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MULTIPLE CRITERIA APPROACH APPLIED TO DIGITAL TRANSFORMATION IN FASHION STORES: THE CASE OF PHYSICAL RETAILERS IN SPAIN

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Abstract. In a very open competitive context where pure online players are consistently gaining market share, the use of digital devices is a steady trend which is penetrating physical retail stores as a tool for retailers to improve customer experience and increase engagement. This need has increased with the COVID-19 pandemic as electronic devices in physical stores reduce the contact between people providing a greater sense of health safety, hence improving the customer experience. This work develops a multiple-criteria decision-making model for retailers who want to digitize their physical stores, providing a systematic approach to manage investment priorities in the organization. Important decisions should involve all different areas of the organization: Finance, Clients, Internal Processes and Learning & Growth departments. This strategic decision can be made hierarchically to obtain consistent decisions, also the use of the Order Weighted Average operator allows for alternative scenarios to be presented and agreed among the different areas of the business. The authors develop a use case for a Spanish fashion retailer. In the most widely agreed scenario the preferred devices were more technologically complex and expensive, while in the scenarios where the head of Finance is more predominant, cheaper and simpler devices were selected.

Keywords: store digitization, multiple-criteria decision making, customer experience, in-store technology, interactive marketing, retail.

JEL Classification: L81, M31, O32, O33, D81.

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Introduction

The disruption prompted by the availability of information has affected many economic sectors, including Retail. The ecosystem around the internet allows a dynamic digital transformation of organizations, which is an opportunity for leading companies oriented towards creating value to their customers. Among the so-called "new technologies" there are new media channels such as social networks and instant messaging, some technologies based on the autonomy of connected objects that provide certain information, such as the Internet of Things (IoT), and systems to capture and analyse the huge amount of data generated in the retail environment, both online and physical. These information systems are supported by statistics and Artificial Intelligence, in their variants of Machine Learning and Deep Learning. At an operational level, the generalization of "broadband" internet access that supports the speed of data traffic has allowed the phenomenon known as "hyper connectivity", in which the customer has access to a lot of information at any time and place, and at the same time companies are able to know their movements and behavior because the concept of privacy has been diluted. We are witnessing a technological revolution which is fostered by the generalization of new devices permanently connected by alternative routes: wifi, data service or bluetooth, which are capable of managing new tools, such as mobile applications, social networks and instantaneous messaging, accelerating the digitization of homes and stores and consolidating a hyper connected society.

The rise of e-commerce in recent years has put many retail companies in a dilemma to evolve and adapt, speeding up a process of digitization that includes the incorporation of new technologies in their processes and at the point of sale, in order to achieve a seamless and consistent customer experience through the physical and digital environments as a means to compete against pure online players. This need has increased in the wake of the COVID-19 pandemic as electronic devices in physical stores eliminate in some cases, or minimize in others, the contact between people providing a greater sense of health safety and therefore improving the customer experience. In this context, the purpose of this paper is to contribute to the understanding of how retailers can enhance the in-store shopping experience by deploying digital devices in the physical store.

From the user's point of view, the new technological environment unquestionably empowers the customer by having more information and being able to exchange it with other users through social networks, instant messaging, product or service evaluations, forums and blogs. This environment creates a greater demand for transparency for companies, in addition, the customer has a greater variety of retailers offering the same product. On the other hand, technology provides the necessary tools to companies to create new relationships between the company and its customers, allowing them to track the buying behavior of customers by collecting a lot of data through mobile devices and online traceability. This paper focuses on the operational use of digital devices in the store in order to provide a better customer service, but the ability to track and use the data generated by those devices are out of the scope of the current work. We specifically develop a framework to facilitate decision making to retailers about in-store technology investment, as they are currently overwhelmed by the options they have. We develop the study in the context of Fashion (apparel) retailing, but the model can be applied to any retail category and sector by changing the devices and technologies in use. We chose the fashion retail context because it is a large industry in Spain, with large multinationals such as Inditex, which owns worldwide recognised brands (e.g. Zara, Stradivarius) and more than 1,500 stores in Spain and 6,000 stores worldwide.

In the context of this accelerated paradigm shift, the authors have developed a model to help retailers' decision making by prioritizing the investment in alternative devices and programs to shed light on the uncertainty regarding the confluence between online and offline shopping behavior and how to drive income and profitability in both, with the underlying goal of improving the customer experience regardless of the sales channel. The authors analyze the relationship between the different technologies in the store and measure the best possible option for the retailer according to different criteria. As this is a strategic project we propose the use of Balanced Scorecard (BSC) as an appropriate methodology. Hence the use case requested the participation of four different areas of the organization (Clients, Finance, Internal Processes and Learning & Growth) to rank alternative digital devices which were shortlisted from the review of literature and industry reports according to some criteria defined by the company's CEO regarding items such as setup cost, maintenance cost, profitability or ROI (Return on Investment) potential, customer experience, health & safety, reliability, management of devices, training and innovation. The devices included in the study were the following: Smart Fitting room, Smart VR (Virtual Reality) Mirror, Tablet, Digital Screens, Smart Shop Windows, and Smiley faces. These devices were ranked along with some ad hoc smart phone application functionalities such as payment and consultation of price & product features.

The authors consider appropriate the use of a Balanced Scorecard (BSC) as the strategic decisions must involve the different areas in the organization, and also to implement it using the Analytical Hierarchy Process (AHP) to model this decision problem, as there is an implicit hierarchy in the organization structure. This model allows to obtain a consistent final output, agreed among the different areas of the organization. As the final decision belongs to the CEO, the use of Ordered Weighted Averaging (OWA) is proposed in order to obtain different decision scenarios according to the degree of agreement between the different areas. The lesser the agreement implies a riskier decision to be assumed by the CEO.

Overall findings of this work provide relevant contribution to the growing body of research in the area of retail technology and provide valuable assistance to practitioners in formulating better strategies to decide on their investment plan of store digitization.

The rest of the article is organized as follows: Section 1 is divided in two subheadings, the first one presents a review of the literature that supports the theoretical framework for store digitization and discusses the alternative technological devices relevant for digitization; the second subheading presents a bibliometric review and mapping of the combined use of the two tools which are used in our study: BSC and AHP. In Section 2 we show the foundations used in the Multi-criteria Decision-Making (MCDM) model. Section 3 proposes our MCDM-based model using as a paradigm a real use case in Spanish physical retail fashion stores in which alternative action plans are suggested with the portfolio of devices obtained in the literature review and their prioritization. In Section 4 the different results obtained by the model are discussed and the conclusions and future work presented, together with the theoretical and practical implications.

1. Theoretical framework

1.1. Store digitization

As mentioned in the introduction, we will review the literature on retail value chain, customer experience and customer journey, customer satisfaction and loyalty and store digitization. An important objective of this section is to determine que technological alternatives for in-store digitization as found in previous literature.

There is extensive research in the literature about the retail value chain. Some authors (Reinartz et al., 2019) highlighted the supremacy of stationary retailing within the retail value chain, and how this supremacy is being structurally challenged and rapidly eroding, as increasing fractions of the retail trade are shifted from physical formats to internet-based formats, including pure players, manufacturer direct online operations, and platforms. To counterbalance this shift to new players, most significantly Amazon (Keyes, 2018), stationary retailers are using multichannel strategies on top of their traditional store labels strategies to add value to consumers and differentiate themselves from pure online players and among each other. Some of the omnichannel strategies relate to making the store more attractive to consumers, and this is where store digitization comes into place.

The impossibility of the physical retailer to adapt the layout of the store to each type of customer was mentioned by Sorensen (2016) in his definition of "Double Chaos", considering the many different products and many different customers in a physical store. The online channel can adapt the store to each customer segment, or even to each individual, thanks to artificial intelligence algorithms and personalized journeys defined by the mining of customer data. In spite of this the physical store can leverage the use of new technologies at the point of sale to smooth the way to this personalized user experience by adapting the purchase itinerary to the customer using connected devices and mobile applications.

Richardson (2010) defines the customer journey as the itinerary by which a consumer gradually interacts with the company through points of interaction (both online and in the physical store) throughout the purchasing process, from when she has a need until she completes her purchase and evaluates and shares her experience. Scientific production in the marketing environment, and in particular customer management, has been slow in adopting these developments in the marketing literature. In terms of customer focus, management has focused primarily on creating customer value for companies (Gupta et al., 2004; Kumar & Shah, 2009), with a focus on some metrics such as Customer Lifetime Value, rather than creating value for customers (Kumar & Reinartz, 2016).

A study by Accenture (2015) reported that the most mentioned item as number one priority for the next 12 months among executives was improving the customer experience. It is a tendency in the last few years that large firms, such as Google, Amazon and KPMG, have chief customer experience officers, or customer experience managers responsible for managing the experience of their customers (Lemon & Verhoef, 2016). One of the first academics to emphasize the importance of customer experience were Pine and Gilmore (1999), who specifically addressed the importance of experiences in modern society and how firms could benefit from creating strong and enduring customer experiences. According to another study by Accenture (2020) among top executives, the emphasis on experience is at its greatest after Covid19 pandemic because "the structure of almost everything we do, how and what people buy, how and where they work, and how they interact with others, has been upended by world events in 2020". The same report reflects that, one of the newer concerns that emerged is "lack of clarity about ROI for Customer Experience investments". Our study is actually addressing this concern on how to better invest on a range of devices to enhance customer experience.

On the same line, a study by Nielsen (2016) reports that the new retail reality is an omni-channel experience, as digital devices enable consumers to shop when they choose, hence they conclude that the "physical store shopping trip needs to be reimagined". They also observe that consumers are not simply "showrooming" (i.e. browsing in store and going online to search for the lowest-cost option); they are also "webrooming" (i.e. research online and buy in stores). The trend on omnichannel shopping has accelerated by the pandemic, as supported by a Consumer Pulse research staged by Accenture (2020b), which reported that over 80% of consumers who increased, during the Covid19 pandemic, their use of digital and omnichannel services, such as home delivery, curb-side pickup or shopping via social media platforms, expect to sustain these activities into the future.

The growing interaction between company and client through countless contact points in different channels and media has led to the development of an increasing focus on the customer experience, as it is a question of interpreting increasingly complex customer itineraries. Companies are also facing accelerating fragmentation of media and channels, and omnichannel management has become the new norm (Verhoef et al., 2015). In addition, peer to peer interactions across social networks are creating compelling challenges and opportunities for companies (Leeflang et al., 2014; Libai et al., 2010). Customer experiences are of a more social nature, and customers are able to influence other customers' experiences.

In addition to the above, it is a fact that companies have less control, in general, over the customer experience and the customer journey, so they need to integrate multiple internal functions to generate positive customer experiences: sales, information systems, logistics, operations and marketing (e.g., Edelman & Singer, 2015; Rawson et al., 2013).

For large retail chains with a strong physical presence, online and offline commerce have to work in a coordinated manner so as not to alienate the current customer of the physical environment, which remains the majority. In this new scenario the term "Retail 4.0" or "Phygital" has been coined within the industry (Belghiti et al., 2018). The Phygital strategy points at integrating the online and offline experience, so that the gap between the physical and digital store reduces, therefore improving the user overall experience.

Homburg, Jozić, and Kuehnl (2017) state that the goal for creating memorable experiences within the customer journey is to improve company results through increased conversion from improvements in customer loyalty and word of mouth, while Inman and Nikolova (2017) studied the financial return and shopper reaction to an array of potential technologies available for grocery retailers. They analysed some elements of retail technology that may increase retailer revenue and some others that may decrease costs, potentially increasing profit one way or the other. They argue that the shopper perceptions have a mediating effect on the financial results of the technology.

A study by Grewal et al. (2017) highlights the five key areas where retailing technologies are moving forward. This work fits in the area of "Technology and tools to facilitate decision making" for consumers and retailers, as we focus on technology that empowers consumers to make more informed decisions and obtain better service. Current technological developments (servers, processors, networks, tools); the use of massively generated data on each interaction, systems such as the Internet of Things and analytical and technological developments such as artificial intelligence, make it possible to take full advantage of these potential sales generators, connecting the consumer with the retail trade and offering dual functionality (Gutiérrez-Toranzo & Llorens, 2018), meaning that they provide a better service and also facilitate the gathering of data by the retailer. Recent work (Verhoef et al., 2017) emphasizes that the extensive adoption of mobile and wearable devices together with the emergence of the IoT allows customers to connect with other people or with their physical environment (e.g., through location based apps), but also enables connection with and between objects through smart products (POP framework). The unprecedented level of connectivity enables new interactions creating customer value. This new in-store connectivity includes Radio Frequency Identification (RFID) technology, which uses electromagnetic fields to identify and track tags attached to objects, e.g. garments.

On the one hand, retailers provide customers at each point of contact with experiences that increase the value of their purchase and motivate them to move from phase to phase in the buying process, increasing sales quota, loyalty and recommendation level. On the other hand, the customer provides data at each point of interaction to the retailer, which becomes the most important intangible asset of the company thanks to the analysis and proper treatment of them, as it allows the company to learn about its customers, their barriers and motivations, while enabling the retailer to make decisions in real time, predict behaviors and anticipate trends. These data give rise to a comprehensive view of their customers, which allows the company to make a micro segmentation of them creating a fully personalized experience.

In summary, we see that the Omni-channel approach by retailers is an answer to the changing customers shopping habits, alternating between online and offline shops, and the increasing use of digital devices (e.g. smartphones and tablets), as well as other digital devices deployed in the store. Therefore, we see how the use of technologies at the point of sale enables the development of the Phygital experience, which in turn allows the exploitation of big data and the use of statistical models.

Many fashion brands integrate interactive technology in their physical stores with the aim of enhancing customer experience (Mintel, 2021; Bonetti & Perry, 2017). This technology enables customers to explore the store interactively. Moreover, consumers can experience both the physical and digital worlds of a fashion brand. This blend of digital and physical experiences can potentially enhance the overall consumer experience (Alexander & Alvarado, 2017; Poncin & Ben-Mimoun, 2014; Dennis et al., 2014; Kent et al., 2016). Some authors (Park et al., 2020) study the consumer acceptance of self-service technologies in fashion retail stores in particular, their perceptions and willingness to adopt in-store technology for fashion purchases.

Hickman, Kharouf, and Sekhon (2020) include technology readiness and customization as two of the four influencing factors of an Omni-channel experience, and study how retailers plan the use of multiple touchpoints concurrently to heighten their overall customer's experience.

In the in-store digitization context, the current retail challenge is to leverage and integrate the full capabilities of mobile devices in the store, as enablers of new touchpoints and interactions. In this setting the authors enlarged the list of devices that may be deployed in a digitised fashion store, in order to include some functionalities sought by consumers in a retailer app, to set a comprehensive list of alternatives for retailers to increase the digitization of their stores.

Mobiles are becoming more pervasive as underlying technology and device capability improves. They incorporate numerous components and software that support various device functions and applications. For example, nowadays smart phones support digital image capture, allowing devices to store numerous digital images. The large development of mobile applications in the last decade has enabled mobiles to enhance an in-store experience for customers. There is the option for the retailer to facilitate the network that allows an in-store mode of an application when the device is within a retail store. The in-store mode may enable enhanced capabilities of the functionalities.

Considering the above, the study also takes into account some functionalities of retailers' apps such as payment and product information, as they complement the digital experience. Hsu and Lin (2016) focused on what motivates a mobile app user to make in-app purchases. They evaluated a model to study perception of mobile apps which provided theoretical understanding of user behavior in regard to in-app purchases. Our study builds on that from the perspective of the retailer as we propose a decision model to prioritize investment directed to digitize the store.

We draw the tested devices from the literature review on in-store digitization (Wolpert & Roth, 2020; Siregard & Kent, 2019; Fundación Orange, 2016). The full list of alternatives is the following:

- *Smart Fitting* room.
- *Virtual Reality* (VR) *Smart Mirror* to try on without undressing.
- *Tablet* in store to buy online products out of stock.
- *Digital screens* with advertising and information.
- *Smart Shop-windows*.
- Customer satisfaction machines with *smiley/angry faces*.
- *App payment* functionality that lets you pay from your phone.
- *App scan* functionality to scan product labels.

A more detailed description of the above devices can be found in section 3.2.

In-store digital devices and retail branded apps are new enablers of customer interactivity and, together with online channels, provide substantial shifts in competition for the customer interface, allowing retailers to provide the customer with perceived benefits. According to Reinartz et al. (2019), this will drive the superiority of a particular interface, namely one that is governed primarily either by the brand (manufacturer), or by the emerging retail platform business model, or by institutional retailers.

Literature on in-store digitization tends to focus on the effect of technology on customer experience and satisfaction (Ryding, 2010; Liljiander et al., 2006), and how retailers are finding alternative ways to incorporate digital technology into the physical retail experience (Tomar & Saha, 2016). Some other research (Marin-Garcia et al., 2021; Babu et al., 2012) focus on likely sustained competitive advantage, new retail formats and key technologies and trends with the potential to change the shopping experience. In this paper we propose the implementation of a strategic frame based on BSC, resolved with OWA-AHP for an in-store digitization solution with an assortment of alternative devices, which has not been found in the literature.

1.2. State of the art of MCDM for strategic decisions using BSC, AHP and OWA

As mentioned above, this paper is mainly based on two tools: BSC and AHP. In order to position our work in relation to what has been done in the field, in this section we will first build a bibliometric map of the combined use of both themes. Science mapping, or bibliometric mapping, is an important research topic in the field of bibliometric, it aims at displaying the structural and dynamic aspects of scientific research in order to allow its interpretation. We follow the methodology inspired by Cobo et al. (2012) and the SciMat tool to obtain such a bibliometric map with data until the end of November 2021. A similar analysis is carried out by Merigó et al. (2015).

The first phase involves recovering the data. Thus, bibliographic records has been downloaded from the main Web of Science collection using the query: *TS* = ((*"BSC" OR "BALANCED SCORE*CARD"*) *AND* (*"AHP" OR "ANALYTICAL HIERARCHICAL PROCESS"*)) where the TS field is a search based on a given topic (title, abstract and keywords). After reviewing the 233 documents retrieved, the next phase is preprocessing. It should be noted that in this phase we have eliminated the terms implicit in the search itself: BSC, AHP, MCDM, etc. as they are obviously the predominant ones in the analysis. After this, we have carried out the remaining phases of the process: network extraction, normalization, mapping, analysis and visualization. The strategic diagram obtained is shown in Figure 1. This diagram makes it possible to identify the importance of each theme according to two measures: centrality (degree of interaction of a network with other networks) and density (the internal strength of the network or keywords that describe the theme in any science mapping workflow).

On the basis of this map, we finally interpret the results obtained. Although in an indirect way our work could be related to all the themes that have been identified, we consider that it is much more closely related to the basic, transversal and motor themes listed below:

- DECISION-MAKING. Obviously we are dealing with a management problem where aspects such as benefits, risks and safety must be taken into account.
- DESIGN. The digitisation of physical shops implies a redesign of the physical stores, choice of the most suitable services and suppliers, implementation, etc.
- SELECTION. In the device selection problem, we will also consider cost, measurement and evaluation of performance.
- MEASUREMENT-SYSTEM. The measurement of the impact of decisions in the different BSC areas will obviously also be taken into account.

In Figure 2 we expand the themes related to our work and also include the keywords which comprise the network of those themes. The more related keywords are highlighted by a grey shadow in the figure.

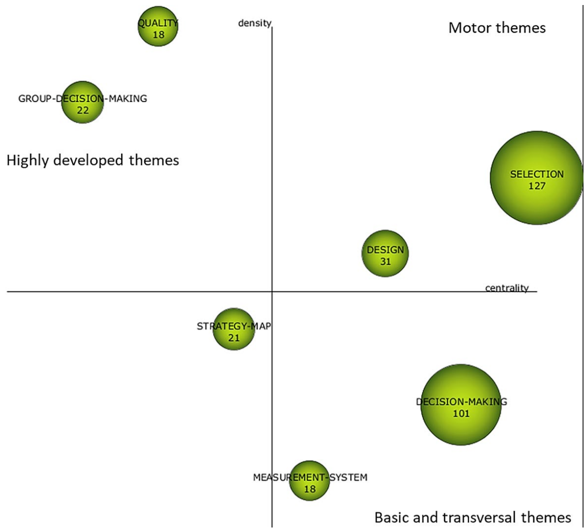

Figure 1. Strategic diagram of the use BSC – AHP in literature

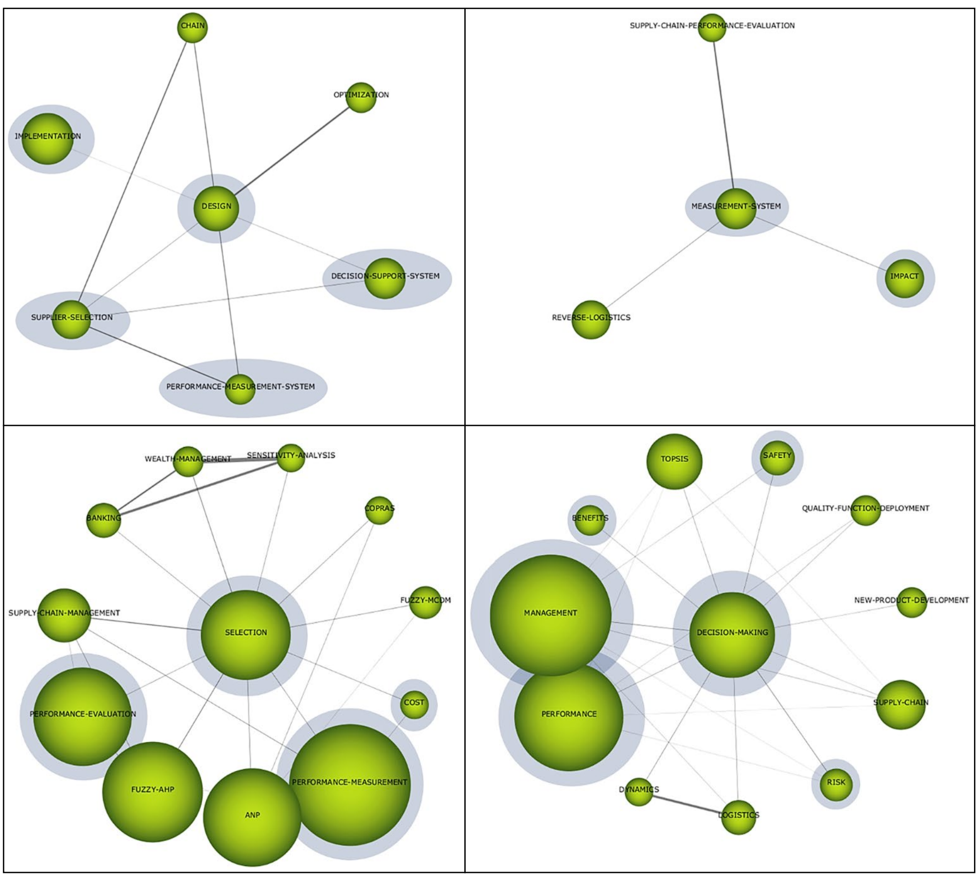

Figure 2. Thematic network of transversal themes, with highlighted related keywords

An important aspect of a CEO's decision making is the risk of the decision. In addition, if we use BSC it is important to take into account the degree of tradeoff of the decision. Thus, in order to give more dynamism, as will be explained below, to the possible decision scenarios, but always measuring both concepts (risk and tradeoff), this paper proposes the use of the OWA operator. Although some authors (Daniel & Merigó, 2021) point to the interest of incorporating this operator into the BSC-AHP pair, we have not found any work that has developed this idea. Hence our work is innovative from a methodological standpoint and also in the application to the retail sector, as the use of the BSC-AHP model for in store decisions in the retail sector is very scarce. The authors only found literature related to the retail supply chain area.

2. MCDM methodology

This section contains the foundations on which our MCDM proposal is based, specifically the Analytical Hierarchy Process (AHP) and the Ordered Weighted Averaging (OWA) operator.

2.1. Analytical Hierarchy Process (AHP)

Saaty (1980) developed the AHP as a tool for helping decision makers to solve complex MCDM problems in which qualitative and quantitative features are involved to classify and select the possible alternatives into a set of pairwise comparisons. With this intention, the decision maker gives a judgment on a scale to each criterion in order to determine their prior importance. Finally, by means of the pairwise comparison matrix proposed by a panel of experts, an optimal decision, that takes into account the importance of each criterion, is achieved. The AHP has already been used in strategic decision making (Zhang et al., 2021; Dong et al., 2018). This system is able to check if the decision makers' evaluations are consistent, ensuring the reduction of bias in the decision. AHP follows four steps which are explained below (Saaty, 1980, 2008; Carrasco et al., 2018).

2.1.1. Decision problem definition

At the first stage, the problem to be solved, the possible outcome or goal of the system and the relevant features and experts that intervene in making the decision, must definitely be identified. Once all this information is gathered, we can move on to the step of assembling the decision problem into a hierarchical model.

2.1.2. Structuring the decision problem hierarchically

At this stage, the goal, criteria, sub-criteria and alternatives previously identified are used to build the hierarchy in order to analyse the decision problem as shown in Figure 3. The hierarchy, H, always has at least three levels, more if sub-criteria are considered. The first level is just formed by the problem's goal, the second level is constructed with the different considered criteria and the last level contains the possible alternatives:

– *Goal*. A single element, named as G, which generally represents the ideal result for the problem. This is the first level of the hierarchy, i.e. $k = 0$.

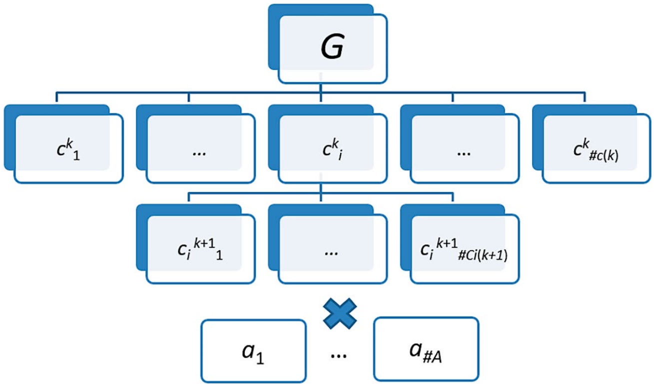

Figure 3. Decision-making problem in a hierarchy H

- *Criteria*. Features taken into account for the goal achievement. We name these hierarchical criteria as:

  $C = \bigcup_{k=1}^{\#H-2} c(k),$

- where $\#H$-2 is the number of levels in which the criteria have been subdivided (at least some of them), k that identify the criterion level, $c(k) = \{c^k{}_1,\ldots, c^k{}_{\#c(k)}\}$, where # symbolizes the number of elements in that set.
- *Sub-criteria.* Each of those criteria $c^k{}_i$ can, in turn, be subdivided into sub-criteria, in a lower levels $k + 1$, $c_i(k + 1) = \{c^{k+1}{}_{i\,1},\ldots, c^{k+1}{}_{i\,\#Ci(k+1)}\}$ and so recursively. The alternatives have to be evaluated for each of the sub-criterion into each criterion. Thus, the hierarchy is traversed from its lowest point to the first level where the criteria are located.
- *Alternatives*. Realizations of the goal given a choice form a collection of outputs: $A = \{a_1,\ldots, a_{\#A}\}$. They are the last level of the hierarchy, $k = \#H$-1.

2.1.3. Making pairwise comparisons and computing the vector of weights

In this step, the opinion of the experts is used to compare, in pairs, the elements of a level k with respect to a parent element in the superior level k-1. They assign a value from a scale that ranges from 1 to 9 to the different elements, these numbers represent how important the surveyed consider an element is in relation to another. In which 1 represents that both elements are equally important, while 9 means that one of the elements is extremely more important than the other. The pairwise importance scale is illustrated in Table 1.

Therefore, each element in an upper level is used to compare the elements in the level directly below it. Let PW one of these pairwise comparison matrix constructed from the data provided by the answers to the questionnaires, then pw_{ij} is the importance of the i_{th} element relative to the j_{th} and satisfies that: $pw_{ij} > 0$; $pw_{ij} = 1/pw_{ji}$ reciprocal property; and $pw_{ii} = 1$ for all i. Then, the vector of weights ω is determine using the eigenvector method through the following equation:

$$\sum_{j=1}^{n} pw_{ij} w_j = \lambda_{\max} w_i, \tag{1}$$

where λ_{max} is the highest eigenvalue of *PW* and *w* is the normalized eigenvector associated with the main eigenvalue of *PW*. Finally, the Consistency Ratio (*CR*) is obtained by dividing the Consistency Index (*CI*) by the Random Consistency Index (*RI*) which represents the consistency of a randomly generated pairwise comparison matrix. The Consistency Index is defined as:

$$\frac{\lambda_{max}-n}{n-1}.$$

The Random Consistency Index was derived by Saaty from a sample of size 500, of a randomly generated reciprocal matrix using the scale l/9, l/8, . . . , 1, . .8, 9. The RI according to the sample size from 1 to 10 is shown in Table 2.

Particularly, if CR ≤ 0.1 the inconsistency is tolerable, otherwise it will require adjusting the values of the elements of the pairwise comparison, and the judgments should be caused once again by the decision makers until they become consistent. Saaty (1980) explained why CR should not be greater than 0.1. He considered that inconsistency itself is important, the

Table 1. Saaty's scale (Saaty, 2008)

Intensity of Importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
2	Weak or slight	Experience and judgement slightly favours one activity over another
3	Moderate importance	
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favours one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
8	Very, very strong	The evidence favouring one activity over another is of the highest possible order of affirmation Reciprocals of above
9	Extreme importance	
Reciprocals of above		If activity *i* has one of the above non-zero numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i*.
1.1–1.9	If the activities are very close	May be difficult to assign the best value but when compared with other contrasting activities the size of the small numbers would not be too noticeable, yet they can still indicate the relative importance of the activities.

Table 2. RI according to the sample size

n	1	2		3	4	5	6	7	8	9	10
RI	0	0		0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

inconsistency is important, without it new knowledge could not be admitted that would generate changes in the order of preferences. On the other hand, assuming all knowledge as consistent is contradictory to the idea of adjusting preferences based on understanding and knowledge. Therefore, the model depends on admitting a certain level of inconsistency. We rely on this result to measure consistency, as many other authors have done in the literature (Gil-Lafuente et al., 2014; Lin et al., 2020; Hussain et al., 2021).

2.1.4. Obtaining the weights of final alternatives via various levels aggregation of weights

In this step, the overall priorities of the alternatives are obtained with the objective to determine their global importance. The way these global weights are calculated is multiplying the sub-criterion weights in one level with their corresponding criterion in the level above and adding, for each alternative in a level according to the criteria it affects. These global priorities are used to weight the local priorities of the alternatives in the level below and so on to the bottom level.

2.2. Ordered Weighted Averaging (OWA)

In 1988, Yager introduced the Ordered Weighted Averaging (OWA), which weights are not assigned by any given criteria but rather affect the position that each observation occupies after ordering them, i.e. each weight (ω_i) is assigned to the i_{th} bigger element (Yager, 1988; Appel et al., 2017):

Definition 1. An OWA operator is a function of dimension τ $\left(F: R^{\tau} \rightarrow R\right)$, that has associated a weighting vector $\Omega = \left(\omega_1, \ldots, \omega_{\tau}\right)$ to it, so that the weights are between 0 and 1 and the sum of all of them is equal to the unity. It is defined to aggregate a list of real values (v) according to:

$$F\left(v_1, \ldots, v_{\tau}\right) = \sum_{i=1}^{\tau} \omega_i \cdot v_{\sigma(i)}, \tag{2}$$

where $\sigma: 1, \ldots, n \rightarrow 1, \ldots, n$ is a permutation such that $v_{\sigma(i)} \geq v_{\sigma(i+1)}$ for all i = 1,…, n-1, i.e, $v_{\sigma(i)}$ is the i_{th} highest value in the set of real values.

Therefore, the difference between OWA operators is established by the weighting function. The fuzzy quantifier is one of them, which is defined as a function $Q[0,1] \rightarrow [0,1]$ where $Q(0) = 0$, $Q(1) = 1$ and $Q(x) \geq Q(y)$ for $x > y$. Using the function proposed by (Zadeh, 1983) we can construct linguistic quantifiers that allow us to represent business requirements expressed in natural language through formal mathematical formulas. There are several approaches to these quantifiers, but we will focus on a parameterized version, which includes several definitions simply by changing the corresponding parameters (Yager, 1996):

$$Q(p) = p^{\alpha}, \ \alpha > 0, \ p \in [0, 1]. \tag{3}$$

With this definition many linguistic quantifiers can be defined as shown in Table 3.

Based on the Q function, the elements of the weighting vector used in the OWA are defined from:

$$\omega_i = Q\left(\frac{i}{\tau}\right) - Q\left(\frac{i-1}{\tau}\right), \ i = 1, \ldots, \tau. \tag{4}$$

Table 3. Definition of various linguistic quantifiers, based on (Boroushaki & Malczewski, 2008)

Parameter (α)	Linguistic Quantifier (Q)
0.001	At least one
0.1	Few
0.5	Some
1	Half
2	Many
10	Most
1000	All

In MCDM problems it is particularly interesting to express the linguistic quantifier used by means of two dimensions (Malczewski & Rinner, 2005): the degree of risk and tradeoff or substitutability among criteria.

The degree of risk, which indicates the position of OWA on a continuum between the *All* or *At least one* quantifiers, is defined by the following operator (Yager, 1988):

$$ORness = \sum_{i=1}^{\tau} \frac{\tau - i}{\tau - 1} \cdot w_i. \tag{5}$$

The degree of tradeoff, that indicates the compensation of low values on one criterion by high values on another criterion, is defined (Jiang & Eastman, 2000):

$$tradeoff = 1 - \sqrt{\tau \cdot \sum_{i=1}^{\tau} \frac{\left(w_i - \frac{1}{\tau}\right)^2}{\tau - 1}}. \tag{6}$$

It has been proposed in literature, to replace the weighted average of the AHP aggregation process (Section 2.1.4) using OWA operators (Yager & Kelman, 1999; Boroushaki & Malczewski, 2008; Zabihi et al., 2019; Linares-Mustaros et al., 2019). This extension makes it easier for decision makers to express what number of sub-criteria need to be satisfied by using high-level concepts, such as linguistic quantifiers. The use of this extension therefore implies including a linguistic quantifier in each of the aggregation processes of the hierarchy.

3. Proposed model applied to fashion retailers in Spain

In this section we present a MCDM model to direct the digitization strategy of the physical stores of a retail company. This model is shown in Figure 4.

The different stages of the model are explained below.

3.1. Decision problem definition

In order to develop the MCDM presented in section 2.1, firstly it is necessary to identify the goal and the basic elements that form the AHP structure. The application of MCDM models in the retail sector has been widely applied in the literature, mainly in order to choose the localization of a new store, point of production, selling point, etc. as in (Chan & Kumar,

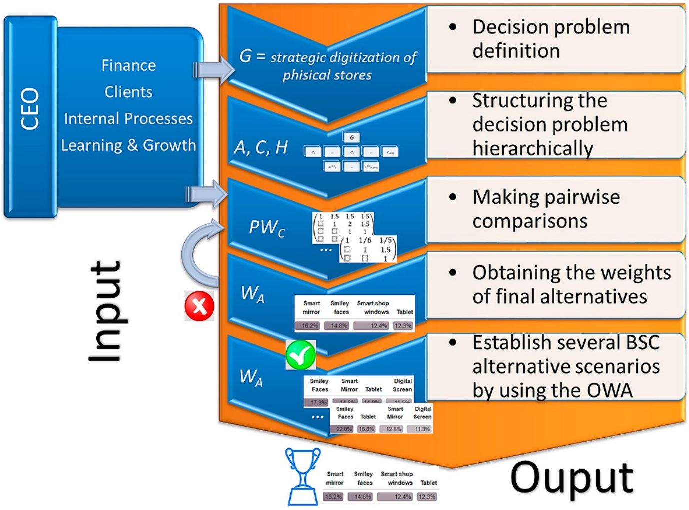

Figure 4. Proposed MCDM model to strategic digitization of physical stores

2007; Chou et al., 2008; Roig-Tierno et al., 2013; Yıldız & Tüysüz, 2019). Other authors have used these models to measure the customer experience or loyalty, or taking into account the retailers as decision makers in a MCDM problem in which they are implicated (Dong & Zhang, 2002; Jalali et al., 2016).

In our problem, the aforementioned goal is the selection of the most suitable retail device to implement in a physical store. The transformation of the physical shops is a decision that will mark the long-term success of the company and is therefore implicitly strategic. Therefore, the different perspectives of the enterprise (both financial and non-financial) must be taken into account in its design and implementation (Merigó & Wei, 2011; Merigó et al., 2012; Oliva et al., 2019). Balanced Scorecard (BSC) (Kaplan & Norton, 1992, 2001) is a widely used strategy performance management tool that focuses on managing the implementation of a strategy activity based on a cross-company perspective that involves the areas: finance, clients, business processes and learning and growth. Once the overall strategic framework for the company has been established, this plan must be implemented at the level of each area. For this reason, the joint use of BSC with a hierarchical decision model such as AHP seems appropriate. This combined use of both models can be found in the literature (Modak et al., 2017; Sundharam et al., 2013; Bentes et al., 2012; Leung et al., 2006).

In view of what has been argued, the set of experts in our model will be department managers related to these four BSC areas. This set of experts will be used to establish both the alternatives to be chosen and the criteria (classified by areas) of our model. Of course, the final decision will be made by the CEO, taking into consideration the judgement by these areas.

3.2. Structuring the decision problem hierarchically

Among the criteria, *C*, that can be evaluated within the four BSC areas, those that are considered to be related to the objective proposed in this contribution have been selected:

- *Finance*:
  - *Setup Cost*: It is the cost incurred to acquire equipment ready to use in the business.
  - *Maintenance Cost*: It is the cost incurred to keep the equipment in good condition.
  - *Profit*: It is the profit potential, i.e. not a guarantee but rather a projection, for a device to generate revenue.
- *Clients*:
  - *Experience*: It is the "cumulative impact of multiple touchpoints" throughout a client's relationship with the organization as Forbes describes it (Zwilling, 2015).
  - *Health* & *Safety*: It is the impact on the customer's perception of the care and appropriateness from the point of view of health and safety of the device.
- *Internal Processes*:
  - *Reliability*: It is a characteristic of a device that consistently performs according to its specifications.
  - *Management*: Includes the ease of administration of the device from a technical point of view.
- *Learning* & *Growth*:
  - *Training*: This characteristic refers to the ease in terms of training required by the employees who manage these devices.
  - *Innovation*: It is the potential for innovation and improvement of features that the device has.

These factors are evaluated over a set of retail devices that represent the alternatives, A, to be implemented in a physical store:

- *Smart Fitting room*: It allows customers to try the available products without going back to the shop floor and call a store assistant to offer advice about models, sizes, etc.
- *Smart Mirror*: It is a two-way mirror with cameras, digital displays and sensors behind the glass. It allows customers to see the fit of the apparel on their body without having to undress.
- *Tablet*: It is a mobile device with a mobile operating system and touchscreen which provides information about products and services.
- *Digital screen*: It is a flat panel screen able to present multimedia content to an audience.
- *Smart Shop Window*: It is a digital showcase that regularly changes the image to be displayed.
- *Smiley faces*: a set of buttons placed normally at the exit of the shop in order to gain customer feedback.
- *App payment*: An app functionality that lets you pay for the shopping from your phone.
- *App scan*: An app functionality to scan product labels and provide information about them (material, sizes, origin, etc.) and price.

Once the elements of the problem have been defined (goal, criteria and alternatives), we build the hierarchical structure H of the MCDM problem, which is composed of four levels, as shown in Figure 5. As we have mentioned previously, the goal is to obtain the most adequate device to implement in a shop and it occupies the highest position of the hierarchical

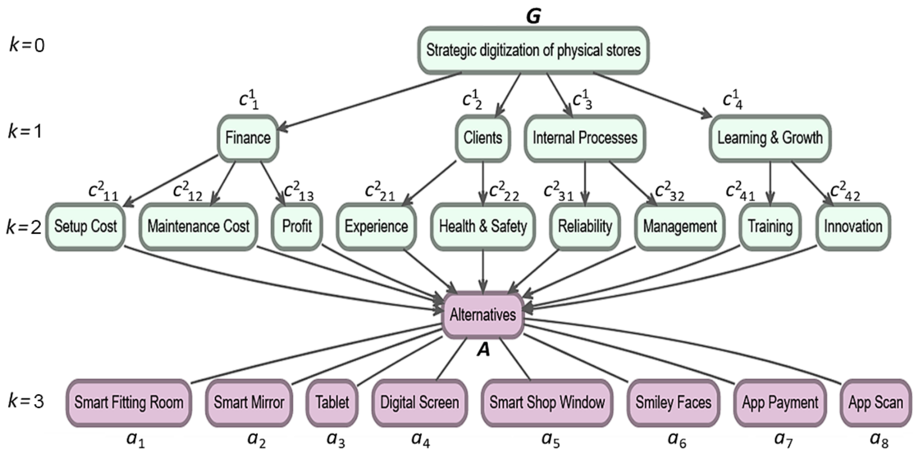

Figure 5. Hierarchy *H* for strategic digitization of physical stores

structure. In order to take this decision, we include a first level of criteria comprising the BSC areas. Obviously these four areas are the responsibility of the company's CEO. In the second level of criteria, each BSC area includes its above mentioned corresponding factors to be considered in the decision problem. In the last stage, the alternatives are evaluated from the point of view of each higher level criterion, i.e. from the perspective of the managers of the relevant BSC areas.

3.3. Making pairwise comparisons

As we have mentioned in subsection 2.1.3, once the criteria are nested, it is necessary to define the pairwise comparison matrices. Therefore, the area of the CEO and each manager of the corresponding BSC area investigates the values of the decision elements in the hierarchy *H* (Figure 4), and incorporates their judgements by performing a pairwise comparison of these elements. In this hierarchy, each decision element in the upper level, $k + 1$, is used to compare the elements of an immediate inferior level, k, with respect to the previous. Thus, the alternatives ($k = 3$) are compared in relation to the sub-criteria ($k = 2$), the sub-criteria are compared with respect to the criteria ($k = 1$) and the criteria are compared with respect to the goal ($k = 0$).

The authors had the opportunity to secure the help of a Spanish Digital Transformation consulting company (Analyticae) specialized in retail and working in the fashion sector. They researched an anonymous Fashion retailer client which was presented with the model and gathered the opinions of managers from the different areas mentioned (Finance, Clients, Learning & Growth and Internal Processes). The matrices defined by each decision maker are shown below:

- *CEO*. Pairwise comparison matrices are built from the comparison of the importance of each BSC area in this decision problem, i.e. with regard to objective *G*, based on the Saaty scale seen in Table 1 (Saaty, 2008). On the criteria $c(1) = \{c^1{}_1,\dots, c^1{}_4\}$, the pairwise matrix provided is:

$$PW_{c(1)} = \begin{pmatrix} 1 & 1.5 & 1.5 & 1.5 \\ & 1 & 2 & 1.5 \\ & & 1 & 1 \\ & & & 1 \end{pmatrix}.$$

– *Finance*. First, they evaluate the area dependent sub-criteria, i.e. $c_1(2) = \{c^{2}_{1\,1},\ldots, c^{2}_{1\,3}\}$ = {*Setup Cost*, *Maintenance Cost*, *Profit*}:

$$PW_{c_1(2)} = \begin{pmatrix} 1 & 1/6 & 1/5 \\ & 1 & 1.5 \\ & & 1 \end{pmatrix}.$$

Besides, the alternatives have to be evaluated for each higher level criteria:

– *Setup Cost*:

$$PW_{c_{11}(2)} = \begin{pmatrix} 1 & 3 & 1/8 & 1/7 & 1/6 & 1/8 & 2 & 2 \\ & 1 & 1/7 & 1/5 & 1/3 & 1/9 & 3 & 2 \\ & & 1 & 2 & 2 & 1/4 & 5 & 6 \\ & & & 1 & 3 & 1/3 & 6 & 5 \\ & & & & 1 & 1/5 & 6 & 5 \\ & & & & & 1 & 9 & 7 \\ & & & & & & 1 & 1/3 \\ & & & & & & & 1 \end{pmatrix}.$$

– *Maintenance Cost*:

$$PW_{c_{12}(2)} = \begin{pmatrix} 1 & 3 & 1/6 & 1/5 & 1/5 & 1/8 & 4 & 3 \\ & 1 & 1/5 & 1/3 & 1/3 & 1/9 & 3 & 2 \\ & & 1 & 3 & 3 & 1/3 & 7 & 6 \\ & & & 1 & 3 & 1/3 & 5 & 4 \\ & & & & 1 & 1/5 & 5 & 4 \\ & & & & & 1 & 7 & 6 \\ & & & & & & 1 & 1/3 \\ & & & & & & & 1 \end{pmatrix}.$$

– *Profit*:

$$PW_{c_{13}(2)} = \begin{pmatrix} 1 & 1/2 & 3 & 5 & 4 & 7 & 1/2 & 3 \\ & 1 & 3 & 5 & 5 & 7 & 1 & 3 \\ & & 1 & 3 & 3 & 5 & 1/2 & 1/3 \\ & & & 1 & 1 & 3 & 1/2 & 1/4 \\ & & & & 1 & 3 & 1/3 & 1/3 \\ & & & & & 1 & 1/5 & 1/5 \\ & & & & & & 1 & 3 \\ & & & & & & & 1 \end{pmatrix}.$$

– *Clients*. With the sub-criteria $c_2(2) = \{c^2_{2\,1}, c^2_{2\,2}\}$ = {*Experience*, *Health* & *Safety*} and this comparison:

$$PW_{c_2(2)} = \begin{pmatrix} 1 & 1/2 \\ & 1 \end{pmatrix}.$$

The evaluations of the alternatives are shown below:

– *Experience*:

$$PW_{c_{21}(2)} = \begin{pmatrix} 1 & 1/3 & 6 & 5 & 5 & 6 & 1 & 2 \\ & 1 & 7 & 6 & 6 & 7 & 3 & 5 \\ & & 1 & 3 & 3 & 5 & 1/3 & 1/3 \\ & & & 1 & 1 & 3 & 1/3 & 1/2 \\ & & & & 1 & 3 & 1/5 & 1/4 \\ & & & & & 1 & 1/7 & 1/6 \\ & & & & & & 1 & 3 \\ & & & & & & & 1 \end{pmatrix}.$$

– *Health* & *Safety*:

$$PW_{c_{22}(2)} = \begin{pmatrix} 1 & 1/3 & 1/2 & 1/5 & 1/5 & 1/2 & 1/2 & 1/3 \\ & 1 & 3 & 1/2 & 1/2 & 2 & 2 & 1/2 \\ & & 1 & 1/2 & 1/5 & 1/2 & 1/2 & 1/3 \\ & & & 1 & 1 & 3 & 1/3 & 1/3 \\ & & & & 1 & 3 & 3 & 1 \\ & & & & & 1 & 2 & 1/3 \\ & & & & & & 1 & 1/3 \\ & & & & & & & 1 \end{pmatrix}.$$

– *Internal Processes*. With the sub-criteria $c_3(2) = \{c^2_{3\,1}, c^2_{3\,2}\}$ = {*Reliability*, *Management*} and this comparison matrix:

$$PW_{c_3(2)} = \begin{pmatrix} 1 & 1.5 \\ & 1 \end{pmatrix}.$$

The pairwise comparison of the alternatives is the following:

– *Reliability*:

$$PW_{c_{31}(2)} = \begin{pmatrix} 1 & 3 & 1/3 & 1/5 & 1/5 & 1/9 & 1/3 & 1/3 \\ & 1 & 1/5 & 1/5 & 1/5 & 1/9 & 1/4 & 1/4 \\ & & 1 & 1/3 & 1/3 & 1/5 & 3 & 5 \\ & & & 1 & 1/2 & 1/3 & 3 & 5 \\ & & & & 1 & 1/2 & 3 & 5 \\ & & & & & 1 & 5 & 7 \\ & & & & & & 1 & 1/3 \\ & & & & & & & 1 \end{pmatrix}.$$

– *Management*:

$$PW_{c_{32}(2)} = \begin{pmatrix} 1 & 1/3 & 3 & 3 & 2 & 7 & 3 & 3 \\ & 1 & 5 & 5 & 5 & 7 & 5 & 5 \\ & & 1 & 1/3 & 1/3 & 5 & 1 & 1 \\ & & & 1 & 2 & 5 & 3 & 3 \\ & & & & 1 & 5 & 3 & 3 \\ & & & & & 1 & 1/3 & 1/3 \\ & & & & & & 1 & 1/3 \\ & & & & & & & 1 \end{pmatrix}.$$

– *Learning* & *Growth*. With the sub-criteria $c_4(2) = \{c^2_{4\,1}, c^2_{4\,2}\} = \{$*Training*, *Innovation*$\}$ and this comparison matrix:

$$PW_{c_4(2)} = \begin{pmatrix} 1 & 1/3 \\ & 1 \end{pmatrix}.$$

The pairwise matrices of the alternatives are the following:

– *Training*:

$$PW_{c_{41}(2)} = \begin{pmatrix} 1 & 1/3 & 3 & 3 & 2 & 7 & 3 & 3 \\ & 1 & 5 & 5 & 5 & 7 & 5 & 5 \\ & & 1 & 1/3 & 1/3 & 5 & 1 & 1 \\ & & & 1 & 2 & 5 & 3 & 3 \\ & & & & 1 & 5 & 3 & 3 \\ & & & & & 1 & 1/3 & 1/3 \\ & & & & & & 1 & 3 \\ & & & & & & & 1 \end{pmatrix}.$$

– *Innovation*:

$$PW_{c_{42}(2)} = \begin{pmatrix} 1 & 1 & 1/2 & 1 & 1 & 2 & 1/2 & 1/2 \\ & 1 & 1/2 & 1 & 1 & 2 & 1/2 & 1/2 \\ & & 1 & 2 & 3 & 2 & 1 & 1 \\ & & & 1 & 1 & 3 & 1/3 & 1/3 \\ & & & & 1 & 2 & 1/2 & 1/2 \\ & & & & & 1 & 1 & 1 \\ & & & & & & 1 & 1 \\ & & & & & & & 1 \end{pmatrix}.$$

3.4. Computing the vector weights for each matrix and obtaining the weights of final alternatives via various levels of aggregation

Once the pairwise comparison matrices have been completed by the decision-makers, we proceed to obtain the vector of weights for each matrix, using the Eq. (1), and the corresponding Consistency Ratio (*CR*). Any matrix whose *CR* exceeds 10% is discarded (see section 2.1.3) and must therefore be modified by the corresponding decision-maker as it is not considered a sufficiently rational decision. Methods for building consistent matrices from non-consistent ones can be found in the literature, however, in our case we prefer to reject any inconsistent matrix because of the strategic impact of the decision.

Table 4. Ranking of the alternatives in the MCDM problem, weights of the different levels of the hierarchy and CR

	Weight	Smart Mirror	Smiley Faces	Smart Shop Window	Tablet	Digital Screen	App Scan	App Payment	Smart Fitting Room	*CR* Inconsistency
Strategic digitization of physical stores	100.0%	16.2%	14.9%	12.4%	12.2%	11.9%	11.5%	10.6%	10.4%	1.7%
Finance	33.0%	4.0%	7.7%	2.8%	5.7%	3.7%	2.3%	3.1%	3.6%	0.5%
Maintenance Cost	17.6%	0.7%	6.4%	1.9%	4.0%	2.6%	0.6%	0.4%	1.0%	9.1%
Profit	12.7%	3.2%	0.3%	0.6%	1.2%	0.6%	1.6%	2.6%	2.5%	6.0%
Setup Cost	2.7%	0.1%	1.0%	0.3%	0.5%	0.5%	0.1%	0.1%	0.1%	8.8%
Clients	29.0%	5.9%	1.9%	4.5%	1.7%	3.2%	5.4%	3.8%	2.6%	0.0%
Health & Safety	19.3%	2.4%	1.6%	4.1%	1.0%	2.8%	4.4%	2.2%	0.8%	8.2%
Experience	9.7%	3.5%	0.2%	0.4%	0.7%	0.4%	1.0%	1.7%	1.8%	6.5%
Learning & Growth	19.6%	3.3%	1.4%	2.0%	3.1%	2.1%	2.7%	2.7%	2.4%	0.0%
Innovation	14.7%	1.5%	1.3%	1.4%	2.8%	1.5%	2.5%	2.5%	1.5%	3.3%
Training	4.9%	1.8%	0.1%	0.6%	0.3%	0.6%	0.3%	0.3%	0.9%	5.0%
Internal Processes	18.4%	3.0%	4.0%	3.1%	1.7%	2.8%	1.1%	1.0%	1.8%	0.0%
Reliability	11.1%	0.2%	3.8%	2.3%	1.2%	1.8%	0.7%	0.6%	0.4%	8.8%
Management	7.4%	2.8%	0.2%	0.8%	0.4%	1.0%	0.4%	0.4%	1.4%	5.0%

From the weight vectors obtained we proceed to obtain the weights of final alternatives via various levels of aggregation using the hierarchy *H*, as we have explained in section 2.1.4. The final results of this step are shown in Table 4: weights of the different levels of the problem, ranking of the alternatives and the *CR* of the pairwise matrices.

3.5. Establish several BSC alternative scenarios by using the OWA operator

Based on the idea provided by several authors (Nielsen & Nielsen, 2015; Barnabè, 2011; Akkermans & Van Oorschot, 2005) to include dynamism in BSC, in this step we propose to obtain various simulation scenarios, alternative to the decision already obtained in the previous section, by incorporating the OWA operator (explained in section 2.2) into the designed AHP model.

In this AHP model, the weights of each BSC area have been obtained from the matrix $PW_{c(1)}$ filled in by the CEO position. Let be $v = (0.3300, 0.2900, 0.1960, 0.1840)$ this vector corresponds to the areas of *Finance*, *Clients*, *Learning* & *Growth* and *Internal Processes* respectively and represents the importance obtained by each area in the decision process. Therefore, the AHP model proposed can be considered balanced since all areas of the company are involved from the perspective of the CEO (whose consistency has also been tested) and this is aligned with the own philosophy of BSC. The BSC approach does not mean that the implied areas are equally balanced, as it is common practice that some perspectives or areas are more important than others in the strategic plan (Bentes et al., 2012). The idea in this section is to provide the CEO with new simulation scenarios that give her/him new, less balanced decisions, but that can be taken into account when the CEO is handling information that has not been included in the system but that she/he may have (for example, a qualitative report on each of the devices). To this purpose, we are going to recalculate the vector v by applying various linguistic quantifiers to the Eq. (4), we also calculate the risk measure or *ORness* (Eq. (5)) and degree of *tradeoff* (Eq. (6)). The results of these calculations are summarised in Table 4. To facilitate the understanding of how we obtain these results, we are going to calculate the values when $\alpha = 0.001$. If we apply Eq. (4) knowing that our vector has 4 elements, then we have:

$$\omega_i = Q\left(\frac{i}{4}\right) - Q\left(\frac{i-1}{4}\right),\ i = 1,\ldots,4,$$

ω_i = (0.9986, 0.0007, 0.0004, 0.0003).

These values represent the first four values shown in the columns of Table 5. The other four are obtained using Eq. (2) as follows:

$$F(v_1,\ldots,v_\tau) = \sum\nolimits_{i=1}^{4} \omega_i \cdot v_{\sigma(i)} = \omega_i \cdot v_{\sigma(i)} \,/ \sum\nolimits_{i=1}^{\tau} \omega_i \cdot v_{\sigma(i)}.$$

For the first element we would have:

$v_1 = (0.9986 \cdot 0.3300)/0.3299 = 0.9990.$

This is the result that can be observed in Table 5, and the other values of v_i would be obtained in an analogous way.

Table 5. Definition of various linguistic quantifiers

α	Q	w_1 *Finance*	w_2 *Clients*	w_3 *Learning & Growth*	$w_\circ$ *Internal Processes*	v_1 *Finance*	v_2 *Clients*	v_3 *Learning & Growth*	v_4 *Internal Processes*	*ORness*	*tradeoff*
0.001	At least one	0.9986	0.0007	0.0004	0.0003	0.9990	0.0006	0.0002	0.0002	0.9992	0.0018
0.1	Few	0.8706	0.0625	0.0386	0.0284	0.9029	0.0569	0.0238	0.0164	0.9251	0.1721
0.5	Some	0.5000	0.2071	0.1589	0.1340	0.5875	0.2138	0.1109	0.0878	0.6910	0.6612
1	Half	0.2500	0.2500	0.2500	0.2500	0.3300	0.2900	0.1960	0.1840	0.5000	1.0000

As can be observed the quantifier *Half* implies that the AHP works the same as the original with a maximum balancing in the decision (*tradeoff* = 1) and a medium risk (*ORness* = 0.5). With the rest of the quantifiers (*Some*, *Few*, *At least one*), the balancing goes down and the risk progressively increases.

Using these new vectors *v*, we recalculate the remaining weights in the AHP model, obtaining new decision scenarios. In Table 6 we show the scenario for the quantifier *Some*, Table 7 for the quantifier *Fe*w and Table 8 for the quantifier *At least one*. As mentioned above, the scenario for quantifier *Half* is the original one (shown in Table 4).

At this point, the CEO must choose one of the scenarios (Table 4, Table 6, Table 7 or Table 8), to decide on the investment priorities for the digitization of the store.

4. Discussion

To manage investment choices, we use MCDM models and retail value creation frameworks against which we put forth possible outcomes for the management of physical retail stores. Thus, our objective in this section is to highlight implications for possible future investments that result from shifts in the weights assigned to decision makers from different BSC areas. In this paper the authors use a case study based on apparel retailers as an example of applicability, but the model proposed here is intended to underlie the decision making process for complex business decisions in different sectors.

Table 6. Ranking of the alternatives and weights of the different levels of the hierarchy using linguistic quantifier *Some*

	Weight	Smiley Faces	Smart Mirror	Tablet	Digital Screen	Smart Shop Window	Smart Fitting Room	App Payment	App Scan
Strategic digitization of physical stores	100.0%	17.8%	14.8%	14.0%	11.5%	10.9%	10.6%	10.3%	10.1%
Finance	58.8%	13.7%	7.2%	10.2%	6.6%	5.0%	6.4%	5.5%	4.1%
Maintenance Cost	31.4%	11.3%	1.3%	7.1%	4.7%	3.4%	1.8%	0.7%	1.1%
Profit	22.5%	0.5%	5.7%	2.1%	1.1%	1.1%	4.4%	4.7%	2.9%
Setup Cost	4.9%	1.8%	0.2%	1.0%	0.8%	0.6%	0.2%	0.1%	0.2%
Clients	21.4%	1.4%	4.3%	1.2%	2.4%	3.3%	1.9%	2.8%	4.0%
Health & Safety	14.3%	1.2%	1.8%	0.8%	2.1%	3.1%	0.6%	1.6%	3.2%
Experience	7.1%	0.2%	2.6%	0.5%	0.3%	0.3%	1.4%	1.2%	0.7%
Learning & Growth	11.1%	0.8%	1.9%	1.7%	1.2%	1.1%	1.3%	1.5%	1.5%
Innovation	8.3%	0.7%	0.8%	1.6%	0.8%	0.8%	0.8%	1.4%	1.4%
Training	2.8%	0.1%	1.0%	0.2%	0.4%	0.3%	0.5%	0.1%	0.1%
Internal Processes	8.8%	1.9%	1.4%	0.8%	1.3%	1.5%	0.8%	0.5%	0.5%
Reliability	5.3%	1.8%	0.1%	0.6%	0.9%	1.1%	0.2%	0.3%	0.3%
Management	3.5%	0.1%	1.3%	0.2%	0.5%	0.4%	0.7%	0.2%	0.2%

Table 7. Ranking of the alternatives and weights of the different levels of the hierarchy using linguistic quantifier *Few*

	Weight	Smiley Faces	Tablet	Smart Mirror	Digital Screen	Smart Fitting Room	App Payment	Smart Shop Window	App Scan
Strategic digitization of physical stores	100.0%	22.0%	16.6%	12.8%	11.3%	10.9%	9.6%	9.1%	7.8%
Finance	90.3%	21.1%	15.7%	11.0%	10.2%	9.9%	8.4%	7.7%	6.3%
Maintenance Cost	48.2%	17.4%	11.0%	2.0%	7.2%	2.7%	1.1%	5.2%	1.6%
Profit	34.6%	0.8%	3.2%	8.8%	1.7%	6.8%	7.2%	1.7%	4.4%
Setup Cost	7.5%	2.8%	1.5%	0.3%	1.3%	0.3%	0.2%	0.9%	0.2%
Clients	5.7%	0.4%	0.3%	1.2%	0.6%	0.5%	0.7%	0.9%	1.1%
Health & Safety	3.8%	0.3%	0.2%	0.5%	0.6%	0.2%	0.4%	0.8%	0.9%
Experience	1.9%	0.0%	0.1%	0.7%	0.1%	0.4%	0.3%	0.1%	0.2%
Learning & Growth	2.4%	0.2%	0.4%	0.4%	0.3%	0.3%	0.3%	0.2%	0.3%
Innovation	1.8%	0.2%	0.3%	0.2%	0.2%	0.2%	0.3%	0.2%	0.3%
Training	0.6%	0.0%	0.0%	0.2%	0.1%	0.1%	0.0%	0.1%	0.0%
Internal Processes	1.6%	0.4%	0.1%	0.3%	0.3%	0.2%	0.1%	0.3%	0.1%
Reliability	1.0%	0.3%	0.1%	0.0%	0.2%	0.0%	0.1%	0.2%	0.1%
Management	0.7%	0.0%	0.0%	0.2%	0.1%	0.1%	0.0%	0.1%	0.0%

Table 8. Ranking of the alternatives and weights of the different levels of the hierarchy using linguistic quantifier *At least one*

	Weight	Smiley Faces	Tablet	Smart Mirror	Digital Screen	Smart Fitting Room	App Payment	Smart Shop Window	App Scan
Strategic digitization of physical stores	100.0%	23.3%	17.4%	12.2%	11.3%	11.0%	9.3%	8.6%	6.9%
Finance	99.9%	23.3%	17.4%	12.2%	11.3%	11.0%	9.3%	8.5%	6.9%
Maintenance Cost	53.3%	19.3%	12.1%	2.2%	7.9%	3.0%	1.2%	5.8%	1.8%
Profit	38.3%	0.9%	3.6%	9.7%	1.9%	7.6%	8.0%	1.8%	4.9%
Setup Cost	8.3%	3.1%	1.7%	0.3%	1.4%	0.4%	0.2%	0.9%	0.3%
Clients	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Health & Safety	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Experience	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Internal Processes	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Reliability	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Management	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Learning & Growth	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Innovation	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Training	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

As the authors focus on customer interaction in-store, the discussion about the investment alternatives open to the retailer is conditioned by the CEO's bias regarding the cross company perspective, in terms of allocating higher or lower weight to each of the BSC areas within the company, namely Finance, Clients (Marketing & Sales), Internal Processes and Learning & Growth. A previous study by Bonetti et al. (2018) evaluated managerial drivers and barriers for the implementation of in store technology in Fashion retailing. Our results provide some interesting insights into decision making for in-store digitization. From the analysis of section 3, we find that the more weight we allocate to the Finance BSC area, the more conservative the decision will be, as the main considerations are maintenance cost, potential profit and setup cost of deployment in stores. Bearing that priority in mind, the ranking of devices is biased towards inexpensive items with low maintenance such as Smiley Faces.

To maximize firm financial performance in the long term, an ideal strategic option would be to balance customer satisfaction and profit. However appealing it may be, this option may not be available at first sight, but it is always a decision of the CEO to drive in that direction. There is abundant literature (Kumar et al., 2000; Lemon & Verhoef, 2016; Fornell et al., 2006) who supports the idea of a market driven strategy as a recipe for company financial success by improving the interactivity with customers in order to deliver positive customer experiences. In this context the authors are in line with Sánchez-Gutiérrez et al. (2019) that state that management capabilities in building customer relationships and in the way they convert knowledge of customer needs into specific management choices in the market can be used as indicators of competitiveness, having a positive effect on customer value creation, financial performance, cost optimization and the use of technology. Also along this line Fornell et al. (2006) state that satisfied customers are economic assets with high returns and low risk.

We can compare results according to the linguistic quantifier applied by the use of the OWA operator seen in Table 5, which provides the different scenarios, from the most to the least balanced among the BSC areas. We compare the different BSC alternative scenarios from Table 4 (*Half*), Table 6 (*Some*), Table 7 (*Few*) and dismiss Table 8 (*At least one*) as the ranking results are the same as those of Table 7, with slight differences in weights. Also we can read by column each of the tables to see the weight of each BSC area and the weight of each criterion on the decision to have that device or app functionality in that particular position in the ranking.

If we look at results in Table 4, the one with the most balanced weights between BSC areas, we see that the first alternative in the ranking is the Smart Mirror (16.2%), followed by the Smiley Faces (14.9%). Reading the Smart Mirror column, we can see the detail of the weights of the different levels of the problem adding to the position in the ranking. In particular, we see how the highest weight was given by the Clients area (5.9%), and within that area coming specifically from the criterion of Experience (3.5%). This reflects on the importance of improving the customer experience in order to increase retail value creation in the store under the mind-set of the Client BSC area (Marketing & Sales). On the other hand, we see that an otherwise interesting device to improve customer experience has been penalised by the Health & Safety criterion (0.8%) due to the current COVID-19 pandemic, as it is an enclosed space, therefore considered less safe.

If we look at Table 6, where the Finance BSC area has an increased weight of 58.8%, we see how Smiley Faces climbs to the top of the ranking, heavily supported by the Finance BSC area (13.7%), in particular boosted by a high contribution of Maintenance cost criterion (11.3%). Also the Tablet gains a third position in the rank for similar reasons.

Finally, Table 7, with the decision balance further skewed towards the Finance BSC area (90.3% weight), we see how Smiley Faces consolidates its first position with a large weight contribution from Maintenance cost (17.4%) criterion. Likewise, in the case of Tablet in the second position, we see a large weight from Maintenance cost (11.0%).

Conclusions and future work

As the organization needs to make decisions, this methodology foster consensus, and the overall choice takes into account the choices of the individual experts from the different BSC areas to make a general ranking of preferences observed in Table 4, where we see that the overall preferences are for the Smart Mirror (lifted by Clients BSC area) and the Smiley Faces (lifted by Finance BSC area), however as we shift the power towards one BSC area, the ranking changes. In this case the shift towards Finance BSC area gave an overall preference for the Smiley Faces followed by the Tablet, which are both relatively cheap to set up and maintain as well as being simple in their functioning therefore perceived as more reliable.

The authors discussed that in order to maximize financial performance, the CEO should find a balance among customer satisfaction and profit, considering satisfied customers as economic assets. In our model the BSC is balanced, as it is designed to allow varying degrees of importance to other areas, such as Client Service. We start from a situation with the OWA in half, where the weighting of Finance is 33%, this weight increases in the different scenarios to the detriment of the rest of areas, including the Client area. There are two indicators (tradeoff and risk) indicating that the CEO is dealing with decisions with more risk and less tradeoff (consensus) in each of the scenarios, which must be assumed by the CEO in his decision.

In the push for digitization of brick & mortar stores in order to make them more appealing to customers and increase their value in the retail chain, retailers have many alternatives to invest their money and focus their efforts on. Here we propose a flexible strategic framework for decision making which will ease the process and already takes into account the conditions created by the COVID-19 pandemic. This is a new model which has not been proposed before in the literature.

The empirical results should be interpreted as directional, with some limitations in mind. We focus on a particular case, digitization of Fashion retail stores, and lay down some particular pairwise comparison matrices which define the balance among the BSC areas and the importance of each criterion in the decision to rank alternatives of investment. The model can work just as well with a different balance by tweaking the pairwise matrices if we decide that more power should be given to a different BSC area. Likewise, a case of use can be found in many different industries.

As practical and theoretical implications, this paper addresses a significant and ongoing transformation which is taking place in retail and sheds light on a theoretical framework to make investment decisions among different technologies and devices to engage their customers. It also offers guidance to practitioners on how to leverage store digitization.

The authors have approached the issue from a theoretical perspective. The added value of this work lies in the fact that it broadens the generalizability of the decision making process to the digital context of in-store devices and mobile apps, focusing on the specific case of use of digitization of fashion retail stores, although similar framework can be applied to other retail categories such as grocery stores by adapting the digital devices used in the stores.

The research helps in the understanding of the decision making involved in a retail organization. It takes a decisive focus from the CEO to push digital technology to improve customer experience as the ROI is not clear yet and the costs of many of the alternative devices are high when the store network is large, for instance 300 stores.

The retailer seeks customer satisfaction to build a strong relationship in the digital layer as well as in the physical one, but as the cost of achieving that customer satisfaction and the return on investment are still unclear, most retailers are holding back waiting for a reduction in the technology cost and to see more cases of use proved successful. So far some pilot testings are carried out by some retailers to check on customer acceptance and adoption. Furthermore, the COVID-19 pandemic is negatively affecting the physical retail and draining resources, which implies that the deployment of interactive technology may slow down.

This study also provides relevant information for retailers as to how a joint decision can reach a conservative consensus to avoid the inherent risk attached to high investment alternatives. The results are directional but this model can be applied to many different industries where complex decision making is required.

Further research might review specific device life cycles and acknowledge more characteristics and alternatives to take into account. Another research direction would be to use the fuzzy linguistic modelling approach in the model set up, which may allow a better management of uncertainty. There is another field to explore attending to decision making strategies based on consensus on incomplete information, where the BSC we developed could be split within each area, being for instance the Finance area broken down in a new BSC model with each criterion split in sub criteria. In this context we will find issues of incomplete information.

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