Towards the Creation of a Holistic Video Analytics Platform for Retail Environments

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Abstract: Retail is expected to be one of the industries that will benefit most from advances in artificial intelligence (AI) in the future. One branch of AI is video analytics, which is used to analyze the behavior, flow, and interactions of customers in a store. Properly implementing features to optimize store operations, prevent theft, or provide targeted advertising can increase a store's profitability and reduce shrinkage. This paper proposes an adaptation and specification of an action design research approach that forms the basis for implementing a holistic video analytics platform that could potentially incorporate a variety of identified beneficial features. In addition, the challenges in this regard are explained and an outlook on the future realization of such a platform is provided.

1 INTRODUCTION

When disruptive scientific or technological means emerge, history has shown that their impact is not limited to the application of that technology, but is also reflected in social structures, moral codes, and laws (Jiang et al., 2022). One of the ubiquitous technologies today is *artificial intelligence* (AI), as it penetrates almost every aspect of our daily lives, including education, the economy, commerce, healthcare, public administration and governments (Kaplan and Haenlein, 2019). In synergy with humans, AI-related technologies, connected sensor systems as well as underlying processing capabilities form the basis of a new societal concept called *Society 5.0* also known as a *super smart society* or *society of imagination* (Carayannis and Morawska-Jancelewicz, 2022; Muslikhin et al., 2021; Nair et al., 2021), where the above are expected to serve the needs of this form of society.

A study by McKinsey & Company revealed that across 19 industries AI is likely to have the biggest impact on the retail sector (Guha et al., 2021). The range of possible applications for AI in retail is manifold, including trend analysis through social media, targeted marketing, implementation of virtual and augmented reality (VR and AR, respectively) so that customers can experience products more vividly, automating customer service via chatbots, or ensuring e-commerce applications recommend products (smarter recommendation systems) that disadvantaged people can afford (Alexandrova and Kochieva, 2021; Bellis and Johar, 2020; Chang et al., 2023; Daase et al., 2023; Ferracuti et al., 2019; H. Zhang et al., 2020). One of the prominent areas for AI in retail is video analytics (VA), either in-store or by

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analyzing online video content. VA can help understand customer behavior and intentions by examining their movements (for in-store scenario) or shopping cart contents (for online scenario) (Kaur et al., 2020; Liciotti et al., 2017). However, almost all tasks that typically require humans (workers) to monitor in-store cameras are of interest for VA in retail. For example, the prevention of loss due to shoplifting is a key component of in-store camera utilization and is now expected to be facilitated by VA. Another use of knowledge gained through VA is to present products to customers that are believed to be of particular interest to them based on prior behavior, which can be summarized under the designation of targeted advertisement (S. Zhang et al., 2021). All in all, VA in retail is seen as an enabler for smart retail business (Chandramana, 2018).

This article presents a methodological approach to constructing a holistic platform for in-store VA by adapting the *action design research* (ADR) *approach* proposed by Sein et al. (2011), which is a methodology from the field of *design science research* (DSR). DSR is a research discipline whose methodologies can be used to create usable IT artifacts to solve organizational problems (Hevner et al., 2004). *Holistic*, in this regard, means that a modular platform is envisioned that can be extended by integrating any generic VA use case while relying on the same input data mode in a consistent context (i.e., visual data in a retail environment). According to Sein et al. (2011), a distinctive / differentiating aspect compared to other DSR methodologies is that ADR specifically addresses the issue that the creation of an artifact must be guided not only by the intentions of the researchers, but also by the interaction with the context of its application. Since VA in retail is highly dependent on the individuals involved (i.e., customers), and human behavior is a factor of uncertainty for IT system developers, the design of a VA platform should be informed by active instantiation. However, the approach describes in the original work on ADR proposes a rather generic approach, which needs to be adapted to the specific research endeavor. This paper aims to provide a design and development proposal for a VA platform, but the adapted methodology could also be used for other business scenarios involving external participants and multiple stages of internal and external implementation. In the light of the above and the existing body of knowledge on the topic, the research question is:

RQ: How can the activities of the action design research methodology be adapted and specified to propose a suitable approach for creating a holistic in-store VA platform in retail?

The article is structured as follows: the following section presents the overall methodology for this article and describes an exploratory systematic literature review (SLR) that is conducted to identify VA use cases for their further integration into the platform in more detail. Section 3 focuses on explaining the choice of implementable use cases. Section 4 is dedicated to the assembly of an adapted ADR approach to implement a holistic VA platform in retail. Potential challenges for VA are explained in more detail. Finally, section 5 summarizes and provides suggestions for further research, as well as the aspired realization of the VA platform.

2 METHODOLOGY

This section presents the research methodology. First, a general approach to the research is presented, as well as those parts that are planned to be implemented in the future are presented. Second, the review protocol for the explorative SLR is presented, including the used databases, search queries, and inclusion / exclusion criteria.

2.1 Overall Approach

This research can be divided into three stages. First, the research is motivated and narrowed down by the exploratory SLR to identify VA use cases in retail that will constitute the knowledge base and serve as an input for the later stages. Second, the ADR methodology (Sein et al., 2011) is purposefully adapted and extended to provide a foundation for a scientifically sound, i.e., evidence-based, real-world / practical implementation of a holistic VA platform in retail. These two phases are addressed in this paper. The third stage, envisioned for the future, is the stage of the implementation of the respective artifact, at which a prototype implementation of such a platform is expected to be proposed and validated. The overall research process is shown in Figure 1.

2.2 Exploratory SLR

To establish a knowledge base and examine how the topic under question has been reflected in the literature over the years, we studied all relevant literature covering this topic. In order to identify relevant literature, the SLR was carried out to form the knowledge base. This was done by searching for relevant studies covered by Scopus and Google

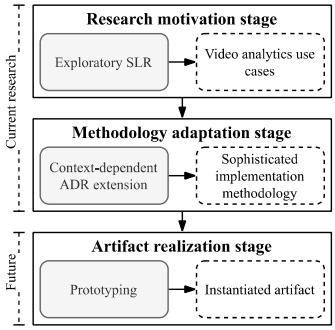

Figure 1: Overall research endeavor.

Scholar, which index most well-known publishers of peer-reviewed literature, thereby allowing us to ensure the knowledge base is as rich as possible. The search query was defined as a combination of the terms "*video analytics*" and "*retail*". We limited the scope of the search to the article title, keywords, and abstract in order to limit the number of articles to those where these topics were the primary object of study, rather than mentioned in the body, for example, as future work. By following this approach, Scopus retrieved six articles, while Google Scholar yielded 23 papers.

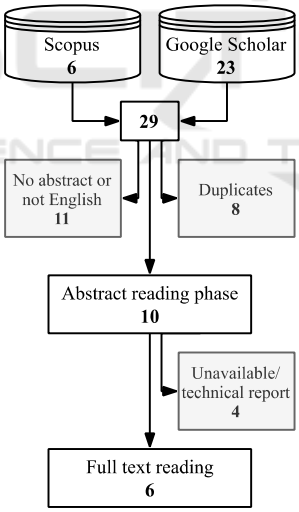

Figure 2: Exploratory SLR search process.

From the initial body of literature of 29 publications, 19 were excluded at the first stage of review when reading the abstracts. Eight out of 19 articles were found to be duplicates, and another eleven articles were either not written in English or were not available for further investigation. In the second stage, the remaining articles were read to retrieve potential use cases and applications of intelligent in-store video systems. Of the ten remaining articles, four were identified as either technical reports or unavailable sources. Finally, six articles serve as the basis for an exploratory review to describe a selection of VA use cases. Figure 2 shows the exploratory review process.

3 VIDEO ANALYTICS IN RETAIL

In order to harness the opportunities that video analytics can provide for the retail sector, it is necessary to be aware of them. Therefore, the following elaborations are intended to give an idea of what capabilities can be realized with a holistic VA platform as it can be built using the methodology described in the following sections. Since this paper presents VA use cases mainly from a technical point of view, the legal requirements have to be taken into account depending on the local law under which a platform such as the one proposed here is to be operated. In addition, it should be noted that strict privacy and data security regulations, as applicable in the European Union, may cause that some of the use cases cannot be realized without extensive anonymization and data security measures.

3.1 Applications from the Literature

This section briefly describes three overarching terms for potential VA application scenarios in retail. These include the use of VA to optimize store operations, safety and loss prevention, and merchandising, which we will discuss in more detail in further subsections.

3.1.1 Store Operations

The first application area of VA can be summarized under the designation of *store operations*. It encompasses various strategies for optimizing the physical store in ways that increase employee productivity / performance and revenue. Cameras can be used to monitor store traffic, queues, and shoppers / customer behavior in general (Connell et al., 2013; Pletcher, 2023; Senior et al., 2007). Moreover, assistance through video cameras can be used to analyze not only customers, but also employees working in the store, for example, in order to optimize their positioning or adjust the number of active staff in the store area (Musalem et al., 2015). By monitoring the entrance and exit of a store, retailers can estimate the *conversation rate*, which stands for the percentage of customers who buy items divided by all people entering the store (Connell et al., 2013; Senior et al., 2007).

Unlike individual customer observations, an alternative with VA is to detect shopping carts and items based on specific patterns (Rai et al., 2011). In this regard, when products are part of the analysis intent, VA can also help optimize shelf layouts (Pletcher, 2023). Especially when considering the interplay of / interaction between customers and products, the following application areas for VA show potential.

3.1.2 Safety and Loss Prevention

The *loss prevention* refers to several scenarios in which a retailer's revenue is reduced due to illegal actions such as shoplifting and employee theft, returns fraud, and tag switching, but it also refers to unintentional shrinkage such as accounting errors (Senior et al., 2007; Singh, 2018). Connell et al. (2013) categorize three types of loss prevention: store-floor (i.e., detecting shoplifters in the public area of a store), back-of-store (i.e., detecting theft and unusual behavior in the warehouse area), and front-of-store (i.e., detecting theft and criminal behavior at the check-out area by employees or customers). VA can help identify shoppers who do not scan all their items properly before payment, switch the tags between items, or when cashiers are involved in such acts.

Another related application scenario for VA in retail is to improve security and safety in case of emergencies or criminal acts that are not directly related to the retail store (Connell et al., 2013). VA systems can be used to detect accidents, technical misbehavior, dangers or hazards, and medical emergencies.

3.1.3 Merchandising

A third area of physical retail where VA can be purposefully applied is merchandising, also related to targeted advertising and product promotion (Pletcher, 2023; Rai et al., 2011; Singh, 2018). In this regard, the estimation of the locations of customers in the store can be a component of such targeted promotional offers. Spots where customers spend an unusual amount of time, or places that attract a lot of customers, can lead to *hot zones* and *dwell times* for customers (Connell et al., 2013). Heat map visualizations of in-store places with increased traffic flow can also help retail managers to optimize spontaneous advertising (Senior et al., 2007). Pricing strategies can also play a role in promotional campaigns when it comes to setting prices based on previously identified trends. If an increased flow of customers is expected based on previous seasonal experience, a retailer may decide to adjust prices while promoting a particular product or group of goods.

In addition to observing physical movements for location-based merchandising, the psychological behavior of customers can also be assessed using VA. One example is tracking eye movements using *gaze analysis* to identify which products or information attract the most attention from individual customers (Connell et al., 2013). Knowing this, shelves can be optimized, and promotional calls can be placed nearby (Pletcher, 2023).

3.2 Further Potential Applications

In addition to the above discussed, we think that further potential applications of VA could be harnessed to provide value to retailers.

For example, like (Musalem et al., 2015), we believe that VA could be useful for monitoring not only customers / clients, but also staff / personnel. However, we think that it can serve not only the purpose of their allocation but also seek to evaluate the quality of assistance they provide to consumers. This would potentially allow the business owner to find pain points, best and worst practices that could be further converted / transformed into training and policies, as well as identify problems in the respective business process (or its specific activities). Improvements based on the above would further improve the image of the business (in the long term).

Similar to what was discussed in 3.1.3 and based on a suggestion by Connell et al. (2013), gaze analysis can be potentially applied to inspect the overall planning / layout of the sales areas, identify areas that are of greater interest to customers (due to their physical location), where then promotions or other types of products or services in whose popularity the business owner is interested most should be located avoiding spots that are typically overlooked by customers, or triggering the redesign activities. Here, however, not only gaze analysis, but also heat maps could be useful, or, preferably, a combination of both, thereby seeking an increased accuracy and validity of the results.

Additionally, with today's technologies, predictive analytics and (near) real-time VA-based predictions / forecasts, in particular, are seen as an emerging trend that has the potential to further contribute to the overall business success. For example, reducing the waiting times between analyses of "as-is" and "to-be" models based only on historical data is possible, thereby allowing business owners to make adjustments to their marketing

strategies faster. This is also in line with (Ghose et al., 2022). This is of particular importance also for daily activities such as the number of cashiers needed at this moment and expected to be needed in one hour based not only on the historical data, meaning the day of the week or season, but considering the actual situation of the given day. Of course, in this example, historical data is used as well, but rather as complementary source and not as primary input (also in line with (Anderson, 2022).

4 IMPLEMENTATION STRATEGY

A platform for VA in retail that integrates a suitable set of the aforementioned capabilities and more requires a tailored design methodology. In this section, ADR is adapted to provide a starting point for constructing such a platform. A multistep approach is taken, starting from scientifically grounding the design to implementing it in artificial scenarios and later real-world environments.

4.1 Action Design Research (ADR)

The adoption of ADR with its focus on organizational contexts for the set goal of creating an adaptive reference architecture may seem partially contradictory. The focus on organizational contexts may indicate the existence of a rather precise scenario, while the goal of providing a universal reference architecture aims at an artifact for multiple use cases. However, considering that the design part in DSR is the "purposeful organization of resources to accomplish a goal" (Hevner et al., 2004), and assuming that the most positive arrangement of integrable tools is revealed only when the context is known, this discrepancy can be resolved by specifying that different levels of detail can be defined for the same reference architecture. Sein et al. (2011) also recognize the disparity of inherent challenges in ADR, noting that the artifact building process must incorporate the influence of users and contextual use in the same way that it must incorporate theoretical precursors and researcher intent. In the following, ADR is presented in a specially adapted version that describes the individual steps required to develop an applicable holistic VA platform in a real business context.

4.2 Adapted ADR to Realize Video Analytics Platform

The first stage of the research process, the problem formulation, is founded on input derived from reliable sources such as experienced practitioners or researchers, the study of existing technologies, and the review of prior research. In this article, this sub-stage of selecting and investigating related references is considered as an initial exploration phase, covered in section 3. In order to position the envisioned VA platform in a scientific context, the findings impact the formulation of precise RQs that are in turn decisive for the assembly of appropriate search queries for an SLR. As a second sub-stage for the first part of the adapted ADR approach, insights gained from an extensive SLR in the future research process represent the main source for design decision support. Furthermore, a solid groundwork will be laid by conducting a comprehensive SLR to justify the research objective, examine comparable approaches to the targeted artifact, and identify key technologies with their potential interplay for a prototypical concept.

Shaping the subsequent entire research process, Sein et al. (2011) note that the critical elements in conceptualizing the workflow are, firstly, that the long-term commitment of participating organization(s) must be secured and, secondly, that the problem to be solved should be defined as an instance of a broader class of problems. Regarding the aspired VA platform with several capabilities integrated, the involved organizations might be retail companies, store owners, or malls in general. Furthermore, the *instance* of a problem can be the implementation of a subset of VA capabilities, while the *class* of problems is the broader domain of VA in general. By relying in the first iteration of the research process on simulated placeholders whose behavior is based on insights from the SLR, both critical elements are addressed. On the one hand, the constancy of the instance setup is ensured. On the other hand, the level of detail of the organizations can be seamlessly adjusted so that both an instantiated specific problem, as well as the superordinate class of problems it belongs to, can be described. The methodological guidelines propose two principles for this stage. First, practice- or problem-inspired research should be pursued to solve a specific problem and generate generally applicable knowledge for the problem class. Second, the targeted artifact should be theory-ingrained, meaning that the initial design is driven by theory and later reshaped by organizational practice. Both principles are met here by reviewing the

scientific literature and considering the contextual implications for the relevant research activities. In an elaborated version of the ADR process model, Mullarkey and Hevner (2019) remark that problem formulation further depends on which iteration of the research is concerned, as the original stages of ADR can be applied with different scopes, starting with a phase of diagnosis of the research objective and progressing to a phase of evolution (i.e., refinement and further development of the final artifact).

The second stage is a potentially cyclical combination of building the artifact, its intervention in the organization, and the evaluation (BIE). The result of this stage is usually an approved variant of an artifact realization that has undergone a continuous and partially repetitive process of designing, evaluating, and redesigning. Sein et al. (2011) present two perspectives from the edges of the ADR spectrum: an IT-dominant BIE process and an organization-dominant one. The former can be summarized as striving for an innovative technological design, creating early designs and alpha versions that are light-weight interventions in an organizational context with limited scope, continuously instantiating the artifact and testing it repeatedly, and finally applying it in a wider organizational setting. The second perspective takes a closer connection to the organizational context, as the inherent design knowledge is mainly oriented to the organizational intervention itself. This present research adopts an IT-dominant BIE process. In the early research stadium, theoretical contributions from the literature are translated into a practical manifestation of the holistic VA platform with placeholders that is artificially tested in a controlled environment. The results are subsequently used to extract design knowledge and, if necessary, influence the redesign for a repetition of the previous step. If the design seems sufficient, it is then adapted for a concrete use case scenario, leading to a specific instantiation. In case this specific instance does not comply with the organizational requirements, a new iteration of the adaptation process can be initiated.

Once the specific instance has been successfully applied in the realistic scenario, the design proposal is returned to the research team to abstract the approved design as a reference architecture. Sein et al. (2011) state three principles for this stage. First, the principle of reciprocal shaping emphasizes the consideration of the influence the artifact has on the organizational context and vice versa. The methodology employed here recognizes these interdependent relationships by integrating two potential cycles between activities related to theoretical research and practical applications of the artifact. On the one hand, the original artificial manifestation commissioned by practitioners is evaluated from the research perspective and proven design knowledge is extracted, whereupon the artificial instantiation is either redesigned and recommissioned or forwarded for adaptation to a concrete application scenario. On the other hand, once the concrete adaptation is taken into an end-user context as a specific instantiation, it is either returned for a refined adaptation if the design is not approved by the end-user, or it is forwarded to the research team to be abstracted into the final reference architecture for different use cases, meaning the integration of a wide range of VA capabilities. The second principle, mutually influential roles, refers to the assignment of individuals to different roles, such as theoretical researchers, practitioners, and end-users, which is related to the respective areas of experience. The third and last principle for this stage, authentic and concurrent evaluation, emphasizes the evaluation of the artifact directly during the building process rather than afterwards. However, since a new version must be fully built before its value to the organization can be assessed, short build-evaluate cycles are chosen in this study instead of an actual concurrent evaluation approach.

The third research stage, reflection and learning, is conducted as a parallel process to the first two stages. According to the ADR methodology, the encompassed tasks relate to mental work such as reflecting on the design, evaluating the adherence of the artifact to certain principles, and analyzing the intervention results compared to the goals. Therefore, the only stated principle for this stage, guided emergence, refers to the integration of acquired knowledge during the conduction of activities of the BIE process into further design, evolution, and refinements.

The last ADR stage is the formalization of learning, which targets the development of a generalized solution based on the findings that could be gained by addressing a specific problem. This stage overlaps with the final activity of the BIE process, which is the abstraction of a specific instantiation into a reference architecture suitable for different levels of detail. In the methodological guidelines, the outcomes of this stage are termed as design principles or, after refinements, theories. The only principle here is to aim for generalized outcomes. Sein et al. (2011) recognize that this poses a challenge for the research endeavor since ADR outcomes are usually organization context-specific. However, the abstraction of the solution (i.e.,

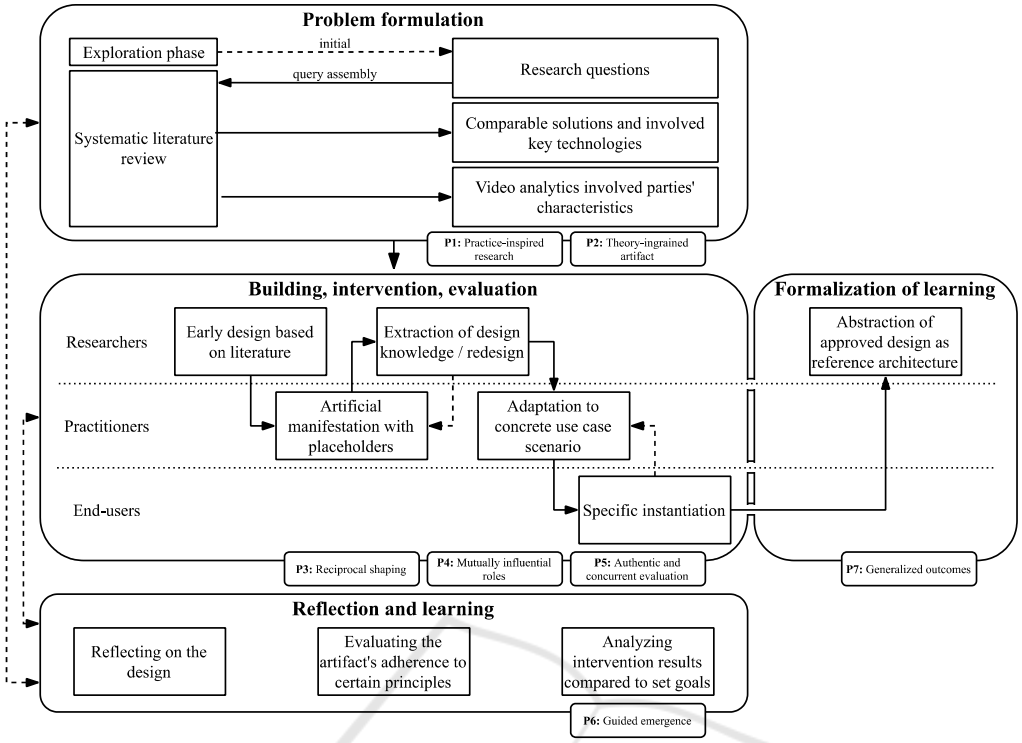

Figure 3: Adapted ADR methodology for VA platform realization.

translating a specific instantiation into a reference architecture) is possible if the problem is simultaneously translated into a broader class of problems. This procedure is considered in the corresponding step in the overall research process.

In this paper, the problem formulation stage, including an exploratory SLR is conducted. In the next section, potential challenges for implementing capabilities of VA are explained in more detail. Figure 3 illustrates the entire research process envisioned with respect to the design and construction of a holistic VA platform in retail environments. The activities are structured as in the original ADR methodology by Sein et al. (2011) and connected to the respective principles. The flow between the steps and additional feedback loops are visually provided.

4.3 Potential Challenges

It should be noted that there are potential challenges which can surface during implementation. The first one, which applies to VA in a general case, is related to data privacy in terms of two types of risks – legal and ethical, since it is seen to fall into grey area. More specifically, this is about unconsented video taking and analytics, which is the case for VA in retail. The customer who visits the store does not provide his or her consent to be filmed with further analysis of this information. Moreover, the customer not only does not provide such consent but is not even asked about it, and thereby does not have an “opt-out” option. A question that arises here is also the ownership of the recorded material, meaning whether the retailer becomes the legal owner of the video footage or whether the customer reserves the right to have access to the recorded data and delete it upon request. While recording the video in the retail area is something the customer tends to be warned about when entering the area through the respective signs on the doors, it is not mentioned that these data are then used for analytic purposes. This might be incompliant with the *General Data Protection Regulation* (GDPR). Thus, although technologies can be available and frameworks can be developed, the risk of data being illegal to be used remains. VA in retail on-site retail stocks can incur costly legal expenses and risk damage to their brand (Pletcher, 2023). However, while providing an information about cameras and further VA of the material being filmed (including face recognition, biometric surveillance etc.) could be at least a partial solution, it was found by (Garaus et al., 2021) that the retailer most probably will not give a preference to this option since the value of the data, when the customer is aware of being filmed, reduces (i.e., the behavior – movements, emotions etc. changes and are not intuitive and natural anymore). While retailers

heavily rely on cameras for surveillance, it is sometimes not appreciated when customers perform so-called *sousveillance*, meaning the recording of activities from their perspective (Mann, 2017). Due to multidimensionality of this issue, it is currently a hot topic, where the predominant body of literature just admits this issue and rather makes a call to action (Gregorczuk, 2022; Pletcher, 2023).

In addition, this technology acceptance by the customers tends to be seen as low. For example, Garaus et al. (2021) found that when the customers were informed that they had been served up advertisements based on an algorithm and their pictures, the customers felt manipulated and discouraged. Hence the need for further investigation of how to find the balance between the benefits VA brings to both the business and its customers, who beforehand VA are targeted with products and services aligned with their interests, and trust in both VA and the result it brings through the technology acceptance theories.

Another challenge comes from the technologies that VA is associated with, namely, machine learning (ML) models and computing power. The first – ML models-related – requires the development of appropriate models (including requirements such as being sufficiently accurate, unbiased, preferably transparent / white-box etc.) and their availability for more mass use in order to ensure that each business owner does not have to have its own ad-hoc ML model in place with an employee with the relevant knowledge and skills responsible for their development, deployment and maintenance. This is even more important considering that the VA in retail depends heavily on the ability to analyze people properly, however, today's ML models often fail when race and ethnicity serve as crucial parameters, which, however, in the case of the retail should be treated accurately. In addition, value-adding VA should employ a variety of different techniques and methods to get the most profit and benefit of VA, including but not limited to deep neural networks, facial recognition, gesture analytics, and motion analytics, emotion mining that preferably should also be combined with audio gathering and processing along with video etc. The latter, in terms of computing power, however, is more related to the amounts of data a VA are expected to deal with. In other words, the larger the amount of data being processed and the closer the idea is to real-time analytics, the more computing power may be needed. Depending on the approach, the amount of data being processed can increase from day to day as they accumulate cumulatively. This, in turn, leads to the need for constant monitoring of the available and required for the near future computing power, as well as the need to assess the feasibility of the selected approach periodically.

An apparent challenge also comes from security and privacy as follows. First, the platform will need advanced technologies to block unauthorized access and have a full access control and authentication to ensure only authorized users can have access. Second, network security will need to be enhanced to ensure VA can be broadcast and disseminated on secure network platforms and protect the network and users' safety and privacy. Third, additional technologies and functions will be developed to identify any impersonators and deep fake technologies to prevent identity theft and the use of deep fake to damage the service and reputation of the VA platform. AI-enabled security can be used to monitor the network and user activities, detect any abnormalities and provide feedback to the VA system, which can then enable security functions, such as authentication, access control, identify management, intrusion detection, quarantine and blockage of any unauthorized uses of VA system.

5 CONCLUSION AND FUTURE RESEARCH

This article examined the current trend of implementing AI technologies in the retail industry, with a focus on video analytics. In the future, this area is expected to help retailers increase store profitability and reduce shrinkage. An adaptation and specification of the action design research methodology were proposed that could be used to develop a holistic VA platform that integrates a variety of the capabilities presented here. The next methodological steps of the overarching research endeavor are planned to first construct a prototype version of such a platform in a controlled environment and then extend its use to real-world scenarios. We also discuss challenges in depth and provide our views and recommendations to reduce any impact. Finally, an instantiation with realistic parameters is to be built and evaluated.

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