# Cross-National Differences in Big Data Analytics Adoption in the Retail Industry


## Abstract

Big data analytics (BDA) has emerged as a significant area of research for both researchers and practitioners in the retail industry, indicating the importance and influence of solving data-related problems in contemporary business organization. The present study utilised a quantitative-methods approach to investigate factors affecting retailers' adoption of BDA across three countries. A survey questionnaire was used to collect data from managers and decision-makers in the retail industry. Data of 2,278 respondents were analysed through structural equation modelling. The findings revealed that security concerns, external support, top management support, and rational decision making culture have a greater effect on BDA adoption in ~~developed countries~~ UK than in UAE and Egypt. However, competition intensity and firm size have a greater effect on BDA adoption in UAE and Egypt than in UK. Finally, human variables (competence of information system's staff and staff's information system knowledge) have a greater effect on BDA adoption in Egypt than UK and UAE. The findings indicate that a "one-size-fits-all" approach is insufficient in capturing the heterogeneity of managers across countries. Implications for practice and theory were demonstrated.



## Keywords

Big data analytics; Technology adoption; Diffusion of innovations model; Cross-national differences; Retail industry.

# 1. Introduction

Over the past few years, many retailers have adopted different innovations to reduce costs, generate knowledge, assist decisions making, and increase productivity (Maroufkhani et al., 2020). One of these innovations is big data analytics (BDA) that has been utilised by many retailers with the aim of providing customers with supreme services and enhancing the business performance (Aversa et al., 2021; Giglio et al., 2019; Mariani et al., 2018; Moro et al., 2017). Big data analytics play a crucial role in enhancing retailers' operations and creating business value (Ranjan and Foropon, 2021; Xu et al., 2017). Retailers can decrease their marketing costs by utilising big data analytics (Bradlow et al., 2017). Mariani et al (2018) indicated that there will be a deficiency of 180,000 to 1,000,000 professionals with deep analytical knowledge and skills by 2025. Big data also consider a main source for Business Intelligence (BI) activities that is a key driver of consumer value (Mariani et al., 2018; Verhoef et al., 2016). Furthermore, Dekimpe (2020) revealed that decisions-making based on data demonstrates greater decisions quality than intuition-driven decision-making. However, different challenges and issues exist related to external and internal variables regarding big data analytics adoption (Mirzaalian and Halpenny, 2019).

We have seen a difference in the rate at which different countries have introduced big data analytics. The difference in BDA adoption patterns can be attributed to a variety of factors, including market environment, government policy, and business leadership (Behl, 2020). As much as it is a logical decision-making mechanism, technology adoption is a cultural problem. Since technology is used in so many different ways, culture is bound to play a role in the implementation and usage of big data analytics. For example, Im et al (2011) demonstrated that the type of information given by accounting systems differed across countries, implying that culture influences how people and organisations use information systems. Another study by Lima and Delen (2020) found that big data analytics adoption and use vary significantly across countries. Thus, our study focuses on the UK, Egypt, and UAE due to the significant cross-cultural variances that help a better comparison and a more critical, robust evaluation of the significant role of national culture in big data analytics adoption. Studies (e.g., Hofstede, 2001) suggested that British and Arab people's perceptions of the cultural dimensions are quite different. For instance, based on the most updated information provided by Hofstede Insights, Arab countries scored higher than United Kingdom (UK) in power distance (UK = 35, Egypt = 70, United Arab Emirates =90 ), and uncertainty avoidance (UK = 35, Egypt = 80, UAE =80). However, the UK scored higher than Arab countries in Individualism (UK= 89, Egypt and UAE= 25) and Masculinity (UK= 66, UAE= 50, Egypt= 45).

The retail sector is seen well-suited for this study due to its unique characteristics and high degree of competition, as well as the fact that big data analytics are deemed critical in the retail industry (Santoro et al., 2019; Ying et al., 20121). For example, collecting huge quantities of data on customers is seen as critical for retail businesses to enhance their competitiveness owing to the tailored product offerings and pricing that can be applied as a result of the data. The past several years have seen dramatic changes in this sector, with consumers being more selective about what they purchase and consume, as well as about pricing. As customers grow more knowledgeable and aware of goods, pricing, and trends, merchants' value chains get more complicated (Santoro et al., 2019). Additionally, this sector is being challenged by declining margins and intense rivalry, which is driving the adoption of new digital technologies to improve efficiency and adaptability (Shankar et al., 2021). Thus, the implementation of big data analytics aides in the management of such complexity.

Innovation adoption theories have been widely adopted in the previous research to explore variables affecting the adoption of big data analytics (e.g., Boldosova, 2019; Daradkeh, 2019; Jayakrishnan et al., 2018; Popovic et al., 2019). However, because the impact of Technology Organization Environment (TOE) variables varies depending on firm size, industry, the type of technology, and the research area (Wang et al., 2019), the results of these studies cannot be expanded and generalised to big data analytics adoption in the retail industry. In another research about the use of new technology, Al-Hujran et al (2018) discovered various TOE variables for various technologies. Thus, our study utilised TOE model as a lens to explore the main variables that can affect the BDA adoption in the retail environment. Furthermore, “Human Organization Technology (HOT) framework” (Yusof et al., 2008) focuses on three main factors of organization, human, and technology that can play a critical role in the success of information systems adoption (Ahmadi et al., 2017). Thus, the significant role of human in enhancing the new technologies and innovations adoption was emphasised through the information technology literature (Carayon, 2016).

Specifically, our examination aims to better explain the variables that can affect the use of BDA under different cultural contexts. Our study was conducted based on three main motivations. The previous studies' results are inconsistent regarding factors affecting BDA adoption, which requires a comprehensive reconciliation and re-investigation of the main factors driving BDA adoption in order to avoid duplicating efforts in future studies. Second, to develop a theoretical basis for future research of innovations adoption, our study investigates factors affecting BDA according to “the Technology–Organization–Environment-Human” (TOEH) model by integrating the human factors into the TOE framework. Thus, this paper utilises a distinct method to offer an integrated model to better understand the main drivers of BDA adoption in the retail industry. Third, our study address the cross culture issue on BDA adoption by exploring how the main drivers of BDA adoption differ between the UAE, the UK, and Egypt. The present paper contributes the following to the IT and big data analytics background: 1) a robust model that can offer a better comprehension of the main determinants of BDA adoption in the retail context; and 2) an investigation of the role of culture in predicting BDA use. Our research can provide retailers with valuable implications to explore the main predictors of BDA adoption and thus the findings support the notion that retailers can invest in big data analytics.

Our paper is conceptualized as follow. The next part concerns the study background. The third part focuses on the suggested framework and hypotheses development. The fourth part discusses the utilized methodology, and the results were demonstrated in the fifth section. The discussion was indicated of the study results. Finally, the research implications and future studies were discussed.

## 2. Literature review

### 2.1. Big data analytics in the retail industry

The BDA concept refers to advanced methods to analyse big data, such as data mining, visualisation, and sense-making (Cabrera-Sánchez and Villarejo-Ramos, 2020). According to Park (2019), the approaches are diverse, so this study contends that BDA activities are critical to the success of big data. Retailers with strong data-driven cultures tend to have top managers who set an expectation that decisions must be anchored in data and that this is normal, not novel or exceptional. As a result, the big data analytics capabilities concept was coined to solve this issue, as it enables a company to effectively execute big data and reap the benefits of its market value (Park et al., 2019).

Practitioners and researchers have always been concerned with the implementation and use of innovations (Alalwan et al., 2017; Ciampi et al., 2021). As a result, numerous innovations adoption studies have been performed in serval environments, such as retailing, education, tourism, and economics (Park et al., 2019). Nonetheless, a significant issue in innovations adoption research is "What determines the propensity of an organization to adopt a particular innovation" (Sun et al., 2018). As a result, various hypotheses have been suggested and investigated to better understand the variables that may affect new innovations' adoption in a company from the organisational point of view (Alalwan et al., 2017).

BDA has become a stimulus that can help companies improve their efficiency and effectiveness due to its strong operational and strategic advantages (Maroufkhani et al., 2020). Firms can use big data strategies to transform data into intelligence and understandable dreams, increasing their productivity (Sun et al., 2018). As a result, BDA has the potential to improve a retailer's efficiency by increasing the pace at which processes are completed (Raguseo, 2018).

### 2.2. Conceptual framework and hypotheses development

Previous studies have utilised different theories as a theoretical basis of technology acceptance studies include "planned behaviour theory (Ajzen,1991)", "the technology acceptance model (Davis,1989)", "Institutional theory" (DiMaggio and Powell, 1983), dissemination of advancement hypothesis (Rogers, 2003), and The innovation association climate system (Tornatzky and Fleischer, 1990).

Despite big data analytics have attracted a great attention from researchers (Cheng et al., 2020; Francia et al., 2020; Sun et al., 2018), little is known on the critical factors affecting big data analytics adoption under different cultural contexts (Buhalis and Volchek, 2021; Mariani et al., 2018). Therefore, our paper seeks to identify the main determinants that can help academics and practitioners to better understand big data analytics adoption under different culture context. Grounded in TOE model, Diffusion of Innovation model (DOI), and the "institutional theory", the present paper seeks to create and empirically test an integrated conceptual framework to explore the critical variables that might affect big data analytics adoption. TOE model is widely adopted and accepted in many disciplines and contexts to investigate and understand the drivers of innovations and new technologies adoption (e.g., Ahmadi et al., 2017; Wang et al., 2016). Prior studies have used the TOE model as a theoretical lenses for investigating the main determinants of IT adoption including “enterprise resource planning” (ERP) software (Awa and Ojiabo, 2016), broadband mobile applications (Chiu et al., 2017), SaaS adoption (Oliveira et al., 2019), Social commerce adoption (Abed, 2020), and hospital information system adoption (Ahmadi et al., 2017). The TOE model was used in the big data environment to examine constructs that can affect big data analytics adoption (Yadegaridehkordi et al., 2020). For instance, Ahmadi et al (2017) utilised the “TOE framework” to explore factors affecting hospital information system’s adoption. They found that “compatibility, relative advantage, mimetic pressures, security concerns, employees’ IS knowledge, and technical competence of IS” are critical drivers of hospital information system adoption, while the other variables were not.

Wang et al (2016) examined the main drivers of adoption of mobile hotel reservation systems (MHRS) using TOE model. The technological dimensions include relative advantage, compatibility, and complexity; the organisational dimensions include “technological competence, top management support, and firm size”; the environmental dimensions include critical mass, information intensity, and competitive pressures. They found that firm size, compatibility, critical mass, complexity, and technology competence are critical determinant of MHRS adoption, while “relative advantage and top management support” were not related to the adoption of MHRS. Lin (2014) has used “TOE framework” as a theoretical basis for examining the main determinants of organisations’ adoption of new innovation. The organisational dimensions contain absorptive capacity, and top management support; The technological factors contain “perceived costs and perceived benefits”; and the environmental dimensions contain competitive pressure and trading partner effect. The results indicated that perceived costs, perceived benefits, absorptive capacity, competitive pressure, and top management support were related to organisations' adoption of new innovation, while firm size and trading partner influence not related to supply chain management systems adoption.

Based on this literature review, factors affecting innovation adoption were observed to differ across different technologies, contexts, industries, and cultures (Wang et al., 2016). Furthermore, the findings regarding a given variable such as relative advantages, top management support, and complexity are inconsistent. Existing innovations adoption models are fragmented to provide a solid theoretical basis for examinations on innovations adoption under different cultural contexts (Mariani et al., 2018). Prior study has proposed that there is a need to construct a comprehensive model of adoption and use for each specific industry, context, and technology (e.g., Oliveira and Martins, 2010; Popovic et al., 2019; Wang et al., 2016). The use of the TOE as a theoretical lenses to the use of BDA under different cultural contexts has not been addressed by prior research. Thus, our paper adopted the TOE model as an overarching theoretical foundation to identify factors affecting BDA adoption under different cultural contexts, in turn expanding its use and application. Fig. 1 indicates our conceptual framework which has been proposed according to the TOE framework. The model demonstrates the main driver of the adoption of BDA including technological factors (i.e., compatibility, relative advantage, complexity, security concern), environmental variables (i.e., external support and competition intensity), organisational variables (i.e., top management support, rational decision-making culture, and firm size), and human variables (i.e., "technical competence of IS staff and IS knowledge"). The adopted theories and hypothesized links are demonstrated in the following section.

Insert Figure 1 about here

#### 2.2.1. Technological factors

Our proposed model examines the technological variables consistent with the “diffusion of innovation model” (Rogers, 2003). This theory has received fundamental support in examining technology acceptance and adoption in various disciplines (e.g., Agag and El-Masry, 2016; Dayour et al., 2019; de Kervenoael et al., 2020). Innovation is defined as “an idea, practice, or object that is perceived as new by an individual or another unit of adoption” (Rogers, 1995, p. 11). Diffusion refers to “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 1995, p. 5). Consequently, “diffusion of innovation theory” suggests that “potential users make decisions to adopt or reject an innovation based on beliefs that they form about the innovation” (Agarwal, 2000, p. 90).

The technological factors in our proposed model were derived from DOI (Rogers, 2003). Relative advantage refers to “the degree to which an innovation is perceived as being better than the idea it supersedes” (Rogers, 2003, p. 229). Prior research revealed that there are two types of benefits related to relative advantage include tangible and intangible benefits such as costs reduction and growth improvement (Rogers, 1995). Premkumar et al (1994) indicated that relative advantage plays an important role in new technology adoption. From a firm perspective, relative advantage includes some elements such as competitiveness and factors related to value, while in terms of business analytics applications, there are some elements that can be used to measure relative advantage such as improving competitiveness, enhancing consumer services, and creating business opportunities. Prior studies revealed that an innovation relative advantage has a significant impact on users intentions to adopt this innovation (Ling et al., 2021; Wang and Lin, 2019). Compatibility refers to “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters” (Rogers, 2003, p. 229). Both the company's needs and the IT infrastructure should be compliant with BDA. Previous research has found a correlation between compatibility and new innovation adoption (Ranjan and Foropon, 2021). Complexity refers to “the degree to which an innovation is perceived as difficult to understand and use” (Rogers, 2003, p. 229). This variable is utilised to evaluate the complexity of big data analytics usage and its applications. This attribute is used to assess the degree of sophistication linked to big data analytics and its implementations. According to previous studies, a new innovation's high degree of difficulty impedes its acceptance (Maroufkhani et al., 2020). Data security represents a main concern in using new information technology and innovations (Agag and El-Masry, 2017; Talwar et al., 2020). Security concern was found in previous research of innovation adoption that significantly impact the decision to adopt innovations (Wang et al., 2016). Consequently, the following hypotheses were suggested:

**H1:** Relative advantage is positively related to retailers’ adoption of BDA.
**H2:** Complexity is negatively related to retailers’ adoption of BDA.
**H3:** Compatibility is positively related to retailers’ adoption of BDA.
**H4:** Security concerns is negatively related to retailers’ adoption of BDA.

### 2.2.2. Environmental factors

External support and competition intensity are also utilised in the environmental factors in prior research of the TOE model and the adoption of information technology (Nam et al., 2019). “External support” refers to the support readiness for utilising and carrying out a technology-based solution (Puklavec et al., 2018). Puklavec et al. (2018) revealed that third-party support and outsourcing is a key determinant of innovation adoption as firms are more likely to implement and use new technology if there is a support from third party and vendor. Furthermore, Lee and Larsen (2009) revealed that external support is a key predictor of adoption and use of IT and innovations. Since some firms have a lack of the IT experts number to motivate and support IT and innovation adoption, external support is a key predictor of the adoption of BDA. Prior research pointed out that external support significantly impacts the adoption and use of IT and innovations (Lee and Larsen, 2009; Puklavec et al., 2018).

“Competition intensity” is defined as the competition encountered by the business in its specific context (Thong, 1999). “Competitive pressure” is a key determinant of a company to adopt new technology (Sun et al., 2019). Firms can achieve a competitive advantage by adopting innovation because of the high level of competition in the market (Amarakoon et al., 2018; Salunke et al., 2019). Companies can avoid losing their competitive advantage if they adopt big data analytics that are using by their competitors (Zach et al., 2020). Prior research revealed that a firm can outperform their competitors by adopting and use big data analytics in their decisions making and business strategy (Puklavec et al., 2018). In support of this notion, Nam et al (2019), and Wang et al (2018) revealed a significant link from competition intensity to big data analytics adoption. Therefore, the following hypotheses are suggested.

**H5:** External support is positively related to retailers’ adoption of BDA.
**H6:** Competition intensity is positively related to retailers’ adoption of BDA.

### 2.2.3. Organisational factors

“Top management support, firm size, and rational decision-making culture” were considered as critical organisational dimensions based on the capability perspective of a firm (Zhu et al., 2003) and the top managers’ functional perspective (Premkumar and Roberts, 1999). Top managers can create the appropriate environment for the innovations and new technology adoption by identifying and demonstrating the benefits of the adoption for the organisation (Hsu et al., 2019; Zach et al., 2020). Prior research indicated that top management support is a key determinant of online supply chain systems adoption (Lin, 2014), while Wang et al (2016) revealed a significant link among top management support and mobile reservation systems adoption. In support of this notion, previous studies empirically supported the significant link among top management support and innovations adoption and use (Haneem et al., 2019; Puklavec et al., 2018).

Damanpour (1992) revealed that larger firms may experience greater economies of scale and capabilities such as technical and financial resources than smaller firms and that facilitate the innovations adoption. Prior research pointed out that large firms often have additional slack resources that enable them to bear the risk of investment, which in turns facilitate the innovations adoption (Zhu et al., 2003). Previous studies empirically supported the significant association between firm size and innovations adoption (Puklavec et al., 2018; Wang et al., 2016). Besides, a sane dynamic culture shows the presence of firm-wide regard for testing, and assessing quantitative procedure in the cycles of choices making. Such a culture assumes a basic part in using information and data to advance work and lead examinations with cutting edge techniques (Lorente-Martínez et al., 2020). Popovic et al (2012) indicated that organisational culture is a key determinant of innovations adoption. Prior research has evidenced a positive link between rational decision-making culture and big data analytics adoption (Puklavec et al., 2018). Thus, these hypotheses are suggested:

**H7:** Top management support is positively related to retailers' adoption of BDA.
**H8:** Firm size is positively related to retailers' adoption of BDA.
**H9:** Rational decision-making is positively related to retailers' adoption of BDA.

### 2.2.4. Human variables

The significance of human variables in the implementation and development of new technologies and innovations has been supported in the IT literature. According to human, organization and technology-fit model, human factors are central to the development and implementation of new technologies adoption (Yusof et al., 2008). The significant role of human factors is neglected in the big data analytics adoption context (Ahmadi et al., 2017). In the innovation industry, human factors should be investigated to evaluate their influence on the adoption and use of innovations adoption (Marques et al., 2011). Based on "HOT-fit model", our investigation explores the role of human components in adopting and implementing BDA. Perceived technical competence is defined as information system (IS) employees' knowledge and capability (Lian et al., 2014). Firms to successfully adopt and implement BDA, IS employees should have enough technologies capability and innovation knowledge. Prior research has supported the significant link between IS employees skills and innovation adoption and use (Lee and Kim, 2007). Employees' technological competencies are a key driver of innovation and new technology use (Lin et al., 2012). It is important for the firms to have IS employees who have sufficient skills and knowledge to develop and implement BDA (Ahmadi et al., 2017). Prior research indicated that employees' IS capabilities and knowledge would help companies to adopt and use new technologies and innovations (Ahmadi et al., 2017; Jebarajakirthy and Shankar, 2021). Consequently, the following hypotheses were posited.

**H10:** Competence of IS staff is positively related to retailers' adoption of BDA.
**H11:** Staffs' IS knowledge is positively related to retailers' adoption of BDA.

### 2.2.5. Culture and BDA adoption

Given the limited cross-cultural research pertaining to UK, UAE, and Egypt, the present overview takes a brief look at examples of cross-cultural research pertaining to big data analytics adoption across a variety cultures. While anthropologists and sociologists have long debated the concept of culture, "few anthropologists are in agreement as to what to include within the general rubric of culture" (Hall, 1976, p. 12). House et al. (2002) described culture as a collection of collective parameters related to "patterned ways of thinking, feeling, and reacting that constitute the distinctive way of life of a community of people" in a ground breaking research on cultural issues (Kluckhohn, 1951, p. 86). In a similar vein, culture is described as "the collective programming of the mind that distinguishes members of one community or category of people from others" (Hofstede et al., 2010, p.6), in which "lifestyle and collective programming of the mind are passed down from one generation to the next through language and imitations" (Adler, 2002, p. 16).

Big data analytics adoption has increased as a result of the advancement of fast communication technologies. Prior research on the link between culture and big data analytics adoption, on the other hand, has shown mixed results (Liyanaarachchi, 2021). The differences in big data analytics adoption across countries are due to a variety of macroeconomic and socioeconomic variables (Bakir et al., 2020). Individuals' perceptions of emerging technology and innovation adoption and implementations are informed by society as a socialisation context. Culture is a key predictor in the adoption and use of inventions, according to a variety of studies. Straub et al (1997), for example, claimed that aspects of the "technology acceptance model" such as perceived usefulness and ease of use varied greatly across cultures. Meso et al (2005) discovered that national culture had a significant influence on the perceived usefulness and ease of use of mobile technology in the sense of mobile technology. Thus, our study directly compared the proposed model between three different cultural countries (i.e., the UK, the UAE, and Egypt) to explore how big data analytics adoption varied across different cultures. Consequently, the following hypothesis was suggested.

**H12:** Factors affecting retailers BDA adoption vary across the UK, UAE, and Egypt.

## 3. Methodology

### 3.1. Sampling procedure

The quantitative phase utilised the survey technique and the self-administered questionnaire method to collect the required data for testing the conceptual framework (Saunders et al., 2019). A survey questionnaire is used to gather analytical data from October to December 2020. A back-translation/parallel-translation technique (Zhang et al., 2018) was employed to translate the original English instruments into Arabic and then translate the Arabic version back to English by two language professionals who were not associated with this study. The degree of correspondence between the back-translated version of the items and the original items was very high indicating the absence of translation biases. Data were collected from three different societies (UK, UAE, and Egypt). These countries were selected for our analysis because of the significant cross-cultural variances that help a better comparison and a more critical, robust evaluation of the significant role of national culture in big data analytics adoption (See Table 1).

Insert Table 1 about here

The target population for this study was retailers in general. The retail industry is a large and diverse group that includes banks, petroleum companies, clothing and grocery stores. Our target respondents were "managers and decision-makers" who possessed a full understanding of big data analytics techniques. The questionnaire included a screening question to filter out participants who are unfamiliar with BDA. Several of the scaled objects were reverse coded to ensure that participants thought about their responses when filling out the survey. The research procedures involved online surveys in Egypt, UAE, and the U.K. administered by a professional panel firm in each country. We distributed 3000 sets of questionnaires to managers and decision-makers at these retailers, of which 1000 questionnaires were distributed in each country. Once the potential participants were identified, emails were sent to them requesting participation. They were followed up a few days later and either agreed to participate or suggested an alternative. The questionnaires were then sent out to those who agreed to participate. These questionnaires were attached to an email requesting the completion of the questionnaire. The participants were informed about the main purpose of our study and their responses will be kept strictly confidential. Overall, 2,370 participants responded but only

2,278 responses were deemed valid for further examination, of which 629 were obtained in UK, 746 in UAE, and 903 in Egypt. The response rate was 62.9% in the UK, 74.6% in UAE, and 90,3% in Egypt. Table 2 demonstrates the demographics of the sample.

Insert Table 2 about here

### 3.2. Variables operationalization

All measuring items were derived from previously validated instruments and slightly adjusted for this study's setting. Multiple-item measures were used to assess all study variables. Each question was phrased as a statement, and respondents were asked to rate their agreement or disagreement with the assertions on a 5-point Likert scale (1: strongly disagree; 5: strongly agree). The study questionnaire consists of two main parts, including information about respondents, independent, and dependant variables measurements. Big data analytics adoption is the dependent variable and was assessed using items utilised from previous research (e.g., Maroufkhani et al., 2020; Raguseo and Vitari, 2018). Reliable and valid measurements were utilised from previous research to evaluate the study constructs. Technological variables (i.e., relative advantage, compatibility, complexity) utilized from prior studies (e.g., Grover, 1993; Ramamurthy et al., 1999; Wang et al., 2016). Security concern was assessed using a scale developed by Soliman and Janz (2004), and Goodhue (1998). Environmental factors (i.e., external support, competition intensity) were utilised from previous studies (e.g., Nam et al., 2019; Puklavec et al., 2018). Organisational constructs (i.e., top management support, firm size, rational decision-making culture) were utilised from prior research (e.g., Soliman and Janz, 2004; Wang et al., 2016). Finally, Human factors (i.e., “technical competence of staff and employees’ information system Knowledge”) were measured through established and validated measures developed by Kuan and Chau (2001) and Ahmadi et al (2017). A pilot test was conducted for both samples (English and Arabic version) with a sample of managers (40) each to evaluate the research instrument validity and reliability. According to the pilot feedback, a few statements were revised to enhance the clarity of expression.

### 3.2. Common method variance

In order to avoid "common method bias", different methods were utilised to test common method bias. First, prevention and post-detection procedures were conducted as suggested by Podsakoff et al. (2003). The survey was completed anonymously by the respondents and the items of the measurements were ordered randomly. Second, the common latent factor method was used (Eichhorn, 2014), which entails combining all of the study items into a single latent factor (CLF). Forty-two items of twelve factors are subsumed into a CLF. A PLS analysis was performed and the regression parameters are based on the bootstrapping of 100 samples. The standardised regression weights of the two models were compared with and without the CLF after adding the LFC to the measurement model. The analysis found that the values were identical (the difference was less than 0.2) (Gaskin et al., 2017). The models' fit indices were identical in both cases (model with CLF: 2/df=1.905; model without CLF: 2/df= 1.984). These studies showed that in our study, traditional method bias should not be a problem.

## 4. Analysis and results

The SmartPLS 3 technique was used to validate the measurement model and test the study hypotheses (Ramayah et al., 2018). The validity and reliability of the variables for both versions (i.e., English and Arabic) were tested in the first step of the analysis, followed by structural model analysis.

### 4.1. Measurement model

Based on Hair et al (2019), the measurement model was evaluated by examining the latent constructs' reliability, convergent, and discriminant validity for both versions (i.e., English and Arabic). Table 4 indicates that the values of all indictor loadings and composite reliability for both versions are above the critical threshold of 0.7, the values were between 0.831 and 0.960. Thus, the measures internal validity for each latent variable was established. The research constructs' "average variance extracted" (AVE) was calculated for both versions. The AVE values are all greater than 0.50, which follows Fornell and Larcker's (1981) guidelines (Table 3). As a result, the findings affirm convergent validity. The AVEs value was compared to the squared between-constructs relations. The AVEs values were found to be greater than the related squared between- constructs relations for both versions (Table 4). As a result, discriminant validity was found to be correct. Furthermore, the discriminant validity of our sample variables was assessed using the "heterotrait-monotrait ratio" (HTMT) (Henseler et al., 2016). The HTMT values for all study constructs for both versions were less than 0.85, indicating that the variables are discriminately accurate. Furthermore, the issue of multi-collinearity was assessed by utilising VIFs for constructs with a value of less than three, as recommended by Bagozzi et al (1991) (Table 3).

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Insert Tables 3 & 4 about here

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### 4.2. Structural model

Following the measurement model assessment, the structural model was assessed using the total sample (N=2,278). A PLS analysis was performed to test H1 through H11. The regression parameters are based on the bootstrapping of 100 samples and not on a sample estimator. This facilitates the computation of the respondents' t-test for each hypothesis, and the generalization of the results (Rasoolimanesh et al., 2017). The results represented in Table 5 indicate the relationship between the different constructs. According to Richter et al. (2016), since all the r-squares are higher than 0.10 the predictive capability of the model is satisfactory. The results revealed that the study model assigns 73% to big data analytics adoption.

Insert Table 5 about here

All the suggested hypotheses are approved, except H1, H2, and H3.. Firstly, the paths between the technological constructs (i.e., relative advantages, complexity, compatibility, and security concern) were evaluated. As hypothesised, H3 and H4 links were significant (β = -0.37, -0.61, $p<0.001$), while H1 and H2 were not. Moreover, H3 is negatively related to BDA adoption and not positively, as previously hypothesized. Regarding environmental factors (i.e., external support and competition intensity), both have a significant effect on BDA ($\beta$ = 0.33, 0.27, $p<0.001$), supporting H5 and H6. The links between organizational factors (i.e., top management support, firm size, and rational decision making culture), and BDA were assessed. The findings indicated that they all have a significant effect on BDA ($\beta$ = 0.56, 0.19, 0.46, $p<0.001$). In addition the human factors (competence of staff and IS knowledge) were related to BDA ($\beta$ = 0.69, 0.40, $p<0.001$, respectively). These results support hypotheses H7, H8, H9, H10, and H11.

Insert Tables 6 & 7 about here

**4.3. Multigroup analysis to test differences across countries**

Because of the variances among the selected three countries, our study also seeks to examine whether the associations between the study variables would vary through the three samples. "a multi-group analysis" (MGA) was performed to explore the significant differences across the countries. Based on Henseler et al (2009), PLS-MGA was used. Measurement invariance issues is a potential concern when utilising MGA to test path differences across countries. We should make sure that the measures of the study variables are invariant across the samples. Based on Henseler et al (2016), a PLS-MGA can be performed when compositional and configural invariance are confirmed. The data treatment, the measurement and structural model were confirmed to be equal across the three samples. Henseler's MGA directly compares group-specific bootstrap estimates from each bootstrap sample. According to this method, a p value of differences between path coefficients lower than 0.05 or higher than 0.95 indicates at the 5% level significant differences between specific path coefficients across two groups (Henseler et al., 2009). We conducted a permutation procedure with a minimum of 1000 permutations and 5% significance level for each combination of countries.

Following this, a comparison was made of the original score correlations c against the empirical distribution of the score correlations obtained through the permutation process (cu), to see whether c exceeds the 5% quantile of cu. Table 6 demonstrates that compositional and configural invariance are established which enables us to employ PLS-MGA (Richter et al., 2016). Furthermore, we also made sure that factor loadings through all three samples were greater than cut off value of 0.70, indicating that the measures are invariant and generalizable across the three countries.

Regarding the effect of relative advantage on BDA, this link was larger in ~~UAE and Egypt~~ UK than in the UAE and Egypt (see Table 7). Nonetheless, the differences are significant for UK-UAE, UK-Egypt, and UAE-Egypt comparisons. As for the effect of complexity on BDA, we found that this relationship is weaker in UAE and Egypt compared with the UK. However, these differences are not significant between the three countries. Concerning the link between compatibility and BDA, this relationship is larger in UK than in the UAE and Egypt. Nonetheless, the differences are significant only for UK-Egypt comparisons. Regarding the effect of security concern on BDA, this link was larger in the UK than in the UAE and Egypt.

Nonetheless, the differences are significant for UK-Egypt comparisons. Regarding the effect of external support on BDA, this link was larger in the UK than in the UAE and Egypt but the differences were not significant. The link between competition intensity and BDA is stronger in the UAE and Egypt compared with the UK however, these differences are significant for only UK-UAE comparisons. Furthermore, the results indicated that the influence of top management supportand rational decision making culture on BDA is significantly stronger in the UK compared with the UAE and Egypt. While the influence of firm size is stronger in UAE and Egypt than UK. These differences are not significant. For technical competence of staff and staff IS knowledge, the results revealed that the effect of these variables on BDA is stronger in Egypt compared with UK and UAE. These differences are significant for UK-UAE comparisons. These results support hypothesis H12.

# 5. Discussion and conclusions

## 5.1. Conclusion

The present paper investigates the main determinants of BDA adoption in the retail industry using the TOE framework as a theoretical basis for our suggested conceptual framework. As suggested, security concern is an impediment of BDA (see Ahmadi et al., 2017; Grover, 1993). Our study findings are consistent with Maroufkhani et al (2020) study, which indicated that both relative advantages and compatibility have no significant effect on big data analytics adoption. Furthermore, these findings are consistent with Ahmadi et al (2017) study, which pointed out that complexity is not related to adoption. Due to a lack of internal knowledge, retailers can find it difficult to implement new technologies. For retailers, managers may lack trust in their company's ability to effectively implement BDA.

While past research on IT and developments reception affirmed that general benefit significantly affects the selection (e.g., Ameen et al., 2018; Li et al., 2011; Wang et al., 2010), our study revealed that relative advantage is not related to BDA adoption. These findings are consistent with previous empirical studies (e.g., Ahmadi et al., 2017; Puklavec et al., 2018; Wang et al., 2016). This insignificant link between relative advantage and adoption can be due to adopters are well aware of the advantages of BDA adoption. Our study also found that security concern is a major inhibitor of retailers' adoption of BDA. Lian et al (2014) indicated that security concern is a major barrier of innovations adoption. The main reason is that privacy and information security are a major concern in the retail industry. Therefore, information security and network reliability should be guaranteed and considered by retailers (Winston et al., 2016).

With regard to environmental factors, the results revealed that external support and competition intensity have significant influence on BDA adoption . Regarding external support, our findings were inconsistent with prior research that did not find a significant effect of external support on adoption (e.g., Premkumar and Roberts, 1999). The results also demonstrate that competition intensity is a key determinant of retailers' adoption of BDA. Prior research indicated that "competition intensity" improves the incentive of utilising innovations (Nam et al., 2019). Thus, retailers highly expect BDA to provide them with a competitive edge. These results differ from Wang et al (2016) study of mobile reservation systems adoption, which found that competition intensity is not related to adoption.

Regarding the organisational factors, the present study results indicated that firm size has an effect on adoption of BDA. The findings are compatible with prior studies (e.g., Ahmadi et al., 2017; Wang et al., 2016), which found that firm size is a key predictor of new technologies and innovations adoption. However, these findings are not in line with Nam (2019), who revealed that firm size is not linked to firms' adoption of new technologies. Furthermore, our study results indicated that top management support is linked to retailers’ adoption of BDA. The findings are inconsistent with prior research by Wang et al (2016), who revealed that top management support is not linked to the adoption of mobile reservation systems. Nevertheless, these findings are in line with Lin (2014), who found that top management support has a significant positive effect on new technologies adoption. While prior studies revealed that there is a lack regarding examining the critical role of “rational decision-making culture” in the innovations adoption context (e.g., Puklavec et al., 2018), our study findings found that rational decision-making culture are associated with BDA adoption.

Our study also indicated that human factors reflect the crucial role of staffs' IS knowledge and competence of IS staff in BDA adoption in the retail industry. Retailers should provide staffs with training to improve their IS skills and knowledge. Prior research found that IS staffs with sufficient IS skills and knowledge facilitate the adoption process (Carayon, 2016; Sulaiman and Wickramasinghe, 2014). Our study findings support Ahmadi et al (2017) study, who found that staffs' “IS knowledge and technical competence of IS staff” are related to the new technologies and innovations adoption. Thus, retailers staffs with greater IS knowledge, skills, and capabilities are more willing to adopt big data analytics. The results of our study revealed that security concerns, external support, top management support and rational decision making culture have a greater effect on BDA adoption in UK than in both UAE and Egypt~~.~~. This finding proposes that investments in security concerns may “pay off” less in UAE and Egypt, where adoption of BDA are more sensitive to other variables such as competition intensity, and firm size. Moreover, the human factors (perceived technical competence of staff and staff IS knowledge) have a greater effect on BDA adoption in Egypt than in UK and UAE.

## 5.2. Theoretical implications

From a theoretical standpoint, the findings of our study contribute to the new technologies and innovations adoption literature in the retail industry in different ways. Our study contributions are derived from developing a new conceptual framework that provides new findings in a new context.

Regarding the new conceptual framework, an integrated model was developed depending on TOE to include different perspectives into a suggested adoption comprehensive model. Drawing upon the “diffusion of innovation theory” (Rogers, 2003), our research revealed that security concerns is the only technological factor that affects BDA adoption in the three countries. Then, according to the capability perspective (Zhu et al., 2003) and top managers functional perspective (Premkumar and Roberts, 1999), our study suggests that firm size, top management support and rational decision making culture constitute organisational factors that affect BDA adoption. Finally, based on competitive bandwagon pressures perspective (Abrahamson and Rosenkopf, 1993) and Puklavec et al (2018) study, our study proposed that competition intensity and external support as environmental factors that can influence BDA adoption.

As for new findings, the results of our study were compared with the results of prior new technologies and innovation studies, indicating to what extent our study results differ from prior research results as well as how these inconsistent findings are interpreted. The inconsistent results with previous studies results and the different interpretation of these findings indicate the novelty of the present study. Regarding the previous theoretical perspectives applicability, our paper found that relative advantage, complexity and compatibility, which have a significant influence on new technologies and innovations adoption in the previous studies (e.g., Ahmadi et al., 2017; Lin, 2014; Puklavec et al., 2018; Zhu et al., 2003), have no crucial role in adopting big data analytics in the retail environment.

Thus the results assert that the theoretical basis for these three variables have no significant influence on new technologies and innovations adoption in the retail context.

Lastly, regarding the new context, previous studies have not paid sufficient attention to big data analytics in the retail environment. Our study bridged this research gap by examining and identifying factors affecting retailers' adoption of BDA in specific context. Thus, our study provides new insights into specific technology in specific context. Furthermore, our study provides researchers with valuable directions for further studies on -BDA adoption in the retail industry. Our study predicts 73 % of the variance of BDA adoption, which indicating that future studies should examine other independent variables that may affect retailers' adoption of BDA.

Although many studies have been conducted on the adoption of big data analytics in various settings (Wang and Hajli, 2017; Wang et al., 2018), there is a dearth of empirical research on big data analytics in the retail sector. Maroufkhani et al. (2019) conducted a comprehensive assessment of the literature on big data analytics and discovered a dearth of research on the subject in the retail environment. Given that the retail environment is distinct from other sectors in terms of resource availability and scale, this research sought to identify the most relevant variables influencing big data analytics adoption in retailing, namely in the United Kingdom, the United Arab Emirates, and Egypt. This research developed a single, unique model for assessing the impact of many variables on big data analytics adoption. The study's findings indicate that, security concern, external support, competition intensity, top management support, firm size, rational decision making culture, competence of staff, and IS knowledge all play a significant role in retail managers'/decision-makers' decision to adopt big data analytics. Whereas relative advantage, complexity, and compatibility~~making~~ have no effect. The discrepancy between our findings and those of earlier research conducted in a variety of settings revealed the presence of distinct drivers of big data analytics adoption in the retail sector and other industries. In contrast to Al-Hujran et al. (2018), who identified relative advantage as a major driver of big data analytics adoption, our results indicated that there was no significant connection between these concepts among retail companies.

Regarding cultural differences among the three countries, our findings show that the factors influencing retailers' adoption of BDA differ among the UK, UAE, and Egypt. As per Hofstede Insights, UAE and Egypt score higher than the UK based on power distance and uncertainty avoidance. In terms of individualism and masculinity, the UK scores higher than UAE and Egypt. In societies with high power distance, such as UAE and Egypt, concentration of authority is at the top-level management and the authoritative managerial style is common. Thus, top-level management support is expected to have a relatively large impact on new technological adoption in these societies. In the UK, however, we find that top management support has a greater impact on BDA than it does in Egypt or the UAE. Also, people who live in high-uncertainty avoidance societies, like the UAE or Egypt, avoid uncertainty and unpredictability. Consequently, security concerns are deemed important for the adoption of new technologies in such societies. However, our results show that security concerns have a greater influence on BDA in the UK, which has a low uncertainty avoidance score, than in the UAE or Egypt.

In societies with high individualism scores, such as UK, there is a high belief in individual decision-making. As a result, any adoption of new technologies in these societies is likely to be strongly influenced by the rational decision-making culture. This is supported by our results, as the influence of rational decision-making culture on BDA is significantly stronger in the UK compared with the UAE and Egypt. Finally, companies in high masculinity societies, such as UK, count on very work-oriented employees. As a result, human factors (competence of IS staff and staffs' IS knowledge) are expected to be relatively important for any adoption of new technologies in such societies. Our results show that the human factors influence on BDA is significantly stronger in Egypt, which is considered as a relatively feminine society, than UK and UAE.

### 5.3. Managerial implications

Our study offers meaningful implications for retailers. First, the findings indicated that relative advantage, compatibility, and complexity, are not related to BDA adoption, while security concern , external support, competition intensity, top management support, firm size, rational decision making culture, competence of staff, and IS knowledge were related to the adoption of BDA. The results suggests that BDA advantages should not be a main focus for BDA systems providers. In order to facilitate BDA adoption process, BDA developers should provide retailers with timely support on the adoption process. For example, providers can provide retailers with the "product supporting data quality management" and decreasing analytics centrality to retailers. Furthermore, retail managers, IT department, and top management should use more sophisticated security features the highest priority is given to ensuring data security. Retailers could share and demonstrate comparable industry success stories. Retailers are reluctant to engage in big data analytics if the advantages are unknown; however, learning about good experiences in other sectors may sway their choice. As a result, merchants of big data analytics may increase the visibility of the big data analytics adoption by giving information on its penetration rate.

Second, our study results indicated that firm size plays a crucial role in big data analytics adoption. Larger retail have additional technical, financial, and managerial resources that can support BDA adoption. Big data analytics systems suppliers should focus on larger retailers as potential users. Moreover, smaller retailers may look for external aid and incentives from other retailers and government. Smaller retailers can also cooperate with other retailers that can help them on the BDA adoption process. Additionally, since security concerns are of the primary impediments to implementing big data analytics, several retailers postpone implementation. As a result, suppliers of big data analytics should offer a trial version in addition to training and technical assistance to help customers overcome such concerns.

Third, “perceived technical competence of IS staff and employee’s IS knowledge” found to be related to BDA adoption. When retailers are making decisions about the adoption of new technologies, IS staff capabilities and skills are necessary and needed for the adoption process. Retailers should improve the level of IS staff awareness, skills, and knowledge through providing them with education and training programs.

Our study offers a meaningful suggestion to practitioners. As the adoption of big data analytics create great national value in the long term, governments should encourage and support retailers to adopt BDA. This is consistent with the some countries such as United Arab Emirate’s vision of 2025 to have information systems and innovations in every sector and in particular retail industry. According to the United Arab Emirate’s vision of 2025, the UAE government offers free education for business intelligence and big data analytics and runs programs that can support and encourage firms to adopt big data analytics. Therefore, policymakers should change their strategies and polices by understanding what retailers and other companies expect from the governments in encouraging and supporting the adoption of big data analytics.

Finally, our findings support the idea that security concerns, external support, top management support, and rational decision making culture, have a greater effect on BDA adoption in UK than in UAE and Egypt. This finding proposes that investments in security concerns, may “pay off” less in UAE and Egypt, where adoption of BDA are more sensitive to other variables such as competition intensity and firm size. Moreover, Egypt is more sensitive to perceived technical competence of staf, and staff IS knowledge than UAE and UK. Multinational companies may first consider entering into the retail markets where consumers with these cultural patterns proliferate. Furthermore, global corporations must consider the cultural background of emerging markets (e.g., the United Arab Emirates and Egypt) in order to compete in this lucrative market.

## 6. Limitations and future studies suggestions

Despite the valuable implications for practitioners and researchers this study has, there are still some limitations. First, our study focused on investigating factors affecting big data analytics adoption in the retail industry. It would be worthy to replicate this research for various industries, to reach more insightful conclusions. Second, since the participants in this study came from the United Kingdom, the United Arab Emirates, and Egypt, the findings maybe not generalise to other cultures. Future studies may use our conceptual framework in a variety of cultural contexts, as well as compare and contrast different cultures to validate our suggested conceptual framework in various societies. Third, our study utilised SmartPLS 3 software method to examine factors affecting retailers' BDA adoption. Future research is encouraged to take into consideration the interaction effects by examining the relationships between the independent variables. Fourth, the research is cross-sectional in nature, with hypotheses evaluated via a questionnaire survey. This method imposes constraints on the capacity to establish causality in connections between variables. The study's findings are skewed by the fact that it was unable to monitor the dynamic changes in big data analytics adoption. To get more accurate findings, a longitudinal research is required to evaluate the established connections over an extended period of time. Finally, further research should be conducted to complement this study's conceptual framework by taking into account other relevant variables such as organisational culture, market pressure, and technological infrastructures (Alalwan et al., 2017; Behl et al., 2019).

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