Organizational Readiness to Adopt Artificial Intelligence in the Exhibition Sector in Western Europe

Abstract

This exploratory study explores perceptions of Artificial Intelligence (AI) and organizational readiness to adopt AI, in the exhibition sector of the events industry. A theoretical framework synthesizing the Technology - Organization - Environment framework and the Technology Readiness Index was developed to guide this qualitative study. Seventeen senior managerial representatives from exhibition organizations across nine Western European countries were interviewed, and a reflexive thematic approach was adopted to analyse the data. The findings suggest that the European exhibition industry is a slow adopter of AI, which may impact its future competitiveness, despite the stimulus provided to AI adoption during the COVID-19 pandemic. The degree of confidence in organizational technological practices, financial resources, the size of the organization, and issues of data management and protection, as well as the impacts of the COVID-19 pandemic, motivate or inhibit readiness for AI adoption in the event industry. A new Exhibition Sector Readiness for AI Adoption Model is presented in this research that managers and researchers can use to analyze inhibitors and motivations for AI adoption, which is contextualized for the current challenges facing the exhibitions sector.

Keywords: Artificial Intelligence, exhibition industry, Technology Organization Environment Framework, Technology Readiness Index, organization readiness

1. Introduction

Artificial Intelligence (AI), as an emerging technology, is widely discussed by scholars and professionals across industries, including Automotive, Transportation & Logistics, Pharma, Agriculture and Manufacturing (Colins et al., 2021; Davenport et al., 2019; PWC, 2020; Towers-Clark, 2019). The event industry has not been excluded from this trend, and trade publications refer to the revolutionizing of event management through AI (CVENT, 2020; Gartner, 2019). These reports identify potential AI applications in events such as chatbots, facial recognition, matchmaking, and service robots, and suggest positive impacts such as better return on investment (ROI), higher efficiency and cost-cutting effects. However, there have been difficulties in implementing AI in the event industry, and the adoption of AI has been relatively slow in event businesses (Davidson, 2019; Ogle & Lamb, 2019).

Business events have a prominent position in the event industry (ICCA, 2018) and are one of its fastest-growing sectors (Anas et al., 2020). The industry's global value was £602 billion in 2017, and it has the potential to grow by 44% by 2025, with a concentration in Europe and the Asia-Pacific (Anas et al., 2020). Exhibitions are a major component of business events. They can be characterized as 'events that bring together, in a single location, a group of suppliers, distributors and related services that set up physical exhibits of their products and services from a given industry or discipline' (Black, 1986). Accordingly, they constitute a key element of the sales, marketing and communication strategies of the companies and organizations that exhibit their goods and services at such events. The European exhibition market is the largest in the world (EEIA, 2020). Europe has 496 exhibition venues, accounting for 48% of the world's exhibition space capacity. Organizers put on 13,700 exhibitions, and around 260 million visitors attended these in 2019 (EEIA, 2020). Therefore, understanding event organizers' readiness for AI adoption will have valuable implications for the sector and its impacts.

Business events contribute to economic development and regional prosperity (Huang, 2016). The literature highlights many challenges facing these events in attracting new exhibitors and customers, providing better networking opportunities and better-quality service (Huang, 2016; Lee et al., 2019). AI adoption could provide a higher ROI for business event organizers, reduce overall costs, help with decision-making and replace repetitive work (Davenport et al., 2019; Dhar, 2016; Grace et al., 2018; Makridakis, 2017).

The event industry is intimately connected with technology and its development, and much research engages with this phenomenon (Davidson, 2019; Getz & Page, 2016; Laing, 2018; Martin & Cazarre, 2016). However, very little has been written about AI and events and even less in the exhibition context. The primary references to AI in events studies refer to works written by Ogle and Lamb (2019) and Davidson (2019), which provide an overview of the potential real-life applications (e.g., security, staging, marketing and operations) together with the benefits (e.g., revenue management, exhibition setting, networking purposes) that AI could provide in events. Although these serve as an introduction to a complex research area, their arguments are generic and lack empirical support. Relevant applications of AI are more often discussed in other service sectors, which have been earlier adopters of these technologies, such as tourism and hospitality (Coombs et al., 2020; Drexler et al., 2019; Ivanov. et al., 2017; Tussyadiah, 2020; Webster & Ivanov, 2020a, 2020b).

This study aims to explore organizations' readiness to adopt AI in the exhibition sector in Western Europe. From the perspective of exhibition professionals, the study seeks to understand the current level of AI adoption and explore influential factors on organizational readiness to adopt AI. Due to its exploratory nature, this research adopted a qualitative research design. Events studies are often criticized for their weak theoretical background (Robertson et al., 2018), and AI research in information systems has also often lacked theoretical perspectives (Collins et al., 2021). Therefore, this research embraced the Technology - Organization - Environment framework (TOE) and the Technology Readiness Index (TRI), which have been previously synthesized and applied in quantitative technology adoption readiness studies but not yet applied qualitatively, or to events (Aboelmaged, 2014; Dewi et al., 2018; Oliveira & Martins, 2011).

This exploratory study aims to contribute to the literature in three ways. First, there is a lack of sector-specific research on organizations' readiness to adopt AI in the exhibition sector. In fact, decision-makers and managers' opinions towards AI adoption in the service sector more broadly have been largely neglected. The exploratory nature of this study was appropriate, as Swedberg (2020) explains, because this research involves theorizing in an empirical setting, at an early stage of AI research in the social sciences in general and in business and events management research in particular. This study aims to address this gap in the events literature and to contribute transferable knowledge for other parts of the service sector that share similar characteristics. Second, research on organizational adoption of AI is still lacking (Alsheibani et al., 2018; Cheng et al., 2019), and only a few recent studies investigate firms' AI adoption (e.g., Alsheibani et al., 2019; Pumplun et al., 2019; Jöhnk et al., 2021). Focusing on the readiness of organizations, this study aims to contribute to the scant literature on AI adoptions at the organizational level by exploring how decision-makers evaluate various factors in this, and their willingness to adopt AI. Third, by empirically exploring the synthesis of TOE and TRI qualitatively, the study aims to contribute to knowledge by emphasizing the situated and contextual complexity of understanding organizational readiness for new technology adoption.

2. Literature review

2.1 AI in the Service Sector

The term "Artificial Intelligence" was coined by Marvin Minsky and John McCarthy in 1956 (Haenlein & Kaplan, 2019), although investigations into the nature of intelligence and its applications has a much longer history that stretches into antiquity (Collins et al., 2021). Tussyadiah (2020 p.2) defined AI as "thinks humanly acts humanly, thinks rationally, or acts rationally". AI is a computing process that tries to emulate human learning, based on data, arriving at decisions similar to human cognition (Boden, 2018), which is especially useful in business decision making contexts where problems can be highly complex and have unclear goals (Johnson et al., 2021). AI is additionally able to learn by repeating specific tasks, adapting and improving over time (Coombs et al., 2020).

One key characteristic of service AI is *connectivity*. The Internet of Things (IoT) is the ecosystem that demonstrates AI's connectivity by linking machines, consumers, organizations, and objects within autonomous networks of data and information (Bello & Zeadally, 2017). Although IoT is highly dependent on up-to-date technology, improvements to Internet connectivity and data storage could bring new possibilities for AI solutions for event stakeholders. In studies about future trends and digitalization in the event industry, authors discuss the increasing role of smart venues and smart devices within the IoT ecosystem and their benefits for event businesses (Laing, 2018; Ryan et al., 2020). The following section examines this context for the adoption of AI by situating the present study within the broader field of research into AI in the service sector.

As a major source of innovation, AI has been increasingly adopted in the service sector. Applications of AI in the service industries range from standardized “mechanical AI” (e.g., cleaning robots) and rule-based “analytical AI” (e.g., intelligent system diagnosing problems) to complex “intuitive AI” (e.g., personal travel concierge) and highly communicative “empathetic AI” (e.g., Robot Sophia) (Huang & Rust, 2018). More than just “standardized” automation, today’s service AI provides a large variety of services with high levels of engagement, interaction, and personalization (Mende et al., 2019).

Studies argue that AI-powered kiosks or service robots will replace, or cooperate with, human employees (Ivanov. et al., 2017; Webster & Ivanov, 2020b). Gadgets equipped with speech recognition can accomplish specific tasks, e.g. speed up the check-in process and provide customer service. In retail, Eisingerich et al. (2021) found customers tend to follow virtual salespersons’ advice rather than peers’ recommendations. In healthcare, rule-based expert systems have been widely adopted to support clinical decisions (Vial et al., 2018). In their study on the adoption of robots and service automation in the tourism and hospitality sector, Ivanov et al. (2017) suggested service robots could be used for catering purposes, in the form of robotic chefs and bartenders.

Although AI has the potential to improve living and working conditions, it also raises questions about privacy, security, legality, and fairness (Boyd & Holton, 2018; Tucker, 2019). Threats to human jobs have been widely discussed in the service sector (Chessell, 2018; Koo et al., 2020). Huang and Rust (2018) developed a theory of AI job replacement to illustrate the progression of AI task replacement from lower to higher intelligence. They argued that with the adoption of AI, the service sector will demand less analytical skills from employees and will emphasize intuitive and empathetic skills. Dhar (2016) argued that AI will create more jobs than it will destroy. However, Huang and Rust (2018) predicted that by leveraging its full potential in the future through human-machine integration (e.g., feeling AI), AI will become a fundamental threat to service employment. The following section provides an overview of the service sector context for this research, the exhibitions industry.

2.2 The exhibitions industry

The exhibitions industry has traditionally been classified as one of the principal components of the business events sector or “MICE”, in which compound term, the ‘E’ derives from exhibitions. Within this industry, a standardized and universally accepted terminology has yet to be developed, and consequently, terms such as “trade fairs”, “trade shows”, and “expositions” are variously substituted for ‘exhibitions’ (Morrow, 2002; Davidson, 2019). However, there is widespread agreement that most exhibitions may be defined as temporary market events, held at regular intervals, where a large number of buyers (attendees or visitors) and sellers (exhibitors) interact for the purpose of purchasing displayed goods and services, either at the time of presentation or at a future date. (Kirchgeorg et al, 2015; Black, 1986).

The uses of exhibitions are many, and most of them are summarized in the list proposed by Jotikasthira (2015): they help promote new products to pre-screened audiences; they allow firms to discover new prospective customers as well as potential trade partners and suppliers; they yield several benefits to the host destinations in forms of local spending, distribution of wealth, attraction of foreign income, stimulation of local businesses, and destination image; they help enhance the image of exhibitors in regards to their respective technological breakthroughs, good causes or other aspects of their corporate image. To these may be added two further benefits suggested by Hanley (2012): they showcase innovations and simultaneously serve as a platform for networking and idea-sharing.

The history of exhibitions can be traced back to the commercial fairs of the ancient world when, according to Morrow (2002:31), ‘A fair was a temporary market where buyers and sellers gathered to transact business. (It) offered the opportunity to barter and sell goods and services within a particular region and became to a central distribution point for entire geographical areas’. However, by the 21st century, a vast, global professionalized industry had been developed to organize and host exhibitions for practically any type of goods and services, fueled by demand from the companies and organizations producing these goods and services, for whom exhibitions represent an effective sales and communications tool.

Reflecting the structure of the broader events industry in general and business events in particular, the exhibition industry is fragmented and made up of many different sectors, organizations and suppliers. In addition to venue suppliers, there is also a whole plethora of specialist suppliers who provide the industry with products and services such as displays, catering, staffing, technical equipment, telecommunications and IT companies, caterers, exhibition contractors, production companies and event insurance specialists (Quick, 2020).

Together, these sectors constitute the supply side of the exhibitions industry, which is the focus of this paper.

The evolution of the exhibition industry is closely connected with technological development. However, the experience or level of readiness and intention that exhibition suppliers have to implement emerging technologies such as AI remains under-researched. In the business events literature, there is very little evidence regarding technology adoption in general (Sangkaew et al., 2019), or AI adoption processes or AI applications specifically, reflecting the relatively slow pace of technology adoption in this industry when compared to other sectors (Soifer et al., 2019).

Technology adoption has been widely discussed at both individual and organizational levels (Cai et al., 2019). Organizations adopting new technologies expect to improve their performance (Hameed et al., 2012). Lokuge et al. (2019) suggested that differing from other "easy-to-deploy" digital technologies, the high complexity of AI sets a knowledge barrier for organizational adoption. Technical and non-technical factors such as the technology capabilities (Zebec & Štemberger, 2020) and leadership (Frick et al., 2021) of a firm influence the adoption and implementation of AI, as well as the integration of AI with other organizational resources (Zhang et al., 2021). Given the breadth of research into technology adoption, it is necessary to apply a clear theoretical perspective in the analysis of this process, and the following section demonstrates how this was approached in this research.

2.3 Theoretical Development

To understand exhibition organizations' readiness to adopt AI, we developed a theoretical framework synthesizing the Technology-Organization-Environment (TOE) framework and the Technology Readiness Index (TRI). Instead of using popular technology acceptance theories such as the Technology Acceptance Model (TAM) or Unified Theory of Acceptance and Use of Technology (UTAUT), the rationale for applying TOE is as follows. First, differing from other theories and models, TOE specifically focuses on technology acceptance at the firm level, which is appropriate for the organizational focus of this study. Second, in addition to technology acceptance, TOE also considers the dimensions of organization and environment, which take into consideration the characteristics and resources of the firm, and the external business environment in terms of AI adoptions. Third, the focus of the study is the readiness of a firm's AI adoption; thus, investigating the three dimensions of TOE offers comprehensive understandings of how various factors influence the willingness for AI adoption.

TRI is used to explore exhibition firms' readiness for AI adoption. The application of TRI helps to narrow the focus to decision makers' conscious willingness and their state of mind when making rational choices (Jiang & Chen, 2010) rather than general perceptions or use, as in other theories. Particularly, the four dimensions of TRI offer a framework to analyze motivators and inhibitors that affect a decision maker's state of mind when adopting AI. TOE and TRI offer a framework to investigate how the affordance of AI artifacts, organizational assets, and external environments act as influential factors that motivate and/or prohibit the firm's decision-making in relation to AI adoption.

Technology-Organization-Environment (TOE) Framework

This study applies the Technology-Organization-Environment (TOE) framework to understand AI adoption in the exhibition sector. The TOE framework was developed by Tornatzky and Fleischer (1990) to explain factors that contribute to decision-making in technology adoption at the organizational level. They argue that in addition to technology, other relevant factors are involved in the adoption of innovations (Tornatzky & Fleischer, 1990). The framework brings together technological, organizational and environmental dimensions to investigate firms' adoption and implementation of technological innovations. TOE has been widely theoretically and empirically examined, and subsequently employed, in sectors such as IT, manufacturing, healthcare, hospitality and financial services (Aboelmaged, 2014; Oliveira & Martins, 2011; Wang et al., 2010; Wang et al., 2016; Yang et al., 2015) to understand organizations' adoption of new technologies. However, it has not yet been applied to events.

The *technological* dimension explores all the available internal and external technological equipment, process and practices related to the firm. Technology infrastructure is a factor that drives technology adoption by eliminating high adoption costs, as the environment has already been equipped with hardware, software and networking technologies (Bhattacherjee & Hikmet, 2008).

The *organizational* dimension characterizes the organization and its resources with a focus on business size, structure, communication mechanisms and decision-making (Aboelmaged, 2014). Top management support involves leaders who have the power to make pivotal decisions and create a positive environment for innovations (Chaubey & Sahoo, 2021; Premkumar & Roberts, 1999). A company's size is directly connected with the adoption of innovation (Rogers, 1995). Larger companies have a more obvious ability to adopt technology as they can absorb the risks and costs (Duan et al., 2010; Sharma & Rai, 2003).

The *environmental* dimension refers to the external environment of the business, including competitors, suppliers, customers and regulatory subjects (Oliveira & Martins, 2011). Competitive pressure is a widely known factor in technology adoption. Significant pressure to adopt new technologies can often come from business partners, and public sector policy initiatives. In several cases, governments have supported the adoption of the new technology by directed incentives. Conversely, innovations can be stopped or slowed down by government's restrictions or policies (OECD, 2018).

The TOE framework has been combined with different theoretical models to explain organizational technology adoptions in various contexts (Arpaci et al., 2012). For example, Li (2008) combined TOE, Diffusion of innovations (DOI) and Institutional theory to understand the adoption of E-procurement, stating that intangible benefits encourage the organization to adopt new technology. Zhu et al. (2006) merged TOE and DOI to investigate E-business usage. Their study revealed factors such as relative advantage, compatibility cost, technological competence, competitive pressure, and partner readiness are crucial for implementing new technology.

In the limited studies on firms' AI adoption, TOE is the predominant applied framework. It has been utilized in understanding AI adoption in the hotel industry (Nam et al., 2020), public organizations (Mikalef et al., 2021), the telecoms industry (Chen and Chen, 2020), and the retail sector (Mahroof, 2019). The TOE framework was applied in Alsheibani et al.'s (2019) quantitative study, which identified factors such as a lack of skills to deploy AI solutions and unclear business cases for AI implementations were inhibiting AI adoptions in Australia. Also investigating the barriers to AI adoptions, Kushwasha and Kar (2020)'s study suggested that issues such as employee training, trust, and security should be addressed for smooth AI adoptions. In Pumplun et al. (2019)'s qualitative study, they extended the TOE framework adding “the availability, protection and quality of data” as a new category of organizational readiness factor for AI adoption. Based on the studies of Alsheibani et al. (2019) and Pumplun et al. (2019), Jöhnk et al. (2021) developed an action-oriented framework and highlighted five AI readiness factors (strategic alignment, resources, knowledge culture and data) and provided actionable indicators. Focusing on AI adoption in the public sector, Mikalef et al. (2021) identified five factors that affect the development of organizations’ AI capacities: perceived financial costs, organizational innovativeness, perceived governmental pressure, government incentives, and regulatory supports. However, the service sector’s and the exhibition industry’s readiness for AI adoption, is yet to be investigated. The present study’s focus on large service firms in the exhibition sector in the Western Europe region will generate rich contextual explanations and theoretical contributions regarding AI adoption.

Along with adoptions of AI, firms’ readiness to adopt AI has been investigated in various contexts (Halpern et al., 2021; Mather & Cummings, 2019). Jöhnk et al. (2021) conceptualized AI readiness, and differentiated AI readiness from AI adoption. Instead of investigating initiation, adoption decision, and implementation, AI readiness, in the pre-adoption stage, focuses on the assessment of organizations’ necessities, commitment and available resources required for AI adoption. Financial resources, particularly a dedicated budget (Pumplun et al., 2019), available internal expertise (Mikalef & Gupta, 2021), including domain experts (Alsheibani et al., 2020) and skilled, trained staff (Pumplun et al., 2019), as well as organizational culture and strategic plans (Jöhnk et al., 2021) are the key AI readiness factors identified in the literature. In a sector-specific analysis, Alami et al. (2020) suggested that healthcare decision-makers considering adopting AI in service delivery should evaluate added value, understand the perceptions and engagements of stakeholders, assess the alignment of technology and the organization, and have a clear and realistic financial plan. To examine exhibition organizations’ readiness for adopting AI in this research, the TOE framework is integrated with the Technology Readiness Index (TRI) to develop a theoretical framework, which will further clarify and explain organizational and technological acceptance and readiness to embrace AI in the exhibition sector in Western Europe.

Technology Readiness Index

First presented by Parasuraman (2000), TRI refers to “people’s propensity to embrace and use new technologies for accomplishing goals in home life and at work” (Parasuraman & Colby, 2015 p.59). TRI reflects an overall state of mind and does not measure competence. The second generation of this concept was introduced by Parasuraman and Colby (2015), with four dimensions: optimism, innovativeness, discomfort and insecurity. *Optimism* and *innovativeness* are motivators contributing to technology readiness. People who fall into the category of *optimism* believes that innovative technology will increase efficiency, flexibility, and control. *Innovativeness* describes those who are opinion leaders and pioneers in adopting new technology. The other two dimensions – *discomfort* and *insecurity* are considered as inhibitors distracting from technology readiness (Parasuraman & Colby, 2015). *Discomfort* describes users who are overwhelmed by and perceive little control with the new technology. People who are in the category of *insecurity* do not trust the technology for the reasons of its functionalities and potential harm.

TRI has been applied in various sectors, such as E-commerce, E-Service and E-tailing, E-banking and E-payment (Celik & Kocaman, 2017; Mukherjee et al., 2018; Mummalaneni et al., 2016; Naidu & Sainy, 2018; Wiese & Humbani, 2020). Although TRI has been adopted to understand the tourism and hospitality sector in the applications of E-services (Huy et al., 2019; Victorino et al., 2009), events studies use this model only superficially, with one exception (Goebert & Greenhalgh, 2020), which investigates fan perceptions of augmented reality in sports marketing.

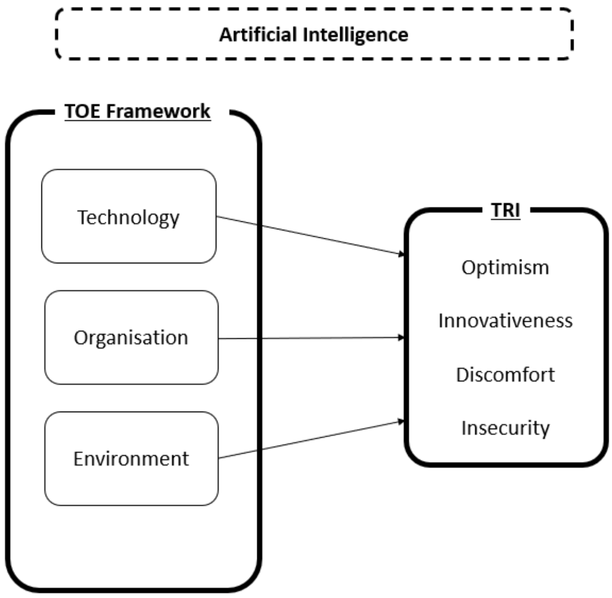

Figure 1 -Theoretical Framework - Organizational Readiness of AI Adoption

In this exploratory study, we synthesize the TOE framework and TRI to explore exhibition organizers' readiness for AI adoption (Figure 1). Firstly, by merging these two theories, the theoretical framework not only provides a framework (TOE) to explore technological, organizational environmental dimensions of AI adoptions but also narrows the focus to 'readiness' through the TRI. Secondly, the four dimensions of TRI offer indicators to identify and further explore the level of readiness. Thirdly, this framework operates contextually given the uniqueness, large varieties, and complexity of AI.

With the novel theoretical synthesis (Figure 3), and the new research setting in the context of AI research, this exploratory approach differs from alternative explanatory studies, where hypotheses are developed from theory and tested empirically. Instead, this exploratory research has been developed to investigate a new field, and to contribute to the development of the field through the dissemination of published findings. This will be helpful for future studies, in a way categorized by Swedberg (2020) as typical of a 'type 1' exploratory study, which is among the most common of these types. Exploratory research of a similar nature, involving theoretical exploration in a new empirical context in the field of service industry technology adoption has been carried out, for example, in retail (Pantano and Vannuci, 2019), financial investing (Atwal and Bryson, 2021) and housing (Angioso and Musso, 2020), and more generally in the case of IT systems adoption (Martin, 2003).

Through this novel synthesis of theory, and the use of an exploratory method, this research also responds to Dennis' (2019) call for exploratory Information Systems research on new phenomena that can help to 'lead practitioners by applying deep academic insight into new problems and opportunities…such as climate change, fake news on social media, artificial and augmented intelligence, virtual and augmented reality, and so on.'. Reiter (2013) however, cautions that exploratory research of this nature in the social sciences should be carried out in a transparent and reflexive way, so that its assumptions and limitations are made clear, and that the role of the researcher in the process is made explicit, to increase the reliability of the findings. The following section of this study sets out the way in which a qualitative, explorative method was developed and implemented, to meet these criteria.

3. Method

Information Management research is increasingly using qualitative methods to focus on the experiences of information users (Nili et al., 2020), and this study contributes to this trend. Qualitative research was appropriate for this exploratory study, which aimed to gain information-rich data from managers in the diverse context of the exhibition industry in Western Europe. Wynn & Hult (2019: 24) explained that qualitative research in information systems has value in capturing "*how things work* at some level of granularity" to represent the realities of complex situations that are not reproducible, reinforcing the seminal position of Silverman (1998), who argued that qualitative research within information systems offers the opportunity to focus on organizational practices *in situ*, with a focus on how people "do things" within firms.

Within organizational research, considerations of reflexivity have come to dominate discussions of the rigor and trustworthiness of qualitative methods (Haynes, 2012; Galdas, 2017), and this is widely held to be the gold standard for determining the trustworthiness of qualitative findings (Dodgson, 2019). Reflexivity refers to the extent to which the researcher is aware of their own positionality in the research process and can consider the impact of the context of their research and the human interactions that take place within this context, on their analysis. In the present study, one author carried out all the interviews in a process that was co-designed within the author team. The use of a single interviewer was a first step in establishing the rigor of this research. The positionality of the interviewer, as a junior researcher with limited industry experience, interacting with senior industry figures, was taken into account in the choice of data collection method, the selection of a qualitative data analysis technique, and the steps that were taken in data analysis to ensure the reflexivity of the approach.

Semi-structured online interviews offering the opportunity to integrate open-ended and theoretically driven questions (Galletta, 2013) were used. This method shows a high level of versatility through the possibility of switching experience-oriented questions to theoretically-guided questions (Galletta, 2013). Opening questions that allowed participants to discuss their experience within the industry and their current roles allowed for establishing rapport with the interviewer, reflexively acknowledging the power imbalances in these social interactions (Dodgson, 2019) and minimizing their impact on the theoretically informed data collection that followed. Later interview questions were thematically designed (see Appendix A) and informed by the theoretical synthesis of the TOE framework with the TRI, shown in Figure 1, with questions asked about every component of the model to ensure that the resulting data could be reliably analysed using the theoretical constructs employed in this study.

All interviews were conducted online due to the constraints on travel associated with the COVID-19 pandemic. Online interviews have some positive aspects in the ability to overcome geographical distance, time and cost connected with travelling for interviews (Mann & Stewart, 2000).

A purposive sampling technique was applied in this study. Participants hold senior management positions in major European exhibition venues and exhibition companies in Western Europe, with the seniority of their roles used as a way of enhancing the trustworthiness of the findings, as participants have substantial and comparable experience of the exhibition industry. Their locations are shown in Figure 1. The organization's size plays a vital role in technology adoption, as they are more likely to demonstrate adoption potential, resources, skills and experience, and they are more resilient against potential technology adoption failure (Matta et al., 2012). Therefore, all participants from venues represent organizations with more than 100,000 square meters of exhibition space, making them among the preeminent exhibition venues in Europe.

Marshall et al.'s (2013) recommendations for qualitative research in information systems suggest that benchmarking sample size against related studies provides a strong justification for the choice of sample size, with theoretical saturation in the analysis providing another. Marshall et al. (2013) recommended sample sizes of between 15-30 participants for qualitative case studies and recent qualitative studies in technology adoption in service sector contexts support this figure, with some significantly smaller sample sizes evident, but very few that exceed this range (Eze et al., 2019; Odeh et al., 2017; Schmitt et al., 2019; Soares et al., 2019). This sample involved 17 interviews with senior managers from across Europe (Table 1), with recruitment stopping once theoretical saturation was reached (Rowlands et al., 2016).

Participant #	**Exhibition Organization type**	**Role**	**Country**
(P1)	International Investment Exhibition	Founder/Exhibition Organizer	United Kingdom

(P2)	Exhibition Venue	IT Manager	United Kingdom
(P3)	Exhibition Venue	Floor Manager	Netherlands
(P4)	Exhibition Venue	Exhibition Manager	Germany
(P5)	Exhibition Venue	Exhibition Manager	Belgium
(P6)	Exhibition Venue	Exhibition Manager	Italy
(P7)	Exhibition Venue	Project Manager	Germany
(P8)	Exhibition Venue	Events & Exhibitions Business Development	Italy
(P9)	Exhibition Venue	Head of Internal Organization	Germany
(P10)	International Medical Technology Exhibition	Head of Events	United Kingdom
(P11)	International Telecoms Exhibition	Event manager	United Kingdom
(P12)	Exhibition Venue	General Manager	France
(P13)	Exhibition Venue	Project Manager	Spain
(P14)	Exhibition Venue	Project Manager	Spain
(P15)	National Exhibition Industry body	President	Poland
(P16)	International Exhibitions Consultancy	CEO	Germany
(P17)	International Exhibitions Consultancy	Managing Director	Ireland

Table 1 – Participant Information


Figure 2 – Map of participant locations

Following Braun and Clarke (2006, 2021), reflexive thematic analysis was conducted after transcribing the interviews. In the stage of familiarization, transcripts were reviewed in light of the aims of the research to highlight gaps or limitations in the data and to identify patterns emerging within it (Lewis et al., 2013). We then applied two rounds of coding. In the first round, a combination of provisional and open coding was applied. The provisional coding process was informed by the theoretical framework (Figure 1), using key terms and concepts as a starting point (Miles et al., 2014). This was followed by a stage of manual, open coding to allow further codes to emerge inductively from the data. This process produced 13 deductive codes that related directly to the theoretical framework and three inductive codes, one related to the specific COVID-19 context that existed during the data collection period, and two related to future AI strategy and application (Table 2). In the second round, axial coding was used to strategically assemble data (Strauss & Corbin, 2014) and look for relationships between the codes in order to generate themes for analysis. In this round of coding, we focus on synthesizing the relationship between TRI and TOE, particularly exploring the four readiness elements within three dimensions of the TOE. After 2 rounds of coding, seven themes: connectivity, lack of AI practice and discomfort, excitement and positive perceptions, organizational size and financial resources, organizations' strategic plan, data management and privacy, COVID-19 as a transformational force emerged from the analysis.

Code #	Abbreviation	Name	Connection to the theoretical framework
(1)	PA	Perception of AI	TOE - Technology
(2)	CA	Current AI Application	
(3)	TI	Technological Infrastructure	
(4)	RA	Relative Advantage	
(5)	OS	Organization Size	TOE - Organization
(6)	OH	Organization Hierarchy	
(7)	EE	External Environment Impact	TOE – Environment
(8)	GI	Government Impact	
(9)	OP	Optimism	TRI
(10)	IN	Innovativeness	
(11)	DC	Discomfort	
(12)	INS	Insecurity	
(13)	FA	Future AI Strategy	Inductive Codes
(14)	FAA	Future AI Applications	
(15)	CV	COVID-19	

Table 2 – Codes used for thematic analysis

These seven themes are organized using the three dimensions of the TOE framework and have been used to structure the findings section that follows.

4. Findings

4.1 Technology Dimension

4.1.1 Connectivity

Digital maturity is vital for implementing new emerging technologies (Davidson et al., 2002; Sox et al., 2014; Talantis et al., 2020). To adopt AI in exhibition venues, connectivity is the fundamental infrastructure to enable AI implementation (BVEP, 2020). The availability of 5G connections offers an opportunity for AI adoptions. Project manager (P7) explained: "at the beginning of this year, our venue implemented 5G connection to make autonomous driving possible. This technological development moved us one step forward to implement AI and the

Internet of things. So, a good IT infrastructure is important". Highly connected to other elements in the ecosystem of IoT, the adoption of AI in the exhibition is largely related to the technological affordances that enable autonomous networks (Bello & Zeadally, 2017).

Participants understood the importance of having technical support to adopt AI. There were three organizations currently using and simultaneously developing networking systems. Project manager (P7)'s organization was investing in their system, and exhibition manager (P5)'s organization used a contractor company for these purposes. General manager (P12)'s organization launched a large project two years ago with the aim to reinvent their facility management. They used AI for the creation of predictive patterns, working with lights, temperature, ventilation, lifts, escalators, overall energy consumption and toilet cleanness: "thank to installed sensors, the organization can monitor all the important data and then use them for AI predictive patterns. So, it helps us increase customers' experience and based on that the organization can provide better and more accurate service for their customers".

4.1.2 Lack of AI practice and discomfort

Internal technological practices also affect organizational adoptions of AI. Although a wide range of AI-powered applications were mentioned, including facial recognition kiosks, networking systems, smart venue features, crowd management tools, chatbots, and business analytics software, participants noted that AI applications have not yet been widely established in the business events industry. Hence, they often talked about the phenomenon in an abstract, futuristic way.

Those who adopted AI are mainly in the initial stages of considerations and pilot tests. For instance, IT manager (P2) talked about facial recognition kiosks at the pilot stage, and how their real-life usage brought issues and occasional errors. Many participants felt overwhelmed by potential AI adoption and did not have clear ideas about its operations and how exactly AI could be helpful to their business. For example:

> As an organiser you do not have an idea where exactly to implement the AI technology. Obviously, you have a clear idea about the event. Although, it is difficult to match the AI technology on your "unique" event. Me as an organiser, I do not know the full scope what the technology can provide and help me with. Although event organisers are open

to AI, they cannot use the entire potential of it just yet. And it brings financial and other insecurities" (P11)

The lack of confidence in AI use and frequent errors from AI pilot tests leads to the "discomfort" of TRI (Parasuraman & Colby, 2015). To cope with such discomfort of AI adoption, participants agreed on the need for training programs to develop employees' skills to use AI effectively.

4.2 Organizational Dimension

4.2.1 Excitement and positive perceptions

This research reveals optimism amongst exhibition sector professionals who have feelings of excitement and curiosity towards AI adoption (Parasuraman & Colby, 2015). Exhibition organizer (P1) stated: "AI is causing much interest amongst investors. Exhibitors organize entire sections about AI, and the investors tend to get into investing in AI early as they are aware of the potential". Beyond organizing events for AI, most of our participants have already come across AI in their roles. Participants mostly agreed that AI is slowly being implemented in the event industry and is considered beneficial with a high level of expectation. Project manager (P13) emphasized that AI can play an important role in venues' or organizers' image: "it not only has this ability going out of its scope as it can do all the designated functions but also have this external positive impact on the promotion and final appeal for the venue or organizer". Participants also agreed that AI technology would increase efficiency, reduce cost, increase quality, improve visitor experiences, assist faster decision-making, and replace time-consuming activities (Davenport et al., 2019; Dhar, 2016; Grace et al., 2018; Makridakis, 2017).

4.2.2 Organizational size and financial resources

Participants reported that organizational size and financial resources play a significant role in their readiness for AI adoption. Most participants saw larger organizations as faster adopters with better potential and financial resources for adopting new technologies, including AI. IT manager (P2) compared his venue with football stadiums and argued that these venues have significantly higher income and, therefore, they will be the first ones to implement AI. Larger companies can absorb risks and initial costs (Duan et al., 2010; Sharma & Rai, 2003), and tend to be innovators in technology (Parasuraman & Colby, 2015). Participants from larger firms were shifting from using contractors, to developing their own AI platforms. Business development manager (P8) stated that the pressure of keeping their competitive advantages (Aboelmaged, 2014) for a firm of such size pushed them to develop their own AI "geolocalization" system.

Conversely, other participants saw smaller companies are innovators when adopting AI. Exhibition Manager (P4) said that the number of venues they have got would mean astronomical introductory investment. Hence, smaller companies are more resilient to the risks. CEO (P16) analysed both pros and cons for small and big companies in terms of AI adoptions: "smaller companies have advantage in the agility, faster reaction, more risk taking; on the other hand, they are lacking budget. Bigger players have finances and Human Resources. At least in numbers not always in skills. Very slow in decision process. So, we see benefits and disadvantages on both sides. But definitely I see is a potential and opportunity for new players to gain competitive advantage".

4.2.3 Organizations' strategic plans

Our participants reported the lack of vision and progressivity from CEOs as a key obstacle to AI adoption. From our interviews, many participants stated the entire industry is not really progressive in adopting new technologies. P10 explained that "organizations would benefit from well-established IT departments. This is not a common practice from my experience. IT departments are often overwhelmed by digital obligations, and they do not have time and space for new technology research and implementation." The top management has the necessary power to make the final decision of technology adoption and create a positive environment for innovations (Premkumar & Roberts, 1999). As the founder of the firm, exhibition organizer (P1) decided to wait and see what is in the market for them, and thereafter they will adopt AI technology. She also saw benefits in being a late adopter.

Concerning the potential harm and disruption that AI might bring to current organizational structures and operations, most top management might perceive "insecurity" towards AI in TRI (Parasuraman & Colby, 2015). Some might also feel out of place towards new technologies, associated with "discomfort" in TRI. Most participants stated that their organizations do not have any plan for implementing AI. Exhibition manager (P4) shared that although they have a

5-year business plan, AI does not appear in this strategy. CEO (P16) explained that “the corporate culture is not ready to drive digital business models”.

Some organizations in our study identified the potentials of AI and implemented plans for adoption. Business development manager (P8)’s organization has a 3-year AI strategy where they focus on transferring their exhibition catalogue to directories and creating an AI-powered marketplace; the organization dedicated €5million to this development in 2018. Project manager (P14) hired a futurist to develop their strategic plan for 2025, who helped to identify that AI will be one of the disruptors and game-changers in the exhibition industry. Since 2016, they have been adjusting themselves to get ready for the adoption: “we started with cleaning our large amount of data. Our organization purchased a data management system and integrated with our associated management system [Salesforce/Marketo]. So, we can help suggesting with better accuracy about services our customers are demanding from us”. P16 explained their own organization’s progress in implementing AI across their firm:

> “We are testing and developing a community management algorithm which helps us to mine data which are followingly used for demographic group identification for our customers. Other AI algorithm helps us booking exhibitors where after analysing CRM software gives us potential candidates for particular show. And lastly, one of the examples which is not working very well is an AI algorithm helping with ideal floor plan positioning.”

From the financial perspective, AI is largely considered as a cost-reduction tool (Davenport et al., 2019). Head of Internal Organization (P9), however, could not see AI as a cost-cutting tool in upcoming years. For their organization, the main investment would go to marketing and sales because that is the core of their business. “The top management does not know how to put AI into real-life”, project manager (P7) said regrettably, but still held hope to see if the IT department can work with and persuade the management board.

4.3 Environmental Dimension

4.3.1 Data management and privacy

Large exhibition venues are connected to local authorities and policymakers. AI technologies require a significant amount of data, and policymakers protect their customers. Governments, as well, can promote and fund new emerging technologies. (P13) explained this: “Looking at the issue from the other point of view. Local authorities have their own agenda. So, if the new technology adoption correlates with their aim. They are more likely to release funding and enforce the proposal”. Our participants were aware of the difficulties of data management and privacy issues in the context of exhibitions. This topic is controversial, mainly in facial recognition solutions (Bowcott, 2020; Davis, 2019). IT manager (P2) was aware of the issue of privacy but disclosed the optimism to adopt facial recognition as a valuable tool. Looking into the issue of privacy from the perspective of attendees, exhibition manager (P5) showed his insecurity in the level of AI readiness and stated that attendees would be skeptical about adopting facial recognition; also, the organization would be required to hire a specialist to clear all the data after the event. (P9) was more positive about the potential benefits of using customer data in AI applications:

> “We need to focus on the data collection and we do so. Our organization constantly updating database about our clients and based on their activities we can suggest their networking opportunities via e.g., push up notification. AI algorithms can do miracles with these data. It can quickly analyse and evaluate and forecast what people want, need and what they will do next”.

4.3.2 COVID-19 as a transformational force

COVID-19, as an environmental factor, has significantly affected the event sector. Despite its devastating impact, participants see the pandemic as a force of transformation to adopt AI: “consequences of the pandemic have proved that we need to go more digital and find new ways of bringing the events to visitors” (P6, exhibition manager). The president of a national exhibition industry body (P15) said: “because of the pandemic, what we see is not getting back a large number of visitors … I see the AI fitting the mix with its networking potential”. He further explained the use of AI for marketing purposes: “the industry needs better market intelligence about people who are coming to the events and how to connect the supply with demand and here I see the potential for the technology in the industry”. Additionally, participants have noticed the urgent need for digitalization and increasing employees’ digital skills to enhance socially distanced working practices. (P14) explained that “our organization has recently incorporated new technology to follow the stated trend in the industry caused by Covid-19. Virtual meetings, virtual reality and augmented reality are areas where we directed significant funding”. For instance, (P8)’s organization adopted a facial recognition system with temperature checks at the entrance. New AI-powered features of smart venues will increase security and trustworthiness for attendees (Intel, 2020).

5. Discussion

5.1 Theoretical Contributions and Implications

The theoretical synthesis (Figure 1) of the TOE and TRI that was applied in this research has provided new insights into the adoption context for AI in the exhibition sector, a novel context for the application of this theoretical lens.

Although TOE has been widely applied in other sectors (Aboelmaged, 2014; Oliveira & Martins, 2011; Wang et al., 2010; Wang et al., 2016; Yang et al., 2015), this study has shown that it is also a useful perspective from which to examine the events industry. This confirms the value of Tornatzky and Fleischer’s (1990) insight in developing the theory, that non-technological factors must be considered when considering the adoption of technology by businesses, in a new context. Jöhnk et al. (2021) synthesized previous work on the TOE to highlight five AI readiness factors that can be used to analyse the adoption of AI by firms, and Mikalef et al. (2021) also identified five factors that affect public sector organizations capacity to adopt AI. However, both of these previous attempts to consider firm-level adoption of AI focused on the pre-adoption phase. The present study has examined a business environment where the adoption of AI has already begun, albeit from a slow start (Davidson, 2019; Ogle & Lamb, 2019), and where research had identified concerns about the late adoption of technological innovations (Sangkaew et al., 2019; Soifer et al., 2019) Because of this, it was important to capture the decision-making processes of senior managers, who have been involved in AI adoption processes, through the synthesis of the TOE with the TRI, which emphasizes the centrality of these individual’s rational decision making (Jiang & Chen, 2010), rather than general perceptions of AI held by managers.

This study has shown the value of this theoretical synthesis, which has been used to produce the exhibition sector’s Readiness for AI Adoption Model (Figure 3), contributing to addressing the lack of theoretical perspectives in AI research in information systems (Collins et al., 2021).

This model provides a framework that can be used by researchers in other service industry contexts, where the interactions between internal and external factors in the TOE will be similar, and where key decision-makers are required to consider the adoption of AI in customer-facing businesses. The model uses TOE dimensions that have been established in multiple studies and clearly indicates how TRI factors can influence these. The way in which this model was derived, through a thematic analysis of senior managers' perceptions of AI adoption, helped to produce contextual, information-rich data, and although this model includes a consideration of the exhibition sector context, approaching this issue in other sectors using the same approach will allow for the model to be modified to reflect diverse industrial settings.

Three factors from TOE either motivate or inhibit the decision-making of AI adoptions, and influence the readiness for the AI adoptions. On the one hand, some factors result in specific challenges of discomfort (e.g., confidence towards new technology use) and insecurity (e.g., data management issues), and some factors lead to an optimistic and innovative outlook (e.g., improved connecting facilities, perceived benefits of AI); on the other hand, some factors act as double-edged swords (e.g., the size of the venue, and COVID-19 impacts) which inhibit and motivate AI adoptions at the same time. The model contextualizes the characteristics of the exhibition sector and the current state and challenges of adopting AI. Categorized using the TOE framework, issues discussed in the findings showed either TRI motivators or inhibitors, which present the exhibition sector's readiness for AI adoption. By synthesizing TOE and TRI and contextualizing the exhibition sector and the situated environment, the model can be used to understand current issues and better implement AI technologies in the event sector by further emphasizing TOE elements that are considered as optimism and innovativeness, and mitigating TRI inhibitors of discomfort and insecurity. Therefore, this model not only reflects the current stage of AI adoption in the exhibition sector, but can also act as a road map for future strategic planning to improve organizational readiness for AI adoption in the sector.

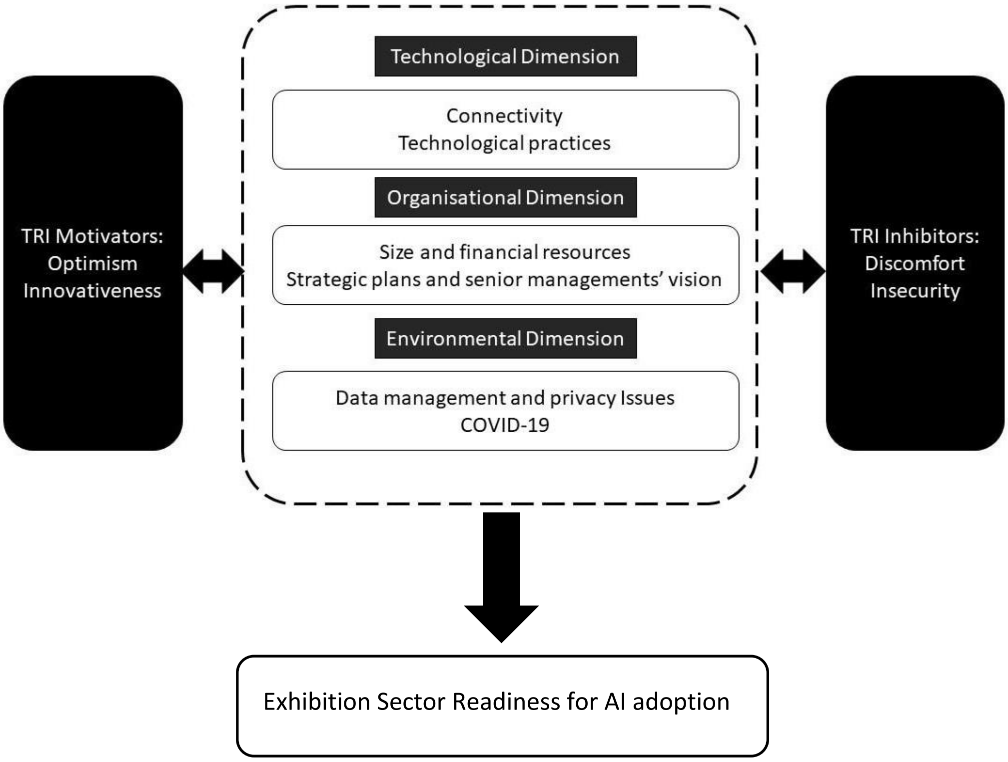

Figure 3: Exhibition Sector Readiness for AI adoption Model

We propose three avenues for future research, along with propositions that can inform this research, building on Figure 3. Firstly, future research should acknowledge that the functionality of AI highly depends on the affordances of the IoT ecosystem. The development of advanced network systems, 5G infrastructure, and emerging new technologies provide increased potential for AI operations in daily tasks. Although the sector generally is optimistic and curious about AI (Ogle &Lamb, 2019; Davison, 2019), it is worth exploring as such developments in connectivity are considered as optimistic and innovative motivators to adopt AI. Future studies can investigate the ways in which this curiosity and optimistic motivations transform into actual AI adoptions. As AI practice is still considered relatively new in the business events sector, the level of confidence and familiarity with new technological practices strongly influences the readiness for adoption. In this study, we found that most adoptions are still in the very early stage. Many managers demonstrate discomfort by not knowing how AI can specifically help in their businesses or lacking the knowledge and skills to implement it. Future studies should compare the positive perceptions of AI and the actual experience of AI implementations, particularly if the competence of AI use and the available infrastructure lead to optimistic outcomes of AI adoption readiness.

Proposition 1: AI adoptions in the exhibitions sector will be highly dependent on the affordances of the IoT ecosystem.

Secondly, at the organizational level, on the one hand, large exhibition venues have more resources and capacities (Aboelmaged, 2014) to drive AI implementation; on the other hand, small firms in the sector tend to be the innovators and risk-takers in adopting new technologies due to their flexibility, techno-driven visions, and flat organizational structures. Future research should explore the relationship between the organization size (including financial resources) and readiness for AI adoptions (innovativeness and optimism). In addition, we found that large venues face constraints from various stakeholders that prevent them from pushing forward an AI implementation agenda. Furthermore, many senior managers in the business events sector do not consider AI implementation as a priority in their strategic plans. Future studies should further investigate the reasoning behind such hesitation and resistance, particularly, the negative attitude (e.g., discomfort) towards AI technology, and the negotiating strategies and experiences of AI implementations at the organizational level.

Proposition 2: Motivators and Inhibitors for AI adoption in the exhibitions sector will be strongly influenced by organizational size and strategic focus.

Thirdly, at the environmental level, and in common with various stakeholders in both the public and private sectors, large exhibition venues face several challenging issues regarding managing data and privacy when considering adopting AI technologies (Duan et al., 2019). Future research should further investigate how insecurity relating to concerns about privacy issues and data management affect AI adoptions, and if improved data management protocols lead to more optimistic readiness for AI adoptions.

Proposition 3: Insecurity surrounding data management and privacy will continue to inhibit AI adoption in the exhibition sector.

In addition, the COVID-19 pandemic is shown in our findings to be a transformational force for the exhibition sector to increase the speed of AI adoptions, in an industrial context where the speed of technology adoption had previously been slow (Davidson, 2019; Ogle & Lamb, 2019; Sangkaew et al., 2019; Soifer et al., 2019). It is worth exploring if AI adoptions served as a short-term, alternative solution during the COVID-19 pandemic, or if the COVID-19 pandemic leads to a transformational, long-lasting effect on adopting AI technology. In addition, studies should also be conducted to explore any new inhibitors and motivators of AI readiness as a result of COVID-19.

Proposition 4: The COVID-19 pandemic will have a transformational effect on the adoption of AI in the exhibitions sector.

5.2 Implications for Practice

The findings of this research will be of value for exhibition managers and those working in large event venues. The proposed model can be adopted by organizations to determine and improve areas of strength and weaknesses for AI adoption. Each TOE-related element of the model has clear links to the operations of specific business departments, and the TRI elements indicate factors influencing these. Moreover, exhibition organizers could use the model in a more holistic way to analyze whether the venues that they use will be innovative enough to apply AI-powered solutions to enhance their events.

A key practical implication of this research is that exhibition sector businesses lack a strategic approach to the adoption and implementation of AI. Firms in this sector should either develop specific strategic approaches to AI adoption, or integrate these considerations within their broader strategic planning, for two reasons. First, the level of complexity involved in AI means that it requires greater attention and resources than other "easy-to-deploy" technologies (Lokuge et al., 2019). Although exhibition firms may have experience of integrating previous technological advances into their business model and practices, the complex interactions of technological and non-technological factors uncovered in this research suggest that a strategic approach to resolving these issues will be needed for AI adoption to be successful. For this to happen, it is important the senior leaders and chief executives in exhibition companies and venues and buy-in to the development of AI strategy, and that the process of strategy implementation is resourced and championed by them. Second, AI technology exists in a complex regulatory space where multiple stakeholders have an interest in its regulation and application. For exhibition firms to navigate this space successfully, a strategic approach needs to be taken where the perspectives of multiple stakeholders can be considered. Managing these complex stakeholder relationships can be challenging, especially as the nature of AI and its regulation means that stakeholder networks will cross multiple sectors. For this reason, it is recommended that, in organizations where resources allow, dedicated staff with expert knowledge of AI in an events context are tasked with managing the networks of internal and external stakeholders necessary for successful AI adoption.

Research into the adoption of AI in the service sector has frequently focused on problems associated with job replacement (Dhar, 2016), as AI develops to the extent that it can begin to be used to carry out complex services tasks that traditionally require human-human interaction (Chessell, 2018; Koo et al., 2020). This research, however, has shown that in the specific service context of the exhibition sector, managers are optimistic about the potential business future adoptions of AI, and these concerns did not feature in their adoption decision-making. This may reflect the nature of the sample used in this study, which did not focus on human resources managers or at the operational level, but this does appear to represent a lacuna in current thinking within the exhibitions industry on this topic that should be considered as AI adoption becomes more established.

5.3 Limitations and Future Research Direction

Several limitations were identified in this study. First, the COVID-19 pandemic paused the entire events industry and limited the availability of participants, many of whom were furloughed or otherwise unavailable. Secondly, online interviews can cause difficulties in capturing rich data from body language, facial expressions, and voice tone. Thirdly, as AI adoption is still relatively new in the exhibition sector, participants' responses were often abstract and lacked real-life evidence. Future research can further explore the transformational force of COVID-19 in the post-pandemic operations in the exhibition sector. Applications of TOE and TRI can be further implemented in other contexts. Field studies, including shadowing and longitudinal studies, can be implemented to investigate the decision-making process of AI adoptions within organizations. Studies on the exhibition sector's readiness regarding AI adoptions can be further investigated in other geographical contexts or smaller venues.

6. Conclusion

This exploratory research aimed to explore organizational readiness to adopt AI in the Western European exhibition industry. This research has shown that although the majority of the participants have come across some form of AI in their organization, their understanding of the application of AI is rather limited and reserved, supporting the findings of previous studies which have found that technology adoption is relatively slow in this industry. Exhibition organizations are largely behind in digitalization, and their technological infrastructure is not ready for AI adoption. Although exhibition organizers believe that AI will increase efficiency, reduce costs and enhance customer experience, most organizations do not have a future strategy to implement AI, despite the recent spike in technology adoption in the industry due to the COVID-19 pandemic. In this study, we also revealed that the confidence level of technological practices, financial resources, the size of the organization, and issues of data management and protection, to some extent, motivate or inhibit the readiness of AI adoptions in the organization. This research has shown that COVID-19 could act as an enabler for the adoption of AI technologies in the Western European exhibition sector, as it recovers from the restrictions on gatherings and meetings with an enhanced level of technological readiness and innovativeness.

This study has contributed to the literature in three ways. First, it addresses a lack of sector-specific research on organizations' readiness to adopt AI in the events industry and, specifically, the exhibitions sector. In helping to fill this gap in the events literature, the present study has also produced transferable knowledge for other parts of the service sector that share similar characteristics, and has provided a new model of AI adoption that can be adapted for other related industrial settings. Because research into the firm-level adoption of AI is still rare, the second contribution of this study comes from its exploration of how decision-makers evaluate various factors in this, and their willingness to adopt AI. Finally, by empirically exploring the synthesis of TOE and TRI qualitatively, the study contributes to knowledge by emphasizing the situated and contextual complexity of understanding organizational readiness for new technology adoption.

References

Aboelmaged, G. M. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing. *International Journal of Information Management*, *34*, 639–651.

Alami, H., Lehoux, P., Denis, J. L., Motulsky, A., Petitgand, C., Savoldelli, M. & Fortin, J. P. (2020). Organizational readiness for artificial intelligence in health care: insights for decision-making and practice. *Journal of Health Organization and Management*.

Alsheiabni, S., Cheung, Y., & Messom, C. (2019). Factors inhibiting the adoption of artificial intelligence at organizational-level: a preliminary investigation. In *Americas Conference on Information Systems 2019* (p. 2). Association for Information Systems.

AlSheibani, S., Messom, C., & Cheung, Y. (2020, January). Re-thinking the competitive landscape of artificial intelligence. In *Proceedings of the 53rd Hawaii international conference on system sciences*.

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. In *PACIS* (p. 37).

Anas, M. S., Maddiah, N. A., Eizamly, N. U. E. N., Sulaiman, N. A., & Wee, H. (2020). Key success factors toward MICE industry: A systematic literature review. *Journal of Tourism, Hospitality & Culinary Arts*, *12*(1), 188–221.

Angioni, M., & Musso, F. (2020). New perspectives from technology adoption in senior cohousing facilities. *The TQM Journal*, *32*(4), 761-777.

Arpaci, I., Yardimci, C., Y., O., S., & Turetken, O. (2012). Organizational Adoption Of Information Technologies: A Literature Review. *International Journal Of EBusiness and EGovernment Studies*, *4*(2), 37–50.

Atwal, G., & Bryson, D. (2021). Antecedents of intention to adopt artificial intelligence services by consumers in personal financial investing. *Strategic Change*, *30*(3), 293-298.

Bello, L., & Zeadally, S. (2017). Toward efficient smartification of the Internet of Things (IoT) service. *Future Generation Computer Systems*, *92*, 663–673.

Bhattacherjee, A., & Hikmet, N. (2008). Reconceptualizing organizational support and its effects on information technology usage: Evidence from the healthcare sector. *Journal of Computer Information Systems*, *48*(4), 69–76.

Black R. (1986) The Trade Shows Industry: Management and Marketing Career Opportunities, Trade Show Bureau, East Orleans

Boden, A. M. (2018). *Artificial Intelligence: A Very Short Introduction* (1st ed.). University Press.

Bowcott, O. (2020). *UK's facial recognition technology 'breaches privacy rights'*.

Boyd, R., & Holton, R. J. (2018). Technology, innovation, employment and power: Does robotics and artificial intelligence really mean social transformation? *Journal of Sociology*, *54*(3), 331–345.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Braun, V., & Clarke, V. (2021). Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counselling and Psychotherapy Research, 21*(1), 37-47.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W W Norton & Co.

BVEP. (2020). *THE UK EVENTS REPORT*. https://www.excel.london/uploads/uk-events-report-2020—the-full-report.pdf

Cai, W., Richter, S., & McKenna, B. (2019). Progress on technology use in tourism. *Journal of Hospitality and Tourism Technology*, *10*(4), 651–672. https://doi.org/10.1108/JHTT-07-2018-0068

Celik, H., & Kocaman, R. (2017). Roles of self-monitoring, fashion involvement and technology readiness in an individual's propensity to use mobile shopping. *Journal of Systems and Information Technology*.

Chaubey, A., & Sahoo, C. K. (2021). Assimilation of business intelligence: The effect of external pressures and top leaders commitment during pandemic crisis. *International Journal of Information Management*, *59*, 102344.

Chen, H., Li, L., & Chen, Y. (2021). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of Management Analytics*, 8(1), 36-68.

Cheng, J. E., Chou, P. K., Rajora, S., Jin, H. B., Tanveer, M., Lin, T. C., Young, Y. K., Lin, C. W., & Prasad, M. (2019). Deep Sparse Representation Classifier for facial recognition and detection system. *Pattern Recognition Letters, 125*, 71–77.

Chessell, D. (2018). The jobless economy in a post-work society: How automation will transform the labor market. *Psychosociological Issues in Human Resource Management*, *6*(2), 74–79.

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*, 102383.

Coombs, C., Hislop, D., Taneva, K. S., & Barnard, S. (2020). The strategic impacts of Intelligent Automation for knowledge and service work: An interdisciplinary review. *Journal of Strategic Information Systems*, *29*(4), 101600.

Corbin, J., & Strauss, A. (2014). *Basics of qualitative research: Techniques and procedures for developing grounded theory*. Thousand Oaks, CA: Sage publications.

CVENT. (2020). *Cvent CEO Urges MICE Industry to Embrace the Fourth Industrial Revolution*. https://www.cvent.com/uk/press-release/cvent-ceo-urges-mice-industry-embrace-fourth-industrial-revolution.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2019). How artificial intelligence will change the future of marketing. *Journal of the Academical Marketing Science*, *48*, 24–42.

Davidson, R. (2019). *Business Events* (2nd ed.). Routledge.

Davidson, R., Alford, P., & Seaton, T. (2002). Sectors. *The Use of Information and Communications Technology by the European Meetings, Incentives, Conferences*, *4*(2), 17–36.

Davis, D. (2019). Facial recognition technology threatens to end all individual privacy. *The Guardian*. https://www.theguardian.com/commentisfree/2019/sep/20/facial-recognition-technology-privacy

Dennis, A. R. (2019). An Unhealthy Obsession with Theory. *Journal of the Association for Information Systems*, *20*(9), 1406-1411.

Dewi, A. A. M., Hidayanto, N. A., Purwandari, B., Kosandi, M., & Budi, A. F. N. (2018). Smart city readiness model based on technology-organization-environment (TOE) framework and its effect on adoption decision. In M. Tanabu & D. Senoo (Eds.), *Proceedings of the 22nd Pacific Asia Conference on Information Systems—Opportunities and Challenges for the Digitized Society: Are We Ready?, PACIS 2018*.

Dhar, R. L. (2016). Ethical leadership and its impact on service innovative behavior: The role of LMX and job autonomy. *Tourism Management*, *57*, 139–148.

Dodgson, J. E. (2019). Reflexivity in qualitative research. *Journal of Human Lactation*, *35*(2), 220-222.

Drexler, N., Lapre, B., & V. (2019). For better or for worse: Shaping the hospitality industry through robotics and artificial intelligence. *Research in Hospitality Management*, *9*(2),

Duan, S. X., Deng, H., & Corbitt, B. J. (2010). A Critical Analysis of E-Market Adoption in Australian Small and Medium Sized Enterprises. *PACIS*, 1718–1726.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63-71. 117–120.

EEIA. (2020). *European Exhibition Industry Alliance Brochure*. http://www.exhibition-alliance.eu/sites/default/files/projects/files/EEIA%20Brochure.pdf

Eisingerich, A., Lin, Y.-T., & Doong, H.-S. (2021). Avatar Design of Virtual Salespeople: Mitigation of Recommendation Conflicts. *Journal of Service Research*, *24*(1), 141–159.

Eze, S. C., Chinedu-Eze, V. C., Bello, A. O., Inegbedion, H., Nwanji, T., & Asamu, F. (2019). Mobile marketing technology adoption in service SMEs: a multi-perspective framework. *Journal of Science and Technology Policy Management*, *10*(3), 569-596.

Fathallah, A., Abdi, L., & Douik, A. (2017). Facial Expression Recognition via Deep Learning. *IEEE/ACS*.

Frick, N. R., Mirbabaie, M., Stieglitz, S., & Salomon, J. (2021). Maneuvering through the stormy seas of digital transformation: The impact of empowering leadership on the AI readiness of enterprises. *Journal of Decision Systems*, 1–24.

Galdas, P. (2017). Revisiting bias in qualitative research: Reflections on its relationship with funding and impact. *International Journal of Qualitative Methods*. https://doi.org/10.1177%2F1609406917748992

Galletta, A. (2013). *Mastering the semi-structured interview and beyond: From research design to analysis and publication*. NYU press.

Gartner. (2019). Artificial Intelligence and Machine Learning. *Accessed*. https://www.gartner.com/en/conferences/na/applications-us/featured-topics/ai-machine-learning.

Getz, P., & Page, J. S. (2016). *Event Studies, Theory, research and policy for planned events* (3rd ed.). Routledge.

Goebert, C., & Greenhalgh, G. P. (2020). A new reality: Fan perceptions of augmented reality readiness in sport marketing. *Computers in Human Behavior*, *106*, 106231.

Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). When will AI exceed human performance? Evidence from AI experts. *Journal of Artificial Intelligence*, *62*, 729–754.

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, *61*(4), 5–14.

Halpern, N., Mwesiumo, D., Suau-Sanchez, P., Budd, T., & Bråthen, S. (2021). Ready for digital transformation? The effect of organizational readiness, innovation, airport size and ownership on digital change at airports. *Journal of Air Transport Management*, *90*, 101949.

Hameed, M. A., Counsell, S., & Swift, S. (2012). A conceptual model for the process of IT innovation adoption in organizations. *Journal of Engineering and Technology Management*, *29*(3), 358–390.

Haynes, K. (2012). Reflexivity in Qualitative Research. *Qualitative Organizational Research: Core Methods and Current Challenges*, 72.

Huang, C. H. (2016). How Does Meetings, Incentives, Conventions, and Exhibitions Industry Attract Exhibitors? *Asia Pacific Journal of Tourism Research*, *21*(1), 72–93.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155–172.

Huang, M. H., & Rust, R. T. (2020). Engaged to a robot? The role of AI in service. *Journal of Service Research*, *24*(1), 30–41.

Hurwitz, J., & Kirsh, D. (2018). *Machine Learning For Dummies*. John Wiley & Sons.

Huy, L. V., Nguyen, P. T. H., Pham, L., & Berry, R. (2019). Technology readiness and satisfaction in Vietnam's luxury hotels. *International Journal of Management and Decision Making*, *18*(2), 183–208.

ICCA. (2018). *A Modern History of International Association Meetings – Update 1963/2017*. *International Congress and Convention Association*. https://www.iccaworld.org/knowledge/benefit.cfm?benefitid=5230

Intel. (2020). *Smart Stadiums Take the Lead in Profitability, Fan Experience, and Security*. https://www.intel.com/content/www/us/en/internet-of-things/solution-briefs/iot-smart-stadiums-brief.html

Ivanov., S., Webster., C., & Berezina., K. (2017). Adoption of robots and service automation by tourism and hospitality. *Revista Turismo & Desenvolvimento*, *27*(28), 1501–1517.

Jiang, Y., Chen, D., & Lai, F. (2010). Technological-personal-environmental (TPE) framework: A conceptual model for technology acceptance at the individual level. *Journal of International Technology and Information Management*, 19(3), 5.

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or Not, AI Comes—An Interview Study of Organizational AI Readiness Factors. *Business & Information Systems Engineering*, *63*(1), 5–20.

Johnson, M., Albizri, A., Harfouche, A., & Fosso-Wamba, S. (2022). Integrating human knowledge into artificial intelligence for complex and ill-structured problems: Informed artificial intelligence. *International Journal of Information Management*, *64*, 102479.

Jotikasthira, N. (2015). Increasing Tradeshow & Exhibition Industry Competitiveness through Competency-based Hiring and Promotion: A Sales Executive Perspective. Global Journal of Management And Business Research.

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons, 63*, 37–50.

Koo, B., Curtis, C., & Ryan, B. (2020). Examining the impact of artificial intelligence on hotel employees through job insecurity perspectives. *International Journal of Hospitality Management*, 102763.

Kushwaha, A. K., & Kar, A. K. (2020). Micro-foundations of Artificial Intelligence Adoption in Business: Making the Shift. *International Working Conference on Transfer and Diffusion of IT*, 249–260.

Laing, J. (2018). Festival and event tourism research: Current and future perspective. *Tourism Management Perspectives*, *25*, 165–168.

Lee, S., Kim, H. S., & Kang, B. (2019). US DMOs and Meeting Planners, do they really ENGAGE with each other? Customer engagement in the context of event industry. *Journal of Convention & Event Tourism*, *20*(5), 351–374.

Lewis, J., McNaughton-Nicholls, C., Lewis, J., & Ormston, R. (2013). *Qualitative Research Practice A Guide for Social Science Students and Researchers* (2nd ed.). SAGE Publications.

Lewis, T. (2019). AI can read your emotions. Should it? *The Guardian*. https://www.theguardian.com/technology/2019/aug/17/emotion-ai-artificial-intelligence-mood-realeyes-amazon-facebook-emotient

Li, Y. (2008). An Empirical Investigation on the Determinants of E-procurement adoption in Chinese Manufacturing Enterprises. *International Conference on Management Science & Engineering*, *15*, 32–37.

Lokuge, S., Sedera, D., Grover, V., & Dongming, X. (2019). Organizational readiness for digital innovation: Development and empirical calibration of a construct. *Information & Management*, *56*(3), 445–446.

Mahroof, K. (2019). A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. *International Journal of Information Management*, *45*, 176-190.

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46–60.

Mann, C., & Stewart, F. (2000). *Internet Communication and Qualitative Research: A Handbook for Researching Online*. SAGE Publications Ltd.

Marshall, B., Cardon, P., Poddar, A., & Fontenot, R. (2013). Does sample size matter in qualitative research?: A review of qualitative interviews in IS research. *Journal of computer information systems, 54*(1), 11-22.

Martin, A. (2003). What drives the configuration of information technology projects? Exploratory research in 10 organizations. *Journal of Information Technology*, *18*(1), 1-15.

Martin, V., & Cazarre, L. (2016). *Technology and Events: How to create engaging events* (1st ed.). Goodfellow Publishers Limited.

Mather, C. A., & Cummings, E. (2019). Developing and sustaining digital professionalism: A model for assessing readiness of healthcare environments and capability of nurses. *BMJ Health & Care Informatics*, *26*(1).

Matta, V., Koonce, D., & Jeyaraj, A. (2012). Initiation, experimentation, implementation of innovations: The case for radio frequency identification systems. *International Journal of Information Management*, *32*(2), 164–174.

Mende, M., Scott, M., Doorn, J. van, Grewal, D., & Shanks, I. (2019). Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses. *Journal of Marketing Research*, *56*(4), 535–556.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434

Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., ... & Niehaves, B. (2021). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. *Government Information Quarterly*, 101596.

Miles, M. B., Huberman, A. M., Saldaña, J. (2014). Qualitative Data Analysis: A Methods Sourcebook, 3rd ed. Thousand Oaks, CA: SAGE.

Morrow, S.L. (2002) The Art of the Show, International Association for Exposition Management

Mukherjee, A., Smith, R. J., & Turri, A. M. (2018). The smartness paradox: The moderating effect of brand quality reputation on consumers’ reactions to RFID-based smart fitting rooms. *Journal of Business Research*, *92*, 290–299.

Mummalaneni, V., Meng, J., & Elliott, K. M. (2016). Consumer technology readiness and e-service quality in e-tailing: What is the impact on predicting online purchasing? *Journal of Internet Commerce*, *15*(4), 311–331.

Naidu, A., & Sainy, R. (2018). Does technology readiness predict banking self service technologies usage in India? *International Journal of Electronic Banking*, *1*(2), 129–149.

Nam, K., Dutt, C. S., Chathoth, P., Daghfous, A., & Khan, M. S. (2020). The adoption of artificial intelligence and robotics in the hotel industry: Prospects and challenges. *Electronic Markets*, 1-22.

Nili, A., Tate, M., Barros, A., & Johnstone, D. (2020). An approach for selecting and using a method of inter-coder reliability in information management research. *International Journal of Information Management*, *54,* 102154.

NIST. (2019). *NIST Study Evaluates Effects of Race, Age, Sex on Face Recognition Software*. https://www.nist.gov/news-events/news/2019/12/nist-study-evaluates-effects-race-age-sex-face-recognition-software

OECD. (2018). *Digital Technology Diffusion: A Matter Of Capabilities, Incentive Or Both?* http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=ECO/WKP(2018)24&docLanguage=En

Odeh, M., Garcia-Perez, A., & Warwick, K. (2017). Cloud computing adoption at higher education institutions in developing countries: a qualitative investigation of main enablers and barriers. *International Journal of Information and Education Technology*, *7*(12), 921-927.

Ogle, A., & Lamb, D. (2019). The Role of Robots, Artificial Intelligence and Service Automation in Events. In S. Ivanov & C. R. Webster (Eds.), *Robots, Artificial Intelligence, and Service Automation in Travel, Tourism and Hospitality* (1st ed., pp. 255–269). Emerald Publishing Limited.

Oliveira, T., & Martins, M. F. (2011). Literature Review of Information Technology Adoption Models at Firm Level. *The Electronic Journal Information Systems Evaluation*, *14*(1), 110–121.

Pantano, E., & Vannucci, V. (2019). Who is innovating? An exploratory research of digital technologies diffusion in retail industry. *Journal of Retailing and Consumer Services*, *49*, 297-304.

Parasuraman, A. (2000). Technology Readiness Index (TRI) A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research*, *2*(4), 307–320.

Parasuraman, Ananthanarayanan, & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, *18*(1), 59–74.

Premkumar, G., & Roberts, M. (1999). Adoption of new information technologies in rural small businesses. *Omega*, *27*(4), 467–484.

Pumplun, L., Tauchert, C., & Heidt, M. (2019). A new organizational chassis for artificial intelligence-exploring organizational readiness factors. *Proceedings of the 27th European Conference on Information Systems (ECIS)*.

PWC. (2020). *All Industries*. https://www.pwc.nl/en/industries.html

Quick, L. (2020). Managing events: real challenges, real outcomes. Sage.

Bernd, B. (2013). The Epistemology and Methodology of Exploratory Social Science Research: Crossing Popper with Marcuse. *Government and International Affairs Faculty Publications*. 99.

Robertson, M., Ong, F., Lockstone-Binney, L., & Ali-Knight, J. (2018). Critical Event Studies: Issues and Perspectives. *Event Management*, *22*, 865–874.

Rowlands, T., Waddell, N., & McKenna, B. (2016). Are we there yet? A technique to determine theoretical saturation. *Journal of Computer Information Systems*, *56*(1), 40–47.

Ryan, G. W., Fenton, A., Ahmed, W., & Scarf., P. (2020). Recognizing events 4.0: The digital maturity of events. *International Journal of Event and Festival Management*, *11*(1), 47–68.

Sangkaew, P., Jago, L., & Gkritzali, A. (2019). Adapting the technology acceptance model (TAM) for business events: The event organizer perspectives. *Event Management*, *23*(6), 773-788.

Schmitt, G., Mladenow, A., Strauss, C., & Schaffhauser-Linzatti, M. (2019). Smart contracts and Internet of things: A qualitative content analysis using the technology-organization-environment framework to identify key-determinants. *Procedia Computer Science*, *160*, 189-196.

Sharma, S., & Rai, A. (2003). An assessment of the relationship between ISD leadership characteristics and IS innovation adoption in organizations. *Information & Management*, *40*, 391–401.

Silverman, D. (1998). Qualitative research: meanings or practices?. *Information systems journal*, *8*(1), 3-20.

Soares, A. L. V., Mendes-Filho, L., & Gretzel, U. (2020). Technology adoption in hotels: applying institutional theory to tourism. *Tourism Review*. 76 (3), 669-80

Soifer, I., Berezina, K., Ciftci, O., & Mafusalov, A. (2021). Virtual site visits for meeting and event planning: are US convention facilities ready?. *Journal of Hospitality and Tourism Insights*. https://doi.org/10.1108/JHTI-09-2020-0165

Sox, C. B., Crews, T. B., & Kline, S. F. (2014). Virtual and Hybrid Meetings for Generation X: Using the Delphi Method to Determine Best Practices, Opportunities, and Barriers. *Journal of Convention & Event Tourism*, *15*(2), 150–169. https://doi.org/10.1080/15470148.2014.896231

Stackowiack, R., Licht, A., Mantha, V., & Nagode, L. (2015). *Big data and the internet of things enterprise information architecture for a new age*. Apress.

Swedberg, R. (2020). 'Exploratory research' in Elman, C., Gerring, J. & Mahoney, J. (eds.) *The production of knowledge: Enhancing progress in social science*, Cambridge. Cambridge University Press. pp. 17-41.

Talantis, S., Shin, H. Y., & Severt, K. (2020). Conference mobile application: Participant acceptance and the correlation with overall event satisfaction utilizing the technology acceptance model (TAM). *Journal of Convention & Event Tourism*, *21*(2), 100–122.

Tornatzky, L. G., & Fleischer, M. (1990). *Processes of Technological Innovation*. Lexington books.

Towers-Clark, C. (2019). Big Data, AI & IoT part Two: Driving Industry 4.0 One Step At A Time. *Forbes Magazine*. https://www.forbes.com/sites/charlestowersclark/2019/02/20/big-data-ai-iot-part-two-driving-industry-4-0-one-step-at-a-time/?sh=35cb979223a0

Tucker, C. (2019). Privacy, algorithms, and artificial intelligence. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The Economics of Artificial Intelligence: An Agenda* (pp. 423–437). University of Chicago Press.

Turing, M. A. (1950). Computing Machinery and Intelligence. *Mind A Quarterly Review of Psychology and Philosophy*, *59*(236), 433–460.

Tussyadiah, I. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. *Annals of Tourism Research*, *81*, 1–13.

Vial, A., Stirling, D., Field, M., Ros, M., Ritz, C., Carolan, M., & Miller, A. A. (2018). The role of deep learning and radiomic feature extraction in cancer-specific predictive modelling: A review. *Transl Cancer Res*, *7*(3), 803–816.

Victorino, L., Karniouchina, E., & Verma, R. (2009). Exploring the use of the abbreviated technology readiness index for hotel customer segmentation. *Cornell Hospitality Quarterly*, *50*(3), 342–359.

Wang, Y. M., Wang, Y. S., & Yang, Y. F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. *Technological Forecasting and Social Change*, *77*, 803–815.

Wang, Y. S., Li, H. T., Li, C. R., & Zhang, D. Z. (2016). Factors affecting hotels' adoption of mobile reservation systems: A technology-organization-environment framework. *Tourism Management*, *53*, 163–172.

Webster, C., & Ivanov, S. (2020a). Future tourism in a robot-based economy. *Tourism Review*, *75*(1), 329–332.

Webster, C., & Ivanov, S. (2020b). Robotics, artificial intelligence, and the evolving nature of work. In B. George & J. Paul (Eds.), *Digital Transformation in Business and Society Theory and Cases* (pp. 127–143). Palgrave-MacMillan.

Wiese, M., & Humbani, M. (2020). Exploring technology readiness for mobile payment app users. *The International Review of Retail, Distribution and Consumer Research, 30*(2), 123–142.

Wynn, E., & Hult, H. V. (2019). Qualitative and Critical Research in Information Systems and Human Computer Interaction: Divergent and Convergent Paths. *Foundations and Trends (R) in Information Systems*, *3*(1-2), 1-233.

Yang, Z., Sun, J., Zhang, Y., & Wang, Y. (2015). Understanding SaaS Adoption from the Perspective of Organizational Users: A Tripod Readiness Model. *Computers in Human Behavior*, *45*, 254–264.

Zebec, A., & Štemberger, M. I. (2020). Conceptualizing a Capability-Based View of Artificial Intelligence Adoption in a BPM Context. *International Conference on Business Process Management*, 194–205.

Zhang, D., Pee, L. G., & Cui, L. (2021). Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse. *International Journal of Information Management*, *57*, 102304.

Zhu, K., K., K., L., & Xu, S. (2006). The process of innovation assimilation byfirms in different countries: A technology diffusion perspective on e-business. *Journal of Management and Science*, *52*(10), 1557–1576.