Explainable Business Intelligence for Video Analytics in Retail

Christian Daase[a], Christian Haertel[b] and Klaus Turowski[c]
Institute of Technical and Business Information Systems, Otto-von-Guericke University, Magdeburg, Germany

Keywords: Artificial Intelligence, Business Intelligence, Video Analytics, Society 5.0, Data Science.

Abstract: This paper explores research questions and perspectives for the next stage of societal development, often referred to as Society 5.0, and the field of modern retail. Artificial intelligence (AI) is seen as a key component that provides retailers with the means to optimize their store layouts, advertising campaigns, and overall business strategy. The need to make AI-based decisions comprehensible and tangible to ensure acceptance by the respective target groups has been emphasized with the concept of explainable AI in various research works. Based on observations from the AI domain and the business world, the need to integrate explainability into commercial AI-driven operations is addressed and the concept of explainable business intelligence (XBI) is proposed. A set of potential research questions for video analytics in retail in the age of Society 5.0, as one of the most promising use cases in this regard, is derived from the literature and the proposal of XBI in terms of the outlined opportunities and challenges is explained, critically discussed, and visualized.

1 INTRODUCTION

Currently, the larger scheme of *artificial intelligence* (AI) is permeating society at large as it is increasing its influence on fundamental areas of science, economics, governments, and social life. While it is not uncommon for technological developments to be accompanied by shifts in social structures and norms, morality, or laws (Jiang et al. 2022), AI is expected to have an impact that goes beyond minor adjustments of communities to the shaping of a new social revolution referred to as *Society 5.0* (Carayannis and Morawska-Jancelewicz 2022; Muslikhin et al. 2021; Nair et al. 2021). The idea, also often mentioned as *smart society*, leads back to a publication from the Japanese government and describes a futuristic human-centered society in which the virtual and physical spaces are converging by means of AI, big data analytics, robotics, virtual and augmented reality, the internet of things (IoT), and other technologies that are connected to them (Carayannis and Morawska-Jancelewicz 2022; Muslikhin et al. 2021). However, although technological advances of this magnitude are generally considered positive, communities tend to express concerns, including fears of potential job losses, social isolation, criminal acts by entities unaware of moral and ethical principles, and seamless surveillance (Elliott et al. 2021).

In recent years, studies provided indicators that AI will most likely have the largest value impact across the technological landscape on the retailing sector (Guha et al. 2021). In turn, the retailing industry is expected to benefit the most from advancements in the field of AI (Bellis and Johar 2020). Since demographics change due to a new generation of digitally educated humans, thus facilitating the evolution towards new societal concepts, retailers need to adapt their business practices (Kahn et al. 2018). One especially promising subfield of AI with manifold use cases in retailing is video analytics, which can take place either in-store (Kahn et al. 2018; Kaur et al. 2020; Liciotti et al. 2017) or detached from physical locations, for example by analyzing prerecorded video content (Agrawal and Mittal 2022; Zhang et al. 2020). The analysis of critical business data in conjunction with the required technological systems and practices with the goal of understanding the business and ultimately making beneficial and timely decisions is also referred to as *business intelligence*

[a] https://orcid.org/0000-0003-4662-7055
[b] https://orcid.org/0009-0001-4904-5643
[c] https://orcid.org/0000-0002-4388-8914

Daase, C., Haertel, C. and Turowski, K.
Explainable Business Intelligence for Video Analytics in Retail.
DOI: 10.5220/0012694600003690

In *Proceedings of the 26th International Conference on Enterprise Information Systems (ICEIS 2024) - Volume 1*, pages 784-791
ISBN: 978-989-758-692-7; ISSN: 2184-4992

(BI) (Chen et al. 2012). As a connector between data and its targeted use, the term *data science* has emerged as an umbrella term for quantitative and qualitative methods developed to make predictions and solve data-related problems (Waller and Fawcett 2013). To draw a clear line in the context of this paper, AI is considered the overarching term for technologies that artificially replicate human intelligence. Thus, it is the umbrella scheme behind video analytics, which in turn is expected to be an integral part of the next evolutionary stage of business intelligence when applied in a commercial context such as retail. With the projected convergence of AI-related technologies and humans in Society 5.0, video analytics systems could become more widespread, while acceptance by stakeholders must be ensured.

When it comes to utilizing data from private persons, even if recorded in public areas, privacy concerns are a closely connected issue. In order to mitigate reluctance in the adoption of AI-driven technologies, the concept of *explainable AI* has emerged to make artificially determined decisions comprehensible for the average user (Bailao Goncalves et al. 2022; Jiang et al. 2022). In this paper, the definitions and characteristics of explainable AI as necessary part of Society 5.0 and the grander scheme of business intelligence are attempted to be merged under the term *explainable business intelligence* (XBI). By carefully approaching the future of business data analysis, reluctance is intended to be avoided from the outset. The focus of this preliminary investigation of XBI is to position video analytics in retail as a potential use case and to describe critical questions for future studies. In summary, this research aims to provide an answer for the following research question (RQ):

RQ: What are potential RQs that can be derived from the AI-based use case of video analytics in retail under consideration of societal shifts towards Society 5.0?

2 LITERATURE REVIEW

To create a knowledge base for the establishment of the potential RQs in Section 4 and the concept of XBI in Section 5, the conduction of a systematic literature review (SLR) is described in this section. The SLR was conducted using four peer-reviewed journals from the database ScienceDirect of the publisher Elsevier that focus on retail, commerce, marketing, and generally technological solutions for the business sector. The selected journals are *Electronic Commerce Research and Applications, International Journal of Research in Marketing, Journal of Retailing,* and *Journal of Retailing and Consumer Services*. As a secondary source of literature, the abstract and citation database Scopus was consulted, which claims to be the largest database of its kind (Kitchenham and Charters 2007). This addition is intended to ensure that potentially relevant literature from other reliable scientific sources is not omitted if it is not covered in any of the primary journals reviewed. Additionally, SpringerLink with its own selection of high-quality research articles (that might not be indexed in Scopus) is considered as another literature source.

To limit the number of articles, certain inclusion and exclusion criteria were defined. First, the time frame to be considered was set to the publication period between January 2017 and October 2023 to ensure actuality. Test searches led to the conclusion that a combination of terms related to *retail* and *video* yield the most appropriate results for the individual databases. The exact queries are stated in Table 1.

Table 1: Literature sources and specifications.

Source	Restrictions
All	- Period: Jan 2017 - Oct 2023
ScienceDirect	- marked as *research article*
Electronic Commerce Research and Applications	---
International Journal of Research in Marketing	- Abstract contains *retail**
Journal of Retailing	---
Journal of Retailing and Consumer Services	- Title contains *retail* or *retailing*
SpringerLink	- Title contains *retail*, *retailing*, or *retailer* - Text contains *video* - *Article* or *conference paper*
Scopus	- Title contains *retail** - Abstract contains *video* - *Article* or *conference paper*

Further selection criteria were set for the two review phases of reading the abstracts and reading the full texts in detail. In the first phase, duplicates were removed, including semantic duplicates from the same authors within a short period of time, as well as articles consisting only of an introduction or missing the abstract. Moreover, articles limited to a too specific geographical region were rejected as it was assumed that they potentially lack generalizability. Finally, articles without an application area that is related to video analytics were removed.

In the second phase, articles whose full texts were unavailable were removed from the list along with publications that did not provide an outlook on future data-related technology impacts or that did not provide a suitable research justification in general. Articles lacking a technical business perspective were rejected as well. Lastly, from the remaining articles, a dedicated selection of the most relevant material was used in terms of this present paper. Figure 1 shows the review process, including criteria and numbers of remaining articles after each stage.

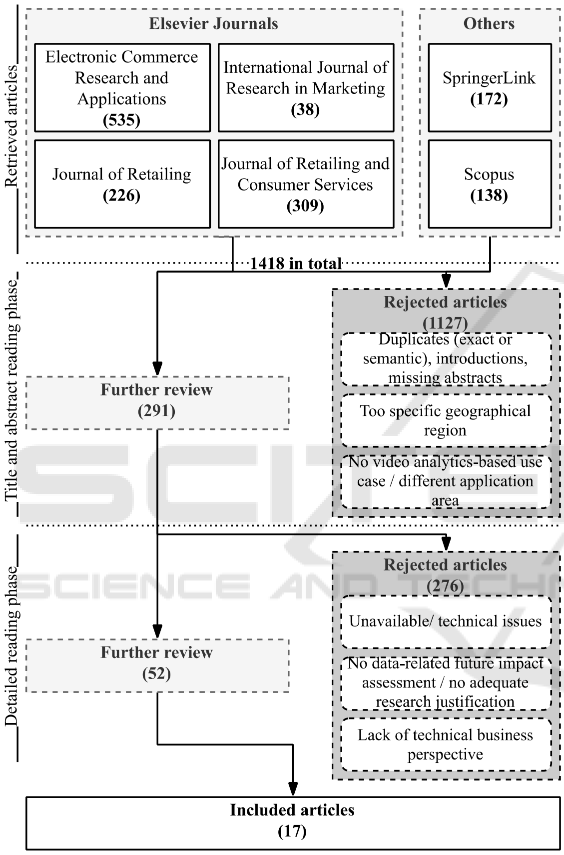

Figure 1: Literature review workflow visualization.

3 BACKGROUND - DATA SCIENCE IN BUSINESS

The societal shifts through the ongoing digitalization have increased the generated amount of data significantly (Yin and Kaynak 2015). As this trend is expected to continue in the future, enterprises with access to a high volume of data seek ways to make use of the data to achieve performance improvements (Chen et al. 2012; Wamba et al. 2017). Accordingly, it can be stated that data is becoming the "*most valuable asset for any organization*" (Nielsen 2017). In turn, the discipline data science (DS) has gained additional attention over the last years. DS is defined as *„methodology for the synthesis of useful knowledge directly from data through a process of discovery or of hypothesis formulation and hypothesis testing"* (Chang and Grady 2019). Since DS is mainly applied in the context of datasets that correspond to the big data paradigm, the term *big data science* emerged. Generally speaking, DS can be interpreted as all activities in an analytics pipeline to derive insights from data (Chang and Grady 2019) and it is regarded as a super-set of other related disciplines such as (big) data analytics, data mining, and statistics. Additionally, in the enterprise context, DS is referred to as *data science for business* or *business intelligence*, as stated in the introduction (Medeiros et al. 2020; Newman et al. 2016). However, there are other interpretations that view DS as a subset of BI (Larson and Chang 2016). Foley and Guillemette (2010) define BI as *"a combination of processes, policies, culture, and technologies for gathering, manipulating, storing, and analyzing data collected from internal and external sources, in order to communicate information, create knowledge, and inform decision making"*, which contradicts the observation of Larson and Chang (2016), as clear conceptual differences become visible.

The benefits of DS for businesses can be manifold. For example, Medeiros et al. (2020) mention increased efficiency and effectiveness in decision-making through better quality of data and information (*data quality*), actionable insights by analysis of resources and data visualization (*analytical intelligence*), improved organizational knowledge and detection of business opportunities (*dynamic capabilities*), as well as enhanced productivity, performance, and profitability (*competitive advantages*). In order to realize these advantages and provide managers with the relevant recommendation and insights (Chen et al. 2012; Waller and Fawcett 2013), the respective BI/DS projects require successful completion. However, these types of undertakings are prone to failure (VentureBeat 2019) due to multi-faceted challenges related to project management and technical aspects (Martinez et al. 2021; Saltz and Krasteva 2022). As DS contains big data and big data analytics (Newman et al. 2016), using the "*appropriate technology for the different activities such as data storage and processing as well as building analytical models*" (Haertel et al. 2023) and deploying the results is required (Saltz and Shamshurin 2016).

4 VIDEO ANALYTICS IN RETAIL

Based on observations from the literature analysis, RQs arising in the sector of video analytics in retail can be divided into three categories: purpose-focused, technical, and juridical. The reason for dividing the research into these three dimensions is that by finding appropriate answers to the overarching questions of "*What should be achieved?*", "*How can it be achieved?*" and "*What is allowed to be done without potential harm?*", businesses can implement successful DS-driven solutions. The following explanations serve to answer the RQ posed at the beginning and form the first contribution of this work, before the subsequent XBI concept.

4.1 Purpose-Focused Questions

Video analytics in retail has already been implemented in various areas, for example for understanding customer behavior in-store (Kaur et al. 2020; Liciotti et al. 2017), marketing reasons (Xiao et al. 2023; Zhang et al. 2020), or extracting sentiments from review videos (Agrawal and Mittal 2022). To enable a comprehensive view on the topic, the areas that it can affect need to be placed in context. In addition, suitable metrics need to be developed to measure the influence of analytical approaches. Since user acceptance is a fundamental prerequisite for the adoption of AI technologies (Jiang et al. 2022), another question that arises is which influence the awareness of being analyzed has on the customers, as it is conceivable that humans adjust their behavior in that case. Summarizing the purpose-focused questions, the interdisciplinarity of the transformation of retail business models through AI, big data, and associated technologies (Alexandrova and Kochieva 2021) can serve as a foundation for the question which research disciplines apart from economic research might benefit from advances in video analytics in retail as well, such as social science.

4.2 Technical Questions

The technical perspective on this topic covers how to store and process data independent of the specific purpose or applicable law. However, legal regulations and deployed technology can sometimes not clearly be separated. Especially privacy issues and the necessity to anonymize people and data force AI developers to consider layers of data abstraction, specifically for video material (Jabłonowska et al. 2018; Kopalle et al. 2022). Thus, one technical question is how to encode data for anonymized processing. Another challenge occurs specifically for in-store analysis, strongly connected to the intended purpose, in terms of camera positioning. For example, approaches to track the general movements of customers or shopping carts in a store (Ferracuti et al. 2019) require a different positioning than cameras for eye tracking to assess which item the customer is looking at and how long the visual inspection lasts (Huddleston et al. 2018). Also, the circumstances and timing of video analytics offer important RQs to be answered. Difficulties from analyzing in-store video data immediately (Kahn et al. 2018; Liciotti et al. 2017) or during live streaming e-commerce sessions (Chen et al. 2023) differ from analyzing material asynchronously, for example from customer review videos (Agrawal and Mittal 2022). Before being able to analyze video content, another question is related to ways to efficiently gather and store such data. Nowadays, developers are turning towards cloud computing as a possible centralized solution to storage issues (Liciotti et al. 2017) while sensors, mobile devices and the IoT in general are utilized for data collection, also to complement data captured with cameras (Kahn et al. 2018; Muslikhin et al. 2021). Due to its range of cost-effective, flexible and easily usable applications, cloud computing is considered a key component of future retail in general (Daase et al. 2023). Lastly on the list of hereby identified potential RQs, the user acceptance needs to be ensured. Hence, in special consideration of neural networks in AI, another question for future research is if and how optimization techniques for such networks can be adapted to make neural networks comprehensible throughout every iteration of optimization for the developer and the targeted user group.

4.3 Juridical Questions

The last category on the list for future RQs, juridical, covers laws and regulations for video analytics in general. The first part of the questions is two-fold, depending on the mode in which videos are analyzed. If data is gathered in an in-store scenario, one of the most important aspects is ensuring the anonymity of customers (Jabłonowska et al. 2018; Kopalle et al. 2022). If prerecorded video content is analyzed (Agrawal and Mittal 2022), another question is which regulations in terms of copyright are applicable. In addition to the technical question how and where to store data efficiently, the physical location of stored data must be assessed regarding local laws for the juridical perspective. Table 2 summarizes these potential RQs for video analytics in retail scenarios, especially focusing on AI with neural networks, thus proposing a preliminary answer to the initially posed RQ of this research-in-progress paper.

Table 2: Potential RQs for video analytics in retail.

Category	Potential research questions
Purpose-focused	· Which areas in retailing can be affected by video analytics? · Which metrics could be used to measure benefits in specific retailing areas? · How do customers adapt their behavior in case of in-store video analytics if they are aware of being analyzed? · How can other research disciplines apart from economic research benefit from video analytics in retail?
Technical	· How should video data be encoded for efficient anonymized processing? · How should cameras be places for specific purposes for in-store analytics? · What technical difficulties arise for in-store video analytics in contrast to asynchronous analysis and vice versa? · Which technologies can be used for gathering and storing video datasets? · How can optimization techniques for neural networks be adapted to ensure user acceptance in improvement iterations?
Juridical	· Which regulations have to be considered for in-store video analytics (privacy)? · Which regulations apply when analyzing publicly available content (copyright)? · Where can data and analytics results be stored to comply with local laws?

5 EXPLAINABLE BUSINESS INTELLIGENCE

The stated questions are focused on one potential research field of retail in the era of Society 5.0. The accumulated definition, opportunities, and challenges of the interconnection between AI, BI, and the necessity to underpin both with explainability in the near future support to the proposal of the concept of *explainable business intelligence* (XBI). On the one hand, BI encompasses techniques and processes to gather and analyze business data from internal and external sources to make beneficial and informed decisions in a business context (Chen et al. 2012; Foley and Guillemette 2010). On the other hand, explainable AI is the aspiration to construct AI applications that allow to understand how the underlying AI works, which factors it takes into account, and how decisions are derived, with the ultimate goal of increasing user acceptance (Bailao Goncalves et al. 2022; Jiang et al. 2022). However, it is important to emphasize that technical understanding is not the only way to realize XAI, as AI solutions and developments may exceed the average human knowledge in this field. Instead, the solutions and decisions made by AI could be validated for correctness and suitability. In this way, the need to understand the functioning of components of AI such as neural networks could be alleviated.

The definition of XBI developed here is that XBI represents the philosophy that all business data retrieved during the production, delivery and retail process must either be analyzed by means that can be understood by human intelligence, or at least the results must be verifiable using tools by humans with limited technical knowledge. Furthermore, the analysis results must be presented in such a way that the average target group and beneficiaries can make informed decisions about whether to trust the results. As stated, an essential component of the proposed concept of XBI is the possibility of checking the results for their trustworthiness.

Developers of business applications in Society 5.0 can adapt their techniques to comply with the argued concept of XBI. For example, AI-based software could be developed with greater involvement of humans whose expertise is to be emulated, as they can be seen as design templates for these systems (Daase and Turowski 2023). A second approach might be to test AI applications more intensively and to make the test procedures public, including inputs and (expected) outputs. Thus, for the more technically experienced audience, the development process and focused intentions of the organization providing the system can become clearer. A third constituent of XBI can be to involve the target audience in the result evaluation. The AI system can be tested with artificial data that is based on suggestions by the user group, making sure that the system's capabilities match the expectations. Finally, as a fourth component, results and AI-driven decisions can be verified by simulations and mathematical analyses, as a supplement or even as a substitute if the technical traceability of the inner workings of AI solutions cannot be realized.

Figure 2 illustrates an abstracted data flow towards XBI. First, data is collected as usual, for example from various sources in different formats, with varying velocities, and in varying volumes, thus complying with the concept of big data. In connection with the analysis of this data in a business context by any means yields business intelligence. If the data is analyzed by an explainable *artificial* intelligence system, incorporating the aforementioned components, the concept of explainable *business* intelligence can be realized.

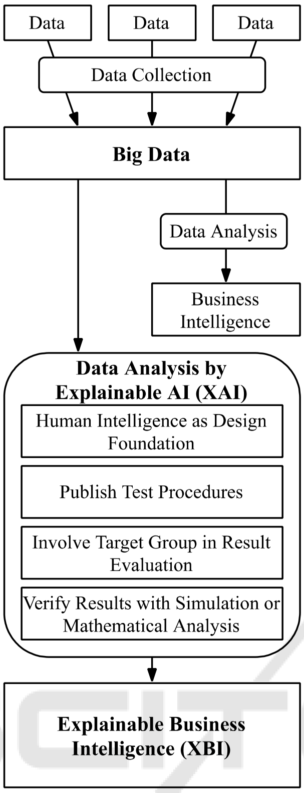

Figure 2: Abstracted data flow towards XBI.

6 DISCUSSION

The evolution from traditional BI to XBI can be considered a natural process as well as a necessity in the modern digitalized business world. While in the past, mathematical models, manual data collection, dedicated analytics units and extensive discussions with decision makers were common for gaining business knowledge, AI solutions are increasingly taking over (parts of) the mentioned tasks (Jiang et al. 2022). Thus, more and more vital actions for organizations are influenced by systems to which humans have limited access to and which, in comparison to human intelligence and decision making, can partly not be explained.

The contribution of this paper is discussed on the basis of a SWOT analysis (*strengths, weaknesses, opportunities, threats*). First, the outcome of this study, meaning the concept of XBI and the questions that necessarily need to be answered when applying the concept to retail video analytics, is considered from the perspective of its potential positive impact when deployed and considered internally (*strengths*). It can be argued that using the XBI concept to analyze business data with AI technologies in a way that enables human decision makers to understand either the entire analysis process or at least the verification of the results could more easily convince stakeholders to invest in and trust AI to a greater extent. This in turn would lead to more effective and widespread adoption and thus an increase in retail revenue, as retail is the industry that is expected to offer some of the greatest potential for AI and is one of the biggest beneficiaries of AI, as mentioned in the introduction (Bellis and Johar 2020; Guha et al. 2021). However, as the concept is generic, this strength can also apply to various other business areas. As for the potential RQs for video analytics listed in Table 2, most of the questions on evaluation metrics, behavioral science, configuration, and legally compliant implementation could be answered much more easily when posed in a setting suitable for XBI.

Weaknesses of the XBI concept become conceivable when considering the current state of AI and the enthusiasm for it. With a wealth of data now readily available as a basis for machine learning models and computing power reaching extraordinary levels (Eling et al. 2022; Jiang et al. 2022), many companies are trying to quickly exploit the potential in this highly dynamic field. If they now switch from mature AI systems to a different approach with a far more human-centric focus, companies could be forced to rethink key parts of their digitalization strategy. In doing so, they risk increased costs and falling behind competitors if the applied XBI concept does not lead to increased business effectiveness, customer loyalty, or other monetarily rewarding compensations.

The *opportunities* of the XBI concept depend on the occurrence of external events and unpredictable factors such as human behavior. Regarding the specific use case of video analytics in retail, some believe that people are becoming unaware of the constant surveillance by cameras and therefore implicitly accept it (Elliott et al. 2021), which would prevent unusual customer behavior due to perceived surveillance. However, it is assumed that trust in AI itself is still insufficient (Jiang et al. 2022). This would mean that the problem is not distrust in the acquisition of video material, as it could just be a store detective reviewing the footage, but the exploitation of inherent knowledge by systems that cannot be looked into. XBI has the potential to bridge this gap by convincing customers to engage in AI-driven business by making them understand how the system works, how the results are verified, and what consequences they lead to.

Finally, *threats* are also caused by external factors that impose undesirable circumstances on an organization. As indicated, such a threat could be a reaction from the target group (i.e., stakeholders or customers) that has a negative impact on the potential benefits of XBI. One fear of unexplained AI and one fear of XAI can be considered as examples respectively. On the one hand, the fear that an AI system can make decisions that are in some way harmful without adequate monitoring is frequently expressed. On the other hand, individuals from the human target group (e.g., customers recorded on video) may fear that the involvement of humans in the AI system will compromise their privacy more than if a mindless machine analyzes the recorded data in a black box. If the second fear outweighs the first, people may become more reluctant towards XAI approaches, not because they do not trust the human-centered development process, but because they do not trust the humans themselves who are involved in it. As a result, the implementation of XBI could be controversial.

This SWOT analysis underlines that the concept of XBI still offers plenty of room for discussion. Particularly with regard to video analytics in retail, XBI could be a sensible approach, even if it is still at a preliminary conceptual stage.

7 CONCLUSION

In this research-in-progress article, a first literature analysis was conducted to position the topic of video analytics in retail as one expectable key component of AI utilization in commercial business. A selection of some of the most pressing issues for implementation was elaborated from the literature to identify potentials and challenges in this regard. With the conceptualization of explainable business intelligence as a link between explainable artificial intelligence and traditional business intelligence, an outlook on a promising new business digitalization strategy with a human-centric focus was given and by means of a SWOT analysis critically discussed.

In further research, the topics of Society 5.0 and its connection to AI technologies are to be explored in greater depth to find answers to the questions developed in Table 2 in the retail sector. In addition, the concept of XBI is to be shaped more precisely, as reducing the reluctance in the adoption of AI technologies is expected to be vital for future businesses. The overall goal in finalizing this research endeavor is to position XBI as a key component of the future economy.

REFERENCES

Agrawal, S. R., & Mittal, D. (2022). Optimizing customer engagement content strategy in retail and E-tail: Available on online product review videos. In *Journal of Retailing and Consumer Services*, *67*, 102966.

Alexandrova, E., & Kochieva, A. (2021). Modern Aspects of Digital Technologies Development in Retail Networks. In *Lecture Notes in Networks and Systems. Comprehensible Science*. Springer International Publishing.

Bailao Goncalves, M., Anastasiadou, M., & Santos, V. (2022). AI and public contests: a model to improve the evaluation and selection of public contest candidates in the Police Force. In *Transforming Government: People, Process and Policy*, *16*(4), 627–648.

Bellis, E. de, & Johar, G. V. (2020). Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption. In *Journal of Retailing*, *96*(1), 74–87.

Carayannis, E. G., & Morawska-Jancelewicz, J. (2022). The Futures of Europe: Society 5.0 and Industry 5.0 as Driving Forces of Future Universities. In *Journal of the Knowledge Economy*, *13*(4), 3445–3471.

Chang, W. L., & Grady, N. (2019). NIST Big Data Interoperability Framework: Volume 1, Definitions.

Chen, Chiang, & Storey (2012). Business Intelligence and Analytics: From Big Data to Big Impact. In *MIS Quarterly*, *36*(4), 1165.

Chen, Q., Yan, X., Zhao, Y., & Bian, Y. (2023). Live streaming channel strategy of an online retailer in a supply chain. In *Electronic Commerce Research and Applications*, *62*, 101321.

Daase, C., & Turowski, K. (2023). Conducting Design Science Research in Society 5.0 – Proposal of an Explainable Artificial Intelligence Research Methodology. In *Lecture Notes in Computer Science. Design Science Research for a New Society: Society 5.0*. Springer Nature Switzerland.

Daase, C., Volk, M., Staegemann, D., & Turowski, K. (2023). The Future of Commerce: Linking Modern Retailing Characteristics with Cloud Computing Capabilities. In *Proceedings of the 25th International Conference on Enterprise Information Systems*. SCITEPRESS - Science and Technology Publications.

Eling, M., Nuessle, D., & Staubli, J. (2022). The impact of artificial intelligence along the insurance value chain and on the insurability of risks. In *The Geneva Papers on Risk and Insurance - Issues and Practice*, *47*(2), 205–241.

Elliott, K., Price, R., Shaw, P., Spiliotopoulos, T., Ng, M., Coopamootoo, K., & van Moorsel, A. (2021). Towards an Equitable Digital Society: Artificial Intelligence (AI) and Corporate Digital Responsibility (CDR). In *Society*, *58*(3), 179–188.

Ferracuti, N., Norscini, C., Frontoni, E [E.], Gabellini, P., Paolanti, M., & Placidi, V. (2019). A business application of RTLS technology in Intelligent Retail Environment: Defining the shopper's preferred path and its segmentation. In *Journal of Retailing and Consumer Services*, *47*, 184–194.

Foley, É., & Guillemette, M. G. (2010). What is Business Intelligence? In *International Journal of Business Intelligence Research*, *1*(4), 1–28.

Guha, A., Grewal, D., Kopalle, P. K., Haenlein, M., Schneider, M. J., Jung, H., Moustafa, R., Hegde, D. R., & Hawkins, G. (2021). How artificial intelligence will affect the future of retailing. In *Journal of Retailing*, *97*(1), 28–41.

Haertel, C., Pohl, M., Nahhas, A., Staegemann, D., & Turowski, K. (2023). A Survey of Technology Selection Approaches for Data Science Projects. In *AMCIS 2023*.

Huddleston, P. T., Behe, B. K., Driesener, C., & Minahan, S. (2018). Inside-outside: Using eye-tracking to investigate search-choice processes in the retail environment. In *Journal of Retailing and Consumer Services*, *43*, 85–93.

Jabłonowska, A., Kuziemski, M., Nowak, A. M., Micklitz, H.-W., Pałka, P., & Sartor, G. (2018). Consumer Law and Artificial Intelligence: Challenges to the EU Consumer Law and Policy Stemming from the Business' Use of Artificial Intelligence - Final report of the ARTSY project. In *SSRN Electronic Journal*.

Jiang, Y., Li, X [Xiang], Luo, H., Yin, S., & Kaynak, O. (2022). Quo vadis artificial intelligence? In *Discover Artificial Intelligence*, *2*(1), Article 4.

Kahn, B. E., Inman, J. J., & Verhoef, P. C. (2018). Introduction to Special Issue: Consumer Response to the Evolving Retailing Landscape. In *Journal of the Association for Consumer Research*, *3*(3), 255–259.

Kaur, J., Arora, V., & Bali, S. (2020). Influence of technological advances and change in marketing strategies using analytics in retail industry. In *International Journal of System Assurance Engineering and Management*, *11*(5), 953–961.

Kitchenham, B., & Charters, S. (2007). *Guidelines for performing Systematic Literature Reviews in Software Engineering: Technical report, Version 2.3 EBSE Technical Report*.

Kopalle, P. K., Gangwar, M., Kaplan, A., Ramachandran, D., Reinartz, W., & Rindfleisch, A. (2022). Examining artificial intelligence (AI) technologies in marketing via a global lens: Current trends and future research opportunities. In *International Journal of Research in Marketing*, *39*(2), 522–540.

Larson, D., & Chang, V. (2016). A Review and Future Direction of Agile, Business Intelligence, Analytics and Data Science. In *International Journal of Information Management 36(5)*.

Liciotti, D., Frontoni, E [Emanuele], Mancini, A., & Zingaretti, P. (2017). Pervasive System for Consumer Behaviour Analysis in Retail Environments. In *Lecture Notes in Computer Science. Video Analytics. Face and Facial Expression Recognition and Audience Measurement*. Springer International Publishing.

Martinez, I., Viles, E., & Olaizola, I. G. (2021). Data Science Methodologies: Current Challenges and Future Approaches. In *Big Data Research 24*.

Medeiros, M. M. de, Hoppen, N., & Maçada, A. C. G. (2020). Data science for business: benefits, challenges and opportunities. In *The Bottom Line*, *33*(2), 149–163.

Muslikhin, M., Horng, J.-R., Yang, S.-Y., Wang, M.-S., & Awaluddin, B.-A. (2021). An Artificial Intelligence of Things-Based Picking Algorithm for Online Shop in the Society 5.0's Context. In *Sensors (Basel, Switzerland)*, *21*(8).

Nair, M. M., Tyagi, A. K., & Sreenath, N. (2021). The Future with Industry 4.0 at the Core of Society 5.0: Open Issues, Future Opportunities and Challenges. In *2021 International Conference on Computer Communication and Informatics (ICCCI)*. IEEE.

Newman, R., Chang, V., Walters, R. J., & Wills, G. B. (2016). Model and experimental development for Business Data Science. In *International Journal of Information Management*, *36*(4), 607–617.

Nielsen, O. B. (2017). A Comprehensive Review of Data Governance Literature. In *Selected Papers of the IRIS*(Issue Nr 8).

Saltz, J., & Krasteva, I. (2022). Current approaches for executing big data science projects - a systematic literature review. In *PeerJ Computer Science*, *8*(e862).

Saltz, J., & Shamshurin, I. (2016). Big data team process methodologies: A literature review and the identification of key factors for a project's success. In *2016 IEEE International Conference on Big Data (Big Data)*. IEEE.

VentureBeat. (2019). *Why do 87% of data science projects never make it into production?* https://venturebeat.com/2019/07/19/why-do-87-of-data-science-projects-never-make-it-into-production/

Waller, M. A., & Fawcett, S. E. (2013). Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management. In *Journal of Business Logistics*, *34*(2), 77–84.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. In *Journal of Business Research*, *70*, 356–365.

Xiao, L., Li, X [Xiaofeng], & Zhang, Y. (2023). Exploring the factors influencing consumer engagement behavior regarding short-form video advertising: A big data perspective. In *Journal of Retailing and Consumer Services*, *70*, 103170.

Yin, S., & Kaynak, O. (2015). Big data for modern industry: challenges and trends [point of view]. In *Proceedings of the IEEE*, *103*(2), 143–146.

Zhang, H., Li, Y., Ai, Q., Luo, Y., Wen, Y., Jin, Y., & Ta, N. B. D. (2020). Hysia: Serving DNN-Based Video-to-Retail Applications in Cloud. In *Proceedings of the 28th ACM International Conference on Multimedia*. ACM.