93 | -.05 |
| Perceived enjoyment | .84 | -.24 |
| Save time | .86 | -.15 |
| Explore product | .81 | -.08 |
| Manipulation feeling | -.16 | .89 |
| Under control feeling | -.21 | .88 |
| Data misuse | .01 | .89 |

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

**Appendix 9:** Regression second trial

| | | ANOVA[a] | | | | |
|---|---|---|---|---|---|---|
| Model | | Sum of Squares | df | Mean Square | F | Sig. |
| 1 | Regression | 753.63 | 1 | 753.63 | 137.69 | <.001[b] |
| | Residual | 1483.19 | 271 | 5.47 | | |
| | Total | 2236.81 | 272 | | | |
| 2 | Regression | 950.43 | 2 | 475.21 | 99.74 | <.001[c] |
| | Residual | 1286.38 | 270 | 4.76 | | |
| | Total | 2236.81 | 272 | | | |
| 3 | Regression | 1041.22 | 3 | 347.07 | 78.08 | <.001[d] |
| | Residual | 1195.59 | 269 | 4.45 | | |
| | Total | 2236.81 | 272 | | | |
| 4 | Regression | 1070.71 | 4 | 267.68 | 61.52 | <.001[e] |
| | Residual | 1166.11 | 268 | 4.35 | | |
| | Total | 2236.81 | 272 | | | |

a. Dependent Variable: Elasticity to be recognized
b. Predictors: (Constant). The technology is funny to use
c. Predictors: (Constant). The technology is funny to use. The technology would make me feel controlled by companies
d. Predictors: (Constant). The technology is funny to use. The technology would make me feel controlled by companies. The technology would allow me to save time
e. Predictors: (Constant). The technology is funny to use. The technology would make me feel controlled by companies. The technology would allow me to save time. The technology would allow me to explore product I could like

| | | Model Summary | | |
|---|---|---|---|---|
| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
| 1 | .58[a] | .34 | .33 | 2.34 |
| 2 | .65[b] | .43 | .42 | 2.18 |
| 3 | .68[c] | .47 | .46 | 2.11 |
| 4 | .69[d] | .48 | .47 | 2.09 |

a. Predictors: (Constant). The technology is funny to use
b. Predictors: (Constant). The technology is funny to use. The technology would make me feel controlled by companies
c. Predictors: (Constant). The technology is funny to use. The technology would make me feel controlled by companies. The technology would allow me to save time
d. Predictors: (Constant). The technology is funny to use. The technology would make me feel controlled by companies. The technology would allow me to save time. The technology would allow me to explore product I could like

| | | | | Coefficients[a] | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Unstandardized Coefficients | | Standardized Coefficients | | | Collinearity Statistics | |
| Model | | B | Std. Error | Beta | t | Sig. | Tolerance | VIF |
| 1 | (Constant) | 1.42 | .33 | | 4.27 | <.001 | | |
| | Perceived enjoyment | .59 | .05 | .58 | 11.73 | <.001 | 1.00 | 1.00 |
| 2 | (Constant) | 4.18 | .53 | | 7.89 | <.001 | | |
| | Perceived enjoyment | .48 | .05 | .47 | 9.44 | <.001 | .87 | 1.15 |
| | Under control feeling | -.31 | .05 | -.32 | -6.43 | <.001 | .87 | 1.15 |
| 3 | (Constant) | 3.35 | .54 | | 6.17 | <.001 | | |
| | Perceived enjoyment | .29 | .07 | .28 | 4.36 | <.001 | .49 | 2.04 |
| | Under control feeling | -.29 | .05 | -.29 | -6.09 | <.001 | .86 | 1.16 |
| | Save time | .29 | .06 | .28 | 4.52 | <.001 | .50 | 1.99 |
| 4 | (Constant) | 3.13 | .54 | | 5.74 | <.001 | | |
| | Perceived enjoyment | .21 | .07 | .20 | 2.87 | .004 | .40 | 2.49 |
| | Under control feeling | -.29 | .05 | -.29 | -6.21 | <.001 | .86 | 1.16 |
| | Save time | .24 | .07 | .24 | 3.66 | <.001 | .46 | 2.16 |
| | Explore product | .17 | .06 | .16 | 2.60 | .010 | .50 | 1.99 |

a. Dependent Variable: Elasticity to be recognized

**Appendix 10:** Eigenvalues and total variance explained

| Total Variance Explained | | |
|---|---|---|
| | Initial Eigenvalues | |
| Component | Total | % of Variance |
| 1 | 8.09 | 44.94 |
| 2 | 3.47 | 19.26 |
| 3 | 1.25 | 6.95 |
| 4 | .74 | 4.09 |
| 5 | .58 | 3.21 |
| 6 | .47 | 2.59 |
| 7 | .44 | 2.46 |
| 8 | .42 | 2.33 |
| 9 | .41 | 2.27 |
| 10 | .35 | 1.95 |
| 11 | .31 | 1.74 |
| 12 | .30 | 1.67 |
| 13 | .27 | 1.49 |
| 14 | .24 | 1.33 |
| 15 | .21 | 1.14 |
| 16 | .17 | .96 |
| 17 | .15 | .83 |
| 18 | .14 | .78 |

**Appendix 11:** Conjoint, Utilities (split by Gender)

| Utilities | | | | |
|---|---|---|---|---|
| | | | Utility Estimate | Std. Error |
| Male | Content Type | Discounts and Promotions | 0.11 | .05 |
| | | Inspirational | 0.07 | .05 |
| | | Informative | -0.18 | .05 |
| | Retailer Typology | Supermarket | 0.14 | .05 |
| | | Beauty Store | -0.43 | .05 |
| | | Apparel Store | 0.29 | .05 |
| | Recognition Modality | Always | -0.42 | .04 |
| | | QR Code Scanning | 0.42 | .04 |
| | Display Medium | Totem | -0.01 | .04 |
| | | Smartphone | 0.01 | .04 |
| | (Constant) | | 5.91 | .04 |
| Female | Content Type | Discounts and Promotions | .21 | .05 |
| | | Inspirational | -.15 | .05 |
| | | Informative | -.06 | .05 |
| | Retailer Typology | Supermarket | -.04 | .05 |
| | | Beauty Store | -.06 | .05 |
| | | Apparel Store | .09 | .05 |
| | Recognition Modality | Always | -.46 | .04 |
| | | QR Code Scanning | .46 | .04 |
| | Display Medium | Totem | -.01 | .04 |
| | | Smartphone | .01 | .04 |
| | (Constant) | | 6.04 | .04 |

**Appendix 12:** Conjoint, Utilities (split by Age Classes)

| Utilities | | | | |
|---|---|---|---|---|
| | | | Utility Estimate | Std. Error |
| 18-26 | Content Type | Discounts and Promotions | .15 | .08 |
| | | Inspirational | -.04 | .08 |
| | | Informative | -.11 | .08 |
| | Retailer Typology | Supermarket | .02 | .08 |
| | | Beauty Store | -.23 | .08 |
| | | Apparel Store | .20 | .08 |
| | Recognition Modality | Always | -.67 | .06 |
| | | QR Code Scanning | .67 | .06 |
| | Display Medium | Totem | -.07 | .06 |
| | | Smartphone | .07 | .06 |
| | (Constant) | | 6.78 | .07 |
| 27-42 | Content Type | Discounts and Promotions | .07 | .04 |
| | | Inspirational | -.01 | .04 |
| | | Informative | -.07 | .04 |
| | Retailer Typology | Supermarket | -.11 | .04 |
| | | Beauty Store | -.20 | .04 |
| | | Apparel Store | .31 | .04 |
| | Recognition Modality | Always | -.59 | .03 |
| | | QR Code Scanning | .59 | .03 |
| | Display Medium | Totem | .04 | .03 |
| | | Smartphone | -.04 | .03 |
| | (Constant) | | 6.61 | .04 |
| 43-58 | Content Type | Discounts and Promotions | .11 | .15 |
| | | Inspirational | .03 | .15 |
| | | Informative | -.14 | .15 |
| | Retailer Typology | Supermarket | .06 | .15 |
| | | Beauty Store | -.19 | .15 |
| | | Apparel Store | .13 | .15 |
| | Recognition Modality | Always | -.22 | .11 |
| | | QR Code Scanning | .22 | .11 |
| | Display Medium | Totem | -.00 | .11 |
| | | Smartphone | .00 | .11 |
| | (Constant) | | 5.70 | .12 |
| 59-75 | Content Type | Discounts and Promotions | .34 | .03 |
| | | Inspirational | -.20 | .03 |
| | | Informative | -.13 | .03 |
| | Retailer Typology | Supermarket | -.22 | .03 |
| | | Beauty Store | -.29 | .03 |
| | | Apparel Store | .07 | .03 |
| | Recognition Modality | Always | -.38 | .03 |
| | | QR Code Scanning | .38 | .03 |
| | Display Medium | Totem | .05 | .03 |
| | | Smartphone | -.05 | .03 |
| | (Constant) | | 4.99 | .03 |