UNIVERSITY OF CAPE COAST

MARKETING ANALYTICS USE INTENTIONS, USER SATISFACTION AND CONTINUANCE USAGE AMONGST FIRM EMPLOYEES IN GHANA

KOJO KAKRA TWUM

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BY

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Thesis submitted to the Department of Marketing and Supply Chain Management of the School of Business, College of Humanities and Legal Studies, University of Cape Coast, in partial fulfilment of the requirements for the award of Doctor of Philosophy degree in Business Administration

OCTOBER 2021

DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature ………………….. Date: …………………………..

Name: Kojo Kakra Twum

Supervisors' Declaration

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

Principal Supervisor's Signature……………… Date …………………

Name: Dr. Isaac Dasmani

Co-Supervisor's Signature …………………………... Date: ………………

Name: Dr. Andrews Agya Yalley

ABSTRACT

This study examines the factors affecting user intentions, actual use, user satisfaction and continuance usage of marketing analytics technology by firm employees in a developing country context. The study adopted an explanatory sequential mixed methods approach. Quantitative data was collected from 213 firm employees through convenience sampling. The study used an online survey to collect the quantitative data, while interviews were used to collect data for the qualitative study. The quantitative data collected was analysed using Partial Least Squares Structural Equation Modelling through SmartPLS 3. The qualitative study using purposive sampling collected data from six firm managers using in-depth telephone interviews. The qualitative data were coded using MAXQDA and analysed using thematic analysis. The results reveal that performance expectancy, facilitating conditions, user attitudes, and perceived trust predict intentions to use marketing analytics. Effort expectancy, social influence, and personal innovativeness in information technology were found not to predict intentions to use marketing analytics. The study also found that intention to use marketing analytics is a predictor of actual use of the technology. Apart from the moderating effect of age and type of innovator on effort expectancy, all the proposed moderating effects were not significant. Actual use was also found to be a predictor of user satisfaction. The study also found that user satisfaction is a predictor of continuance usage of marketing analytics technology. The study concludes that intentions determine the actual use of innovative technologies, while user satisfaction affects continuance usage. This study has practical implications for firms seeking to enhance the use of marketing analytics technology in developing countries.

KEY WORDS

Continuance usage

Developing countries

Intention to use technology

Marketing analytics

Technology acceptance

User satisfaction

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DEDICATION

To my beloved daughter, Akosua Kwartemaa Twum

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CHAPTER ONE

INTRODUCTION

The adoption and use of technologies by firms is a prerequisite for attaining competitiveness and enhanced performance. Consequently, the interest in how firms adopt innovative technologies has been acknowledged (Oliveira & Martins, 2011). Scholars have also been concerned about how individual end-users accept innovative technologies (Brandone-Jones & Kauppi, 2018; Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012; Venkatesh & Zhang, 2010). Following the proposal of Venkatesh et al. (2012), studies, therefore, use theories and introduce new constructs to study how individual technology users in other cultural contexts accept innovative technologies.

From theoretical and empirical perspectives gained from scholars such as DeLone and McLean (2003), Bhattacherjee, Perols and Sanford (2008) and Gorla, Somers and Wong (2010), the acceptance to use, the level of satisfaction, and the willingness to continue using innovative technologies such as marketing analytics is vital to gain competitiveness from investments. Therefore, the research lacuna is related to understanding what factors influence firm employees' acceptance of adopted marketing analytics technologies and how their satisfaction with these technologies leads to continuance usage.

This chapter presents the background to the study, statement of the problem, the purpose of the study, research objectives, research questions, research hypotheses, the significance of the study, delimitation, limitations, definition of terms, and organisation of the study.

Background to the Study

The very complex and competitive business environment demands that businesses adopt innovative ways to differentiate themselves from competitors (Demirkan & Delen, 2013). In order to be very competitive in this changing business environment, there is the need to use data to understand the market. McAfee, Brynjolfsson, Davenport, Patil and Barton (2012) posit that data use enables managers to understand the business environment better and use this knowledge to enhance firm performance and decision-making. The extensive use of big data has led to the use of business analytics tools (Holsapple, Lee-Post, & Pakath, 2014) and marketing analytics (Wedel & Kannan, 2016) for decision-making.

Various stakeholders have promoted the use of innovative technologies by firms and individuals as it contributes to socio-economic development (Armentia, Serrano, Cabrera, & Conte, 2012). Consequently, considerable investments in innovative technologies have been witnessed (Hall, Lotti & Mairesse, 2013), including marketing analytics, which constitutes 5.8 per cent of the marketing budget (CMO Survey, 2018). Along with the increased investments in new technologies, there is a corresponding motivation to research on technology acceptance (Sun & Zhang, 2006).

The philosophy that might explain the use of innovative technologies to attain competitive advantage is Darwinism (Moore, 2007). Darwinism explains the struggle for survival in a social system (Hofstadter, 1955). Moore (2007) proposes that markets operate with the same rules as organisms in the natural ecosystem and concerns the ability to innovate forever. Innovation is necessary at every stage of a company's evolution, which is crucial in ensuring the firm stays competitive in the marketplace. Darwin's seminal work, 'The Origin of Species', has provided an explanation of organisational evolution and survival (Abatecola, Belussi, Breslin, & Filatotchev, 2016). Schuster (1996) compares Darwin's view of biological evolutions to technological developments in terms of technologies having finite lifetime just like biological organisms, and technologies also helping to form networks and mutual dependencies just as species do in ecosystems.

As a philosophy, technology Darwinism helps explain that technology is a complex system composed of many sub-systems that enable the interaction and evolution of existing technologies to generate innovation (Coccia, 2019). Consequently, Darwinism has been used to explain the adoption of new technologies such as Bitcoin as a new payment system (Wonglimpiyarat, 2015). Moore (2007) argues that innovation must not be viewed as adding common features in the marketplace in the wake of intense competition but the ability to create unique and differentiated offerings.

From the earlier discussions on Darwinism in the technological context, marketing analytics could be considered a new Darwinism of marketing decision making and managing marketing function, as this technology seeks to replace reliance on managers' intuition and perception of the marketplace. Marketing analytics technology has been recognised by Vollmer (2010) as a digital Darwinism as it has the opportunity to drive change in an organisation. The use of marketing analytics technology can also explain the survival of organisations in a very competitive business environment.

It is worth noting that the emergence of "big data" has catapulted marketing analytics technology. In recent times, the growing interest in big data by businesses has resulted in integrating analytics in business functions such as marketing. Big data represents the availability of enormous volume (the amount of data), variety (the many sources and types of data), and velocity (the speed at which data is collected and used), which firms use in improving decision making (Chen, Chiang, & Storey, 2012). De Luca, Herhausen, Troilo and Rossi (2020), citing the survey by Davenport and Bean (2019), state that about 91.6 per cent of Fortune 1000 companies are increasing their investments to accelerate the development of big data.

Erevelles, Fukawa and Swayne (2016) posit that analytics related to the consumer is the epicentre of the big data revolution making marketing analytics an important aspect of big data. The assertion of Lapointe (2012) that big data has penetrated all aspects of business decision making is supported by Erevelles et al. (2016), Xu, Frankwick and Ramirez (2016) that marketing analytics has been made possible through big data. Marketing analytics is referred to as using technology to harness data and knowledge to support marketing decisions (Lilien, 2011). Marketing analytics is becoming a major business tool that uses technology to harness data about the market and customers to improve decisions (Germann, Lilien, & Rangaswamy, 2013).

Marketing analytics is one of the various forms of business analytics, which influences decision-making effectiveness through the existence of a data-driven environment (Cao, Duan, & El Banna, 2019). Apart from the application of business analytics in marketing, all other business analytics forms in retail, risk management, supply chain, and human resource, have greatly affected business decision-making (Holsapple et al., 2014). Analytics in modern-day business can be best described as using data, which may be structured or unstructured, and applying formal analysis that helps make better business decisions (Agrawal, 2014).

The use of marketing analytics has been well documented. Davenport (2006) makes reference to the use of analytics by Barclays Bank, Marriot, Honda, and Intel, while Germann et al. (2013) reveal the use of the technology by Fortune 1000 companies in the US. Cao and Duan (2017) also report on the use of marketing analytics by reputable firms in the UK. The CMO Survey (2017) reports that 37.5 per cent of decision making, 37 per cent of customer acquisition, 36.7 per cent of digital marketing decisions, and 34 per cent of customer insights are based on marketing analytics.

The growth in the use of marketing analytics can be attributed to the involvement and marketing of the technology by global software companies such as IBM, Microsoft, Oracle, SAP (Zhang et al., 2012). SAS, an analytics service provider, for instance, provides marketing analytics services to 91 of the top 100 Fortune 500 companies such as Nestle and Honda (https://www.sas.com/en_nz/company-information/why-sas.html). It is important to note that data analytics savvy firm managers are needed to take advantage of the growth of big data (Manyika et al., 2011; Parks, Ceccucci, & McCarthy, 2018). Therefore, the need for employees with skills and expertise in business analytics is on the rise and would be necessary for firm competitiveness.

There is also evidence of the use of analytics technology in sub-Saharan Africa and Ghana. On the websites of analytics service providers such as Nokia (Nokia, 2017), Deloitte (https://www2.deloitte.com/gh/en/pages/deloitte-analytics/topics/deloitte-analytics-services.html), Google (Google Marketing

Platform, 2021), and IBM (https://www.ibm.com/gh-en), firms are provided with analytics services in countries such as Ghana and Nigeria. Afful et al. (2018) also assert that big data use in Ghana is growing due to enormous digitalised data created by the increased provision of government services online, increased mobile communications devices, and electronic transactions. Consequently, analytics has been applied in the agricultural sector (Lokers, Knapen, Jansen, Randen, & Jansen, 2016) and in the banking sector (Kester & Preko, 2015) in Ghana.

The use of analytics technology is recommended because scholars such as Amidu, Effah and Abor (2011); Hinson and Boateng (2014); Osabutey, Williams and Debrah (2014); and policymakers (World Bank, 2019) have proposed that the use of information technology is needed to enhance business performance and economic development in developing economies. From a policy perspective, the Ministry of Communication and Digitalisation of Ghana has begun to promote analytics technologies through promoting database management systems and digital transformation programmes (Ministry of Communication and Digitalisation, 2021). The United Nations is leading a strategy to introduce analytics into data gathering, analysis and use among member countries (United Nations Office of Information and Communication Technology, 2021).

The use of analytics technology will greatly depend on firm managers and employees' perceptions and decisions to use the technology (Germann et al., 2013; Verma, Bhattacharyya, & Kumar, 2018). The need to understand the acceptance and use of marketing analytics technology brings to the fore attempts by scholars to understand what factors will influence firm employees to use the systems. The starting point is to consider the knowledge acquired from existing technology acceptance theories and models to study end-user acceptance and use of innovative technologies.

From a theoretical perspective, scholars such as Venkatesh et al. (2003) developed the UTAUT that proposes that the intention to accept and use technology is dependent on the firm employees' performance expectancy (perceived usefulness), effort expectancy (perceived ease of use), social influence, and facilitating conditions. From an empirical perspective, the UTAUT theory also explains the effect that technology user characteristics have on technology acceptance. Venkatesh et al. (2003) postulate that firm employees' age, gender, and experience will play a key role in their intentions to use innovative technologies.

Using the Technology Acceptance Model (TAM) by Davis (1985) and the Theory of Planned Behaviour by Ajzen (1991), the UTAUT explains that the intention to use technology is the strongest predictor of actual use behaviour. Also, from the Diffusion of Innovation Theory perspective, scholars have proposed the effect of the personal innovativeness of technology users to be an important determinant of use intentions of many technologies (Agarwal & Prasad, 1998; Chen & Chen, 2011; Joo, Lee, & Ham, 2014; Lu, Yao, & Yu, 2005; Shorfuzzaman, Hossain, Nazir, Muhammed & Alamri., 2018; Yi, Fiedler, & Park, 2006). The acceptance of technology has also been proposed to be dependent on the attitude of the end-users (Davis, 1985; Davis, Bagozzi, & Warshaw, 1989; Dwivedi, Rana, Jeyaraj, Clement, & William, 2019; Kim, Chun, & Song, 2009; Verma et al., 2018; Yang & Yoo, 2004). Verma et al.

(2018) support the consideration of user attitude in understanding the acceptance and use of analytics technology.

The adoption of technology has also been a concern, especially the risk they pose for business and customers and issues relating to the trust of the technology and supplier. Studies on the adoption of innovative technologies propose that the risk and trust issues affect the intentions of end-users to adopt them (Carter, Shaupp, Hobbs, & Campbell, 2011; Escobar-Rodríguez & Carvajal-Trujillo, 2014; Kamal, Shafiq, & Kakria, 2020; Oliveira, Faria, Thomas, & Popovič, 2014; Pavlou, 2003; Slade, Dwivedi, Piercy, & Williams, 2015; Yuan, Lai & Chu., 2019). The protection of firm and customer data is an important issue that marketers consider in using analytics systems (Petrescu & Krischen, 2018).

Despite studies proposing that intentions to use innovative technologies will affect actual use (Dwivedi et al., 2019; Zhang et al., 2019), the external environment such as the industry in which a firm operates may serve as a determining factor in predicting the actual use of marketing analytics technology (Hernández-Ortega, Martinez, & Jose Martin De Hoyos, 2006). From the Technology-Organism-Environment (TOE) framework by Tornatzky and Fleischer (1990), an argument can be raised that the industry (service, manufacturing) in which a firm operates may play an important role in influencing the use of marketing analytics technology.

The marketing literature also takes a strong position in ensuring firms benefit from innovative technologies to enhance their competitiveness. One major marketing concept contributing to the acceptance and continuance use of innovative technologies is user satisfaction. Dalcher and Shine (2003) emphasise the importance of the level of satisfaction with technology since this has a better likelihood of influencing behavioural responses. Using the Expectancy confirmation theory perspective, Oliver (1980) argues that the satisfaction derived from a product or service results from evaluating expectations and actual performance of the service.

In the technology context, user satisfaction explains the belief that an information technology system meets the needs and expectations of the end-user (Kim & Chang, 2007). Hence, the acceptance and continuance use of technology will be based on the evaluation made by firm employees about their expectations and actual performance of the technology. This view is supported by Mahmood, Burn, Gemoets, and Jacquesz (2000) that the continuance use and success of information technology systems depend on the level of user satisfaction.

In the developing country context, scholars have opined that the expected benefits from using innovative technologies depend on the acceptance and use of these technologies (Hinson & Boateng, 2007; Saffu, Walker, & Hinson, 2007). The advocacy for firms to adopt business analytics technologies can be supported with a corresponding interest and positive attitude from firm employees. A lesson can be drawn from Venkatesh et al. (2003) that firm employees are the most important actors in the diffusion of innovative technologies. Therefore, the use of marketing analytics by firm employees in developing economies will depend on the intentions to use the systems. It is also crucial to ensure marketing analytics users are satisfied, leading to the continuance usage of the systems.

Statement of the Problem

Marketing analytics has been seen as having the potential of improving firm competitiveness and performance (Cao & Tian, 2020; Germann et al., 2013), but researchers are concerned about the challenges firms face in adopting the technology (Kwon, Lee, & Shin, 2014). Available research indicates a low prevalence of marketing analytics among firms in the US (see Germann et al., 2013), which has led to managers' reliance on their heuristic judgements in decision making (Xu et al., 2016).

The CMO Survey (2017) also expressed a view that the adoption and use of marketing analytics remain very low, even in developed economies. In 2020, about 37.7 per cent of business decisions in the United States depend on marketing analytics (CMO, 2020). In South Africa, 50 per cent of top businesses indicate that 60 per cent of decision marking depends on analytics, making intuition a significant part of corporate decision making (https://www.sas.com/content/dam/SAS/en_za/doc/research1/2014-business-analytics-in-south-africa.pdf). These challenges are a manifestation of the assertion made by Davis (1993) that lack of user acceptance has impeded the success of new information systems.

The lack of interest in marketing analytics by some employees may emanate from the existence of few studies espousing the benefits and positive impact it has on businesses, therefore leading to managerial scepticism (Germann et al., 2013). The CMO Survey (2017) reports that about 1.9 per cent of firms in the US have firm managers who have the right skills to use marketing analytics technology. It is expected that the use of marketing analytics technology will improve the acquisition of analytics skills by firm managers.

Germann et al. (2013) found that marketing analytics skills are an important predictor of marketing analytics adoption.

The main challenge with innovative technologies such as marketing analytics is that users remain unconvinced about the benefits of their use (Germann et al., 2013). Xu et al. (2016) posit that firms still rely on managers heuristic judgements to make marketing decisions with the low level of use of marketing analytics technologies. The acknowledgement of these studies on the low use of marketing analytics even in developed economies such as the US (Germann et al., 2013) and the UK (Cao et al., 2019; Cao & Tian, 2020) led to studies that sought to identify factors that will promote the use of marketing analytics by firm managers (see Verma et al., 2018).

Purkayastha and Braa (2013) suggest that in developing countries, the multi-layered view of the digital divide means inequality of ability to exploit the potential of technology, inequality in access to technology, and inequality of outcomes of technology use. In developing countries, many studies have questioned the readiness of firms to implement big data analytics (Kalema & Mokgadi, 2017; Luna, Mayen, Garcia, Almerares, & Househ, 2014).

Verma et al. (2018) propose that more research is needed in developing countries since results on analytics in both developed and developing economies cannot be generalised. Therefore, studies in a developing country like Ghana on assessing the use of the technology by firm employees becomes imminent. The question is raised about what factors influence firm employees to accept and use marketing analytics technology in a developing country context like Ghana?

To this end, a review of the literature on acceptance and use of marketing analytics leads to identifying research themes and gaps. The review of the literature reveals many research gaps relating to the little attention on acceptance and use of marketing analytics theme (issue gap), lack of research efforts on marketing analytics in Ghana (context gap), the little use of technology acceptance theories and inclusion of new constructs in understanding marketing analytics acceptance and use (theoretical gap), and an over-reliance on quantitative research approaches (methodological gap). These research gaps are explained next in this chapter.

Issue gap

The extant literature on analytics in the business field of study has witnessed a plethora of studies on big data (Chen, Chiang, & Storey, 2012; Holsapple, Lee-Post, & Pakath, 2014; McAFee et al., 2012). Recent studies on business analytics have focused on factors affecting organisational adoption of big data (Lai, Sun, & Ren, 2018; Sun, Cegielski, Jia, & Hall, 2018; Sun, Hall, & Cegielski, 2018; Verma & Bhattacharyya, 2017). There are now emerging streams of studies on marketing analytics studies focusing on research issues such as factors leading to the development of analytics technology by firms (Germann et al., 2013), performance implications of using the technology such as new product success (Germann et al., 2013; Xu et al., 2016), generating insight, firm competitiveness and decision making (Cao et al., 2019; Cao & Tian, 2020).

A considerable number of studies are focused on promoting marketing analytics through education (Atwong, 2015; Haywood & Mishra, 2019; Liu & Burns, 2018). Marketing analytics studies have also been dedicated to developing the concept and providing contributions to the marketing discipline (France & Ghose, 2019; Hauser, 2007; Wedel & Kannan, 2016). Despite the concern about the low rate of adoption of marketing analytics (Germann et al., 2013), little research attention has been given to the acceptance and use of the technology.

To fill the gap of the paucity of research on understanding the factors affecting the acceptance and use of marketing analytics technology, researchers must follow the direction proposed by scholars such as Venkatesh et al. (2003), Venkatesh et al. (2012) and Dwivedi et al. (2019) to focus on end-users of innovative technologies. Studies by Silva et al. (2019) and Cabrera-Sanchez and Villarejo-Ramos (2019) respond to this research call in the context of big data, representing a very scant focus of analytics technology acceptance and use. To date, little research attention has been given to understanding the factors affecting firm employee's acceptance of marketing analytics technology. This study responds to the call by researchers to look into the factors affecting the acceptance of innovative technologies by taking a closer look at marketing analytics technology.

Theoretical research gaps

A way to address the paucity of research in acceptance and use of marketing analytics is to use technology acceptance theories to determine the factors affecting acceptance and use. Studies on technology acceptance and use have extensively applied the TAM and the UTAUT in examining the intentions to accept technology (Venkatesh et al., 2003). Recently, the UTAUT has dominated research into the acceptance and use of technology. Venkatesh, Thong and Xu (2016) assert that the theory has extensively been used to study information systems and other fields.

The studies that have applied the UTAUT include the adoption of mHealth (Hoque & Sorwar, 2017), e-government (Rodrigues, Sarabdeen, & Balasubramanian, 2016), internet banking (Rahi, Mansour, Alghizzawi, & Alnaser, 2019). Despite using the UTAUT to explain the adoption of technologies, just a few studies have applied it on acceptance and use of big data (see Cabrera-Sanchez & Villarejo-Ramos, 2019; 2020; Silva et al., 2019; Sun et al., 2019). There is little evidence existing to show the application of the UTAUT in marketing analytics research. Therefore, the application of the UTAUT in the study of marketing analytics technology forms a major theoretical contribution of this study.

Researchers have also attempted to include new constructs into existing technology acceptance theories to explain better the factors affecting technology acceptance (e.g., Agarwal & Prasad, 1998; Dwivedi et al., 2019; Venkatesh et al., 2012). These extensions of existing technology acceptance theories and models, in the view of Venkatesh et al. (2012), is an opportunity to make theoretical contributions. With careful theoretical consideration, Venkatesh et al. (2012) call for the inclusion of constructs that can help expand the theoretical horizons of the technology acceptance theory. Dwivedi et al. (2019), extending the UTAUT to include attitude, relied on the theory of planned behaviour. Similarly, Agarwal and Prasad (1998), in including the personal innovativeness in information technology (PIIT) construct in the TAM, relied on the diffusion of innovation theory.

Based on the proposition by Agarwal and Prasad (1998) to include PIIT construct in the UTAUT, researchers have since tested this empirically in many technology contexts, including wireless internet (Lu et al., 2005), mobile commerce (Sair & Danish, 2018), cloud computing (Cao, Shang, Mok, & Lai, 2019), and mobile payment (Patil, Tamilmani, Rana, & Raghavan, 2020). Despite the limited research on how the PIIT construct influences the use of business analytics technologies, Kabra, Ramesh, Akhtar and Dash (2017) have applied PIIT construct in extending the UTAUT to study how humanitarian workers accept using data mining technology. Therefore, this study seeks to include PIIT construct in the limited use of the UTAUT in studying the acceptance and use of marketing analytics.

In line with the proposition by Dwivedi et al. (2019), scholars have attempted to introduce user attitude from the TAM in the study of innovative technologies. Researchers have responded to this call by involving user attitudes in the study of electronic document systems (Donmez-Turan, 2020), information systems in health care (Kuek & Hakkennes, 2020), learning management systems (Buabeng-Andoh & Baah, 2020), and mobile payment (Chawla & Joshi, 2019). Despite the extension of technology acceptance theories with user attitude construct, there is little attention given to how this affects user acceptance and the use of marketing analytics. This study seeks to address this gap by extending the UTAUT in the context of marketing analytics by including user attitude towards marketing analytics and how user attitude influences intentions to use the technology. This approach permits the blend of the TAM and the UTAUT to study factors affecting the acceptance of marketing analytics technology.

Additionally, the issue of trust in the adoption of technology has been a concern for some researchers. It is important to note that the UTAUT provided little understanding and insight into how trust could affect the acceptance of technologies (Slade et al., 2015). The initial UTAUT and subsequent extensions of the theory (UTAUT 2) seem not to focus on the issue of trust. It is worth noting that researchers have responded to calls to look into the issue of trust by including the construct in subsequent extensions of theories such as the TAM (Slade et al., 2015). Kaur and Rampersad (2018) assert that there are concerns about security and trust with new technologies, which must be subjected to scrutiny. The trust of the marketing analytics supplier or retailer and the confidence in the system to protect company and customer data is a crucial factor that may affect acceptance and use. This study attempts to address the little research on investigating the effect of trust on marketing analytics acceptance.

Similarly, the use of experience of employees, age, and gender as moderating factors in the study of technology adoption may also be a valuable inclusion in the study of marketing analytics adoption. Studies on technology acceptance and use have acknowledged the importance of employees' characteristics (Venkatesh et al., 2003, Venkatesh et al., 2012). Acheampong et al. (2018) advocate examining the effect of user demographic variables in technology acceptance studies.

Researchers focus on how the category of innovators (early adopters and late adopters) affects acceptance of innovation have been lacking. Tzou and Lu (2009) attempted to examine the differences in the category of innovators on technology acceptance. This study considering the limited study on management experience, age, gender, and category of an innovator (early adopter, late adopter) as moderators in the study of marketing analytics adoption, seeks to address this gap. This approach will build on the theoretical stance of the UTAUT that firm employees characteristics are an important predictor of technology acceptance using the marketing analytics context.

There is also rare research linking intentions to use technologies to actual use behaviour proposed by the UTAUT and the TPB. Despite the focus of empirical studies to prove that intention is the strongest predictor of actual behaviour in the context of technology (Venkatesh et al., 2003), few empirical studies have attempted to investigate how this relationship works in the marketing analytics arena (Cabrera-Sánchez & Villarejo-Ramos, 2020; Demoulin & Coussement, 2020). Therefore, this study seeks to address this gap by testing whether intentions to use marketing analytics predict the actual use of the technology.

One critical area technology researchers are interested in is the use of technology due to the industry conditions. The extant literature indicates scholars have made some attempts to examine the effect of the type of industry (service and manufacturing) on the use of technologies (Hernández-Ortega et al., 2006). In marketing analytics studies, the use of industry type as a moderator by Germann et al. (2013) and Cao et al. (2019) was applied to examine the performance implications of marketing analytics depending on the industry. It is clear that the use of the type of industry as a moderator in investigating the relationship between intentions and actual use of marketing analytics is lacking. This empirical result is needed to understand whether there is a difference in how intentions to use marketing analytics affects actual use due to the end-user's industry. Studying the moderating effect of the type of industry in understanding the actual use of marketing analytics is needed.

Marketing and information systems researchers have also been concerned about the little focus on promoting technology acceptance through marketing concepts such as user satisfaction of information systems (Au, Ngai, & Cheng, 2008; Chikara & Takahashi, 1997). These studies propose that end-user satisfaction of information technology systems is paramount in ensuring the success of technology adoption since the effectiveness of these technologies hugely depends on psychological issues.

The information success (IS) model extension by DeLone and McLean (2003) proposes the inclusion of user satisfaction as a factor determining the success of information systems. There seems to be little research attention given to how marketing analytics user satisfaction influences continuance usage of the technology. This study sees an opportunity to address the little use of the Expectancy Confirmation theory by Oliver (1980) to investigate how the satisfaction of marketing analytics will affect the continuance usage of the technology. This study seeks to introduce user satisfaction as an important marketing concept to offer a rare opportunity to understand the acceptance and use of marketing analytics technology and contribute to the inclusion of the information success model and expectancy confirmation theory in the study of marketing analytics.

Contextual research gap

This study on marketing analytics adoption and use in the Ghanaian context seeks to address the little attention on research in developing countries. It is worth noting that some scant marketing analytics studies and big data studies, for that matter, are in the developed country context, such as the UK (e.g., Cao & Tian, 2020; Cao et al., 2019) and the US (Germann et al., 2013).

Studies that have applied the UTAUT in studying acceptance of big data are not focused on sub-Saharan Africa (see Cabrera-Sanchez & Villarejo-Ramos, 2020; Sun et al., 2020). It is evident that even in developed economies, studies on the use of marketing analytics still remains low (Germann et al., 2013), making a case for studies in developing economies with a huge disadvantage in technology adoption and acceptance more crucial.

There is a call for the application of the UTAUT in other contexts. Im, Hong and Kang (2011) justified that due to differences in culture and management of firms, there is the need to subject the UTAUT to test in other economies. Using Korea and the US, Im et al. (2011) found a significant difference between the antecedents of technology adoption among these countries. In testing technology acceptance across cultures, Straub, Keil and Brenner (1997) discuss that culture dimensions from Hofstede's model, including power distance (large power between firm manager and workers), individualism-collectivism (the extent to which individuals are integrated into groups), and assertiveness.

Sun et al. (2018) propose that individualism promotes the use of technology since individuals perceive it as an avenue to perform a task better. On the other hand, Straub et al. (1997) propose that individuals in collectivist societies may have a lower response to technologies since they rely on other people for assistance and may prefer social interactions to technology. Empirically, studies have found that employees in collectivist and high-power distance societies have a lower propensity to accept innovative technologies (Sunny, Patrick, Rob, 2019; Tarhini, Hone, Liu, & Tarhini, 2017). Due to the digital divide and cultural beliefs, the application of technology acceptance theories such as the UTAUT in developing countries has been advocated by researchers since it may not be adequate in predicting technology acceptance (e.g., Bawack & Kamdjoug, 2018; Hoque & Sorwar, 2018).

Despite the calls to test the UTAUT in developing countries, little research attention has been given to the adoption of marketing analysis in developing economies. Using the UTAUT to understand the acceptance and use of marketing analytics in a developing country context like Ghana is long overdue, considering its importance to marketing practice. Therefore, the focus of this study in Ghana will be a valuable contribution to literature and improve the understanding of the acceptance of marketing analytics technology in a developing country context.

The gap in methodological approach

This study acknowledges that the most apparent methodological gap is the paucity of mixed methods studies in technology acceptance research. Technology acceptance studies have usually used quantitative approaches against qualitative studies through structural equation modelling to determine the factors affecting acceptance and use (e. g., Dwivedi et al., 2019; Venkatesh et al., 2003; Venkatesh et al., 2012). On the other hand, Huang, Teo and Zhou (2019) opined that qualitative studies enable the observation of what is occurring and ensure the collection of detailed, in-depth and describe how this information is interrelated.

Johnson, Onwuegbuzie and Turner (2007) posit that mixed methods approach uses qualitative and quantitative, which embraces multiple viewpoints, perspectives, positions, and standpoints. Cohen, Bancilhon, and Jones (2013), in a mixed methods study using the UTAUT, collected quantitative data and later used qualitative data to examine physicians' acceptance of e-prescribing technology.

In a developing country context, an in-depth analysis of firm employee's perceptions about marketing analytics technology will help understand from different context factors affecting the acceptance of the technology. The need to use a qualitative approach emanates from studies that found that only using the UTAUT (see Bawack & Kamdjong, 2018; Odoom & Kosiba, 2020) and the theory of planned behaviour (see Liu, 2010) may not help predict better intentions to use innovative technologies. These studies have adopted the use of a sequential explanatory approach to use both qualitative and quantitative data.

The sequential explanatory design, which is very popular among researchers, quantitatively analyses the data followed by a qualitative analysis in two consecutive phases in the same study (Ivankova, Creswell, & Stick, 2006). Therefore, interviews with firm managers in firms with adopted marketing analytics technology will help understand the factors that influence them to accept and use the technology. The quantitative aspect of this study follows a current trend of using the Partial Least Squares approach in the model building in technology adoption research (e.g., Cabrera-Sanchez & Villarejo-Ramos, 2020).

Purpose of the Study

The present study seeks to examine the factors that affect the intention to use, actual use, user satisfaction, and continuance usage of marketing analytics technology by firm employees in developing countries using Ghana as a context.

Research Objectives

The study seeks to achieve the following objectives:

1. To examine the factors affecting the behavioural intention to use marketing analytics by firm employees in Ghana.
2. To assess the effect of behavioural intention on the actual use of marketing analytics technology by firm employees in Ghana.
3. To examine the effect of actual use of marketing analytics on user satisfaction in Ghana.
4. To examine the effect of user satisfaction on the continuance usage of marketing analytics technology by firm employees in Ghana.

Research Questions

The following research questions were stated to aid in the qualitative study:

1. What are the factors affecting the behavioural intention to use marketing analytics technology in Ghana?
2. What is the influence of intention to use marketing analytics on the actual use of the technology in Ghana?
3. What is the influence of the actual use of marketing analytics on user satisfaction among firm employees in Ghana?
4. What is the influence of user satisfaction on continuance usage of marketing analytics by firm employees in Ghana?

Research Hypotheses

The study proposes the following hypotheses:

H1a: *Performance expectancy has a positive and significant relationship with intentions to adopt marketing analytics.*

H1b: *Effort expectancy has a positive and significant relationship with intentions to adopt marketing analytics.*

H1c: *Social influence has a positive and significant relationship with intentions to adopt marketing analytics.*

H1d: *Facilitating conditions has a positive and significant relationship with intentions to adopt marketing analytics.*

H1e: *Perceived trust has a positive and significant relationship with intentions to adopt marketing analytics.*

H1f: *Personal innovativeness in information technology has a positive and significant effect on intentions to use marketing analytics.*

H1g: *User attitude towards marketing analytics has a positive and significant relationship with usage intentions.*

H2a: *Age of firm employees will significantly moderate the relationship between UTAUT constructs and the intentions to use marketing analytics.*

H2b: *Gender of firm employees will significantly moderate the relationship between UTAUT constructs and the intentions to use marketing analytics.*

H2c: *The experience of firm employees will significantly moderate the relationship between UTAUT constructs and the intentions to use marketing analytics.*

H2d*: The type of innovator group will significantly moderate the relationship between UTAUT constructs and the intentions to use marketing analytics.*

H3: *Intention to use marketing analytics has a positive and significant effect on actual use.*

H4: *Type of industry moderates will significantly moderate the relationship between the intention to use marketing analytics and actual use.*

H5: *Actual use of marketing analytics has a positive and significant relationship with user satisfaction.*

H6: User satisfaction of marketing analytics has a positive and significant effect on continuance usage.

Significance of the Study

From a research perspective, the advocacy for the use of technology by businesses in developing countries has been supported with adequate research. The emergence of new technologies demands that academic researchers must provide knowledge about their adoption and use. Concerning marketing analytics, its use has been dominated by reputable firms in developed countries. It must be acknowledged that the marketing discipline is beginning to accept the use of analytics technologies as the main source of decision making and performing many marketing tasks. The performance of marketing activities using artificial intelligence and analytics technologies is taking over the marketing discipline. Therefore, the study of marketing analytics in developing countries needs to be intensified to understand the state of acceptance and use. There is a duty on academics through research to help in the assimilation of knowledge on marketing analytics as a technology to help in decision making.

Considering the limited study on the subject matter in developing countries like Ghana, this study contributes to the literature. It makes an initial attempt to understand the intentions of firm employees in Ghana on accepting marketing analytics. A major contribution to literature is building on the UTAUT to determine the factors affecting the intentions to adopt marketing analytics. Apart from the UTAUT, this study makes a contribution to the literature by examining the role of other important technology adoption antecedents, including personal innovativeness, attitudes, and perceived trust of technology, which can be used to examine the acceptance of marketing analytics in Ghana. This study also contributes to the knowledge on how user satisfaction as a marketing concept predicts continuance usage of marketing analytics technology from a developing country context.

On the significance of this study to practice, this study is directed at improving the understanding of firms on what critical conditions need to be satisfied to ensure the acceptance and use of marketing analytics. Therefore, firms can dedicate their efforts to ensure the existence of conditions to develop marketing analytics knowledge and awareness among employees. The perceptions of employees towards marketing analytics are crucial in gaining managers' support to serve as advocates of marketing analytics in their respective firms. This study is dedicated to assessing the current state of marketing analytics from the employees' perspective as their perceptions will clearly demonstrate the readiness of firm employees in developing countries to accept and use the technology. Therefore, assessing the level of satisfaction of marketing analytics technology will help firms determine the effectiveness of the technology. The results of the study may help direct firm management on actions to put in place to enhance the acceptance of the technology in order to generate the desired benefits.

From a policy perspective, this study will provide valuable insight into the use of marketing analytics and also the current intentions, satisfaction, and willingness to continue using the systems by firm employees. Policymakers that are working to promote the use of innovative technologies by firms may tap into the findings of this study to recommend possible areas of improvement to enhance firms' readiness to adopt marketing analytics. The ministries and agencies responsible for communication and digitalisation in developing economies can be informed about the areas to focus on promoting analytics technology use among firm employees. The increase in the use of marketing analytics can be achieved through educational programmes and capacity building developed using the factors recommended in this study.

Delimitations

This study is among the first to research factors affecting marketing analytics acceptance and continuance use by firm employees in a developing country context such as Ghana. The data collection was possible due to some Ghana Club 100 companies that have adopted marketing analytics technologies. The study used a survey and interviews to collect data from firm employees in the service and manufacturing sector. The use of Google forms made it possible to conduct an online survey during the COVID-19 pandemic. Telephone interviews proved to be an effective way to conduct interviews with study participants who were physically not accessible.

A mixed methods approach was adopted to enhance understanding of the use of marketing analytics. The study's main strength is the use of existing technology acceptance theories by combining the constructs of these theories to explain the acceptance and continuance usage of marketing analytics technology.

Limitations

The study acknowledges some limitations. First, the study used a sample of firm employees in reputable firms in Ghana. It was difficult to identify the study population due to the hidden nature of the study population (users of marketing analytics technology). This approach was adopted because it is difficult to obtain the sample frame of users of marketing analytics technology in Ghana. The identity of firm employees using marketing analytics is not known. A convenience sampling aided the researcher to identify the users of marketing analytics. The study participants were recruited using a respondent-driven approach. This limitation may affect the generalisation of the study results.

Second, the study adopted a cross-sectional study to collect data from study participants. The responses on the independent and dependent variables were collected at one time. The use of a single time to collect data for testing and making inferences may lead to difficulty in examining theoretical relationships. The reliance on the perception of firm employees as the basis for rating measurement items may also lead to bias. A limitation of using a cross-sectional survey is that it reduces the ability to uncover the true relationship among variables. Therefore, this study may not establish a cause-and-effect relationship leading to caution in generalisation of the results of the study.

Finally, this study acknowledges that variables included in the research model may not be exhaustive. The limitation, therefore, is that this study could not include other important factors in predicting usage intentions and continuance usage. Nonetheless, the variables and theoretical principles adopted provided an acceptable result. The inclusion of other important variables in the research model may enhance the predictiveness of the model.

Definition of Terms

The following important concepts in the study are defined:

Marketing Analytics: it is the use of technology that enables the collection, processing, and analyses of large, current, regular, quality, and valuable data for marketing decision making.

Performance Expectancy: the degree to which an individual believes that using a technology will enhance their performance.

Effort Expectancy: the degree to which an individual perceives that a technology is easy to use and learn.

Social Influence: the degree to which an individual perceives that important people expect them to use a technology.

Facilitating Conditions: the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system.

Perceived Trust: the belief that the other party will behave in a socially responsible manner and, by so doing, will fulfil the trusting party's expectations without taking advantage of vulnerabilities.

Attitudes: an individual's positive or negative feelings (evaluative affect) about performing the target behaviour.

Personal Innovativeness in Information Technology: the willingness of an individual to try out any new information technology.

Intentions: the determinants that affect behaviour; they are indications of how hard people are willing to try, of how much effort they are planning to exert to engage in a behaviour.

User Satisfaction: the extent to which users believe the information system available to them meets their information requirements.

Continuance Usage of Technology: users' decision to continue using information technology over the long run.

Organisation of the Study

This study contains nine (9) chapters. Each chapter represents an essential part of the research. Chapter One provides an introduction to the research. Chapter Two looks at the contextual issues relating to the use of marketing analytics. This chapter reviews the literature on marketing analytics, focusing on the definition of marketing analytics, some statistics on the use of marketing analytics, the application of marketing analytics by businesses, and current research themes. Chapter Three focuses on the theoretical foundations of the research. Chapter Four presents a conceptual review of pertinent research related to the subject matter.

Chapter Five performs a review of empirical studies and present a conceptual framework depicting the relationship between technology adoption factors and intentions to adopt marketing analytics. The review assisted in the design and collection of empirical data for the study. Chapter Six of the study considers methodological issues on how data was collected and analysed. Chapter Seven presents the data results based on the research objectives, hypotheses, and conceptual framework. Chapter Eight performs a detailed discussion of the findings based on the various propositions presented in developing the conceptual framework.

This chapter performs a triangulation of the qualitative and quantitative results to satisfy the demands of a mixed methods. Chapter Nine presents the summary, conclusions, and implications of this study and also propose some future research directions.

CHAPTER TWO

CONTEXT OF THE STUDY

Introduction

This chapter provides a review of existing literature on marketing analytics technology. The purpose of this chapter is to explain how marketing analytics works in the performance of marketing functions. The review aims to describe marketing analytics and the use of marketing analytics. Furthermore, the chapter reviews existing studies to examine the research direction and research gaps in the context of marketing analytics.

Marketing Analytics Technology

The development of marketing analytics emanated from the concept of big data (Wedel & Kannan, 2016; Xu et al., 2016). Studies on marketing analytics acknowledge the genesis of this marketing practice by addressing that marketing analytics and other forms of analytics relating to business functions benefited from development in big data (Xu et al., 2016). The term "big data", according to Gandomi and Haider (2015), is regarded as nascent and has uncertain origins, which can be traced to the mid-1990s.

In the view of Gandomi and Haider (2015), the hype about big data is due to the promotional initiatives by service providers such as IBM. Big data gathers data from transaction-related and other unstructured external data (Nam, Lee, & Lee, 2019). According to Chen et al. (2012), big data represents the availability of enormous volume (the amount of data), velocity (the speed at which data is collected and used), and variety (the many sources and type of data), which firms use in improving decision making. Researchers widely conceive these three issues as very important in defining big data

(Ghasemaghaei, Erahimi, & Hossanein, 2018). These three issues form the main features of big data, namely volume, velocity, and variety explained in Table 1. Notwithstanding these widely used features, scholars such as Erevelles et al. (2016) provide details of new features of big data such as veracity, and value, which must be given attention.

Table 1: Features of Big Data

Feature of Big Data	*Description*	*Sources*
Volume	This refers to the ability to use technology to collect and process large amounts of data. It enables the integration of external and internal data for the management information systems.	Pence (2014), Erevelles et al. (2016)
Velocity	This refers to the speed of data collection and creating rich and insightful data. This feature means that speed of data creation on issues such as consumer transactions, purchases, consumer social media activities is important.	Erevelles et al. (2016)
Variety	This is the ability to integrate various sources of data. The data can be structured (databases, sensor data), semi-structured (videos, images), unstructured (text messages, blogs).	Erevelles et al. (2016)
Veracity	This refers to the quality and accuracy of data that represents the true state of a situation.	Erevelles et al. (2016); Gandomi and Haider (2015)
Value	This refers to putting together different types of data to generate insight that could improve the decision making and competitive position of a firm.	Chandarana and Vijayalakshmi (2014)

Source: Author’s construct, Twum (2021)

In the view of Xu et al. (2016), marketing has benefited from the disruptive increase in big data. Marketing analytics is seen as a business activity emanating from big data as it enables firms to obtain insights on consumers, markets, and competitors in real-time using Web 3.0 (Xu et al., 2016). This assertion is collaborated by Nair, Misra, Hornbuckle, Misra and Acharya (2016) that the advent of big data has led to the tracking and measurement of customer behaviour, thus affecting the way marketing is performed. Big data has enabled firms to conduct evidence-based management, which implies that decision making is supported by data (Nair et al., 2016). An assertion by Hauser (2007) that seems to suggest marketing analytics is basically about technology and databases gives more credence to the argument that marketing analytics has grown out of big data. Big data is primarily used in decision-making and improving business functions such as marketing (Khan & Vorley, 2017).

The statistics on the adoption of marketing analytics make a compelling case on the prevalence and wide acceptance of the technology in marketing. The CMO Survey (2018) provides the following statistics on the use of marketing analytics technology:

a. consistent increase in the use of marketing analytics over the last five (5) years
b. there is a considerable amount of investment in marketing analytics across industries. The current budget spent on marketing analytics by the communications/media industry, consumers packaged goods, consumer services, and manufacturing is 5%, 7%, 6%, and 6%, respectively.
c. the use of marketing analytics in decision making is 55.7% and 53.8% in the services and manufacturing sectors, respectively.
d. on a scale of 1 to 7 (1 = not at all, 7 = very highly), firm managers indicated that marketing analytics contributes to company performance on a mean value of 4.1.

These statistics on the use of marketing analytics, according to the CMO Survey (2018), is an indication that more and more organisations are investing and dedicating much of their marketing budgets to use the technology.

Definition of Marketing Analytics

The application of big data in marketing is termed "Marketing Analytics". Marketing analytics involves collecting, managing, and analysing data to generate insight to make marketing effective and improve firm performance (Wedel & Kannan, 2016). Marketing analytics presents the opportunity to collect data about customer's brand preferences, purchase frequency and patterns using multiple sources (Miles, 2014). Germann et al. (2013) refer to marketing analytics as to the extent to which insights gained through marketing analytics serve as the foundation for decision making. The explanation by Germann et al. (2013) clearly draws a distinction between marketing analytics and other forms of business analytics.

There are definitions of marketing analytics provided by scholars and analytics service providers. Understanding what constitutes marketing analytics has been a concern of scholars, as this will help promote conceptual and theoretical development of the technology. In Table 2, some definitions of marketing analytics are provided to enhance the understanding of the technology. Based on these definitions, a working definition is proposed that Marketing Analytics is the use of technology that enables the collection, processing, and analyses of large, current, regular, quality, and valuable data for marketing decision making.

Table 2: Definitions of Marketing Analytics

Author(s)	Details of Definition
Branda, Lala, and Gopalakrishna (2018)	Marketing analytics makes use of processes, technology, people, and mathematics to generate facts from data to enhance marketing decision making.
SAS (https://www.sas.com/en_us/insights/marketing/marketing-analytics.html)	The use of technology and processes to enable marketers to evaluate the success of marketing initiatives or how marketing programmes are performing.
Iacobucci, Petrescu, Krishna, and Bendixen (2019)	The use of data and modelling tools to perform marketing and customer-related decision making.
Wedel and Kannan (2016)	The collection, management, and analysis of data relating to marketing function and using analytical tools to optimise firms' return on investment.
Lilien (2011)	The ability to systematic approach to collect data and knowledge using technology to inform marketing decision making.

Source: Author's construct, Twum (2021)

Marketing Mix and Marketing Analytics

A way to conceptualise marketing analytics is to describe how the technology fits into performing the basic marketing functions. Marketing analytics make use of techniques such as predictive analysis and data mining (Hair Jr, 2007). The benefit of analytics to marketing involves the management of all phases of marketing, including customer acquisition, revenue maximisation, and retaining customers.

According to Wedel and Kannan (2016), some common analytics methods can be performed using ACIII files, Excel, while statistical packages such as STATE, SPSS, and SAS analyse small-sized structured data. The SAS, for instance, is applicable in the retailing, government sector, financial services. The use of sophisticated analytical tools is resorted to when data become too many, usually by employing relational databases such as MySQL and NoSQL (Wedel & Kannan, 2016). The relational databases enable the storage and retrieval of large amounts of data for analysis.

It is imperative to indicate some marketing analytics approaches used to create value from information. From the website of SAS (https://www.sas.com/en_us/insights/analytics/big-data-analytics.html), a popular analytics provider, analytics approaches include machine learning, data mining, in-memory analytics, predictive analytics, and text mining. The details of these analytics approaches are presented in Table 3.

Table 3: Forms of Marketing Analytics Techniques

Marketing Analytics Approach	Description
Machine Learning	This approach enables the training of machines to learn, making it possible to develop models to analyse large and complex data faster and accurately.
Data Mining	Using data mining techniques to discover patterns in data to answer complex business questions.
In-memory Analytics	This analytics uses data from system memory to obtain insight from existing data, test new scenarios, create models, and take decisions in real-time.
Predictive Analytics	This analytics applies machine-learning and statistical algorithms to identify the likelihood of future outcomes from past data.
Text Mining	This approach collects data from the comment fields, web, books, and other text-based sources such as Twitter feeds, surveys, blogs to uncover insights that are not obvious to detect.

Source: SAS (2021)

It is also worth knowing that the use of marketing analytics in retaining customers is informed by the relationship marketing concept, where marketers emphasise on building long-lasting and valued relationships. In order to improve on the value offered to customers and increase firm profitability, firms may employ analytical techniques to enhance the detection of customer switching factors, which are referred to as churn drivers. The ability of a firm to collect data at each customer touchpoint helps to develop a customer relationship management (CRM) strategy, which integrates all firm activities around the customer (Lichtenstein, Bednall, & Adam, 2008). Marketing analytics could also build up a firm's competencies in responding to customer needs, creating some form of competitive action (Nam et al., 2019). Hair Jr (2007) asserts that the motive for deploying marketing analytics is to detect churn drivers due to the marketing philosophy of customer retention, which is deemed less expensive to undertake than acquiring new customers.

In an attempt to conceptualise marketing analytics, Hauser (2007) posit that the main objective of using the technology is to manage every customer touchpoint, from creating customer awareness, interest and making a purchase. This description of the marketing analytics concept is in line with the customer relationship management argument proposed by Hair Jr (2007), Litchtenstein et al. (2008) and Nam et al. (2019). This implies that for marketing analytics to be developed, data must be gathered at every touchpoint and with every customer interaction. Another essential marketing analytic technique is customer analytics. Sun, Morris, Xu, Zhu and Me (2014) assert that customer analytics helps provide insight into customer behaviour using structured and unstructured data. Customer analytics is currently the most dominant strategy to gain competitiveness (Hossain, Akter, & Yanamandram, 2020). It enables firms to analyse data to inform fact-based management decisions (Bijmolt et al., 2010).

From the earlier discussions, analytics can be regarded as being applied extensively in marketing but needs an apparent linkage. Fan et al. (2015) assert that the concept of big data can be demystified using the marketing mix elements. These marketing mix elements can be developed using data analytical technologies, which enable marketers to identify key factors for strategic decision making. These key factors needed for strategic decision-making include customers' opinions toward a company, a product, or a service.

In a more specific manner, Fan et al. (2015) posit that big data analytics could be applied in marketing in the following ways, including customer segmentation, primarily using segmentation applications for profiling customers, monitoring competitor offerings and strategies, managing the marketing promotions and measuring the impact of promotional efforts on sales, delivering personalised services, and providing location-based services. The result of effectively using analytics in marketing, in the view of Erevelles et al. (2016), is transforming marketing practice by providing behavioural insights about consumers, enabling marketers to gain some competitive advantage.

The financial implications of deploying analytics imply that the marketing side of analytics must become a priority and dominate the analytics focus of firms (Wedel & Kannan, 2016). The key domains of analytical data applications, according to Wedel and Kannan (2016), include personalisation of marketing mix to individual consumers, customer relationship management focusing on customer acquisition, retention, and satisfaction, and managing the marketing mix. In Table 4, the application of analytics technology in marketing regarding how marketers apply the technology in performing the various marketing functions.

Table 4: The Use of Marketing Analytics in Marketing

Marketing Mix Element	Description of Use of Marketing Analytics	Related Papers
Product	Marketing analytics helps in new product development, diffusion, and positioning. Information gathered from consumers about product performance are used to improve products and develop new offerings.	Germann et al. (2013), Wedel and Kannan (2016), Xu et al. (2016), Fan et al. (2015)
Pricing	The use of analytics in price-related issues introduces a discipline to understand customer expectations and accurately align product placement and pricing with customer segments. It also involves using automation to monitor and adjust to competitor prices.	Cross, Higbie and Cross (2011), Xu et al. (2016), Fan et al. (2015)
Distribution	The use of analytics to track and map the customer journey across touchpoints, managing customer locations, managing channel budgets, and evaluating profits.	Hair Jr. et al. (2007), Bradlow, Gangwar, Kopalle and Voleti (2017)
Promotion	This approach explains using analytics to perform location-based advertising, enhancing the delivery of digital marketing, measuring the performance of communications on the internet.	Erevelles et al. (2016), Rosenkrans and Myers (2018)

Source: Author's construct, Twum (2021)

Mapping the Research on Marketing Analytics

This section of the chapter reviews the extant literature on marketing analytics to understand the research areas covered and identify the gaps in existing research. This study relied on the literature on marketing analytics collected using google scholar, Scopus, and Web of Science to perform the review. In all, 42 scholarly publications were reviewed to identify research gaps. In appendix C and Appendix D, the list of published articles used for the review is presented.

From the initial identification of marketing analytics studies, the study analyses the various research areas dominating the study area. The analysis led to identifying four main research areas, including performance implications of using marketing analytics, development of marketing analytics courses/curriculum, marketing analytics techniques, and marketing analytics adoption. These four main research areas are explained next.

Performance implications of marketing analytics

A stream of studies has been identified on the use of marketing analytics to improve firm performance. Notable among these studies is that of Germann et al. (2013), Germann, Lilien, Fiedler and Krauss (2014), Cao and Tian (2020) and Ashrafi and Ravasan (2018). The performance implications of marketing analytics studies are usually conducted using survey data collected from employees of firms across industries. These firms, mostly in advanced stages of using marketing analytics, were used as cases to provide empirical evidence of the ability of marketing analytics to imply overall firm success. The performance issues of marketing analytics studied are in the areas of innovativeness (Kiron, Prentice, & Ferguson, 2012; Shuradze, Bogodistov, & Wagner, 2018), sales, return on investment, profits (Germann et al., 2013; Germann et al., 2014), relationship marketing performance (Cao & Tian, 2020; Hallikainen, Savimäki, & Laukkanen, 2020), improved decision making (Cao et al., 2019; Kauffmann et al., 2020), and product development (Cao et al., 2019).

Marketing analytics adoption process

The analysis of extant literature on marketing analytics shows that the research on the factors affecting marketing analytics is the least researched. This finding is surprising due to the abundance of research on technology acceptance in other technological contexts. The few studies that have focused on marketing analytics adoption have focused on factors such as top management advocacy, analytics culture, analytics skills, data and information technology (Germann et al., 2013), marketing analytics funding, marketing analytics professionals, top management risk-taking (Branda et al., 2018).

The studies reviewed did not adopt the mainstream technology adoption factors from theories such as the UTAUT, TAM. The studies focus on firm adoption of marketing analytics technology and not on employees' acceptance of the technology. The research on using technology acceptance theories to study factors affecting the intentions to adopt marketing analytics is therefore limited. The lack of research makes a strong case for further studies on factors affecting firm employees' intention to use and continuance to use marketing analytics.

Marketing analytics techniques

The analysis of existing studies reveals that most studies are on demonstrating the use of marketing analytics. These studies aim to explain how marketing analytics is used to perform various marketing activities such as segmentation (France & Ghose, 2019), customer acquisition (Bijmolt et al., 2010), sentiment and detection of fake reviews (Kauffmann et al., 2020), advertising (Hair Jr. 2007), understanding of consumer needs (Moe & Schweidel, 2017), consumer tracking (Kakatkar & Spann, 2019), customer relationship management (Acker, Gröne, Blockus, & Bange, 2011), and identification of customer emotion and experiences (Jussila, Boedeker, Jalonen, & Helander, 2017).

The practical marketing analytics studies are dedicated to providing details on the software and agencies involved in the provision of marketing analytics (Jobs, Aukers, & Gilfoil, 2015). Mizik and Hanssens (2018), in their handbook on marketing analytics, for instance, presented studies that experiment the use of marketing analytics. Marketing analytics was found to be applied in machine learning and big data to understand market competition and profile customers (Mizik & Hanssens, 2018) and calculating customer lifetime value (Grigsby, 2015).

The literature is dominated by practitioner studies and reviews of how the technology is used to perform marketing functions. This focus on showcasing the techniques, the type of data, steps and methods used explains the difficulty of marketers understanding the practicality of marketing analytics. A focus on developing and conceptualising constructs and variables in marketing through review studies is key in demystifying marketing analytics. Academic research stands to benefit profoundly from these technical studies as it improves the understanding of academic researchers on how to apply the concept in empirical research.

Marketing analytics education

Another major stream of research on marketing analytics is the attempt made by researchers to promote the concept in marketing education. Marketing analytics is an integral part of most higher education programmes in marketing, especially at the Masters level. A study by Liu and Burns (2018) employed analytics to mine text on marketing analytics and seek practitioners and academics' opinions on what should be included in the marketing analytics course. These studies focus on the development of marketing analytics courses that reflect the current practice (Atwong, 2015; Liu & Burns, 2018; Mintu-Wimsatt & Lozada, 2018; Wilson, McCabe, & Smith, 2018). The literature on developing an effective marketing analytics curriculum aims to provide a structured way to deliver marketing analytics courses in higher education institutions.

CHAPTER THREE

THEORETICAL REVIEW

Introduction

The theoretical explanations that underpin the adoption of technology are critical in understanding the current study. This chapter looks at some prevailing theories in the literature, which can explain the factors affecting the adoption of innovative technologies. In the marketing analytics field, some theoretical roots exist in the literature explaining the adoption and use of marketing analytic. The chapter conducts a review and discussion of the various theories to aid understand the factors and conditions that are likely to influence marketing employees to accept marketing analytics.

The Use of Theories in Technology Acceptance Studies

Research has extensively used several theories and models to study the adoption of innovative technologies (Lai, 2017). This review is needed as Yu and Tao (2009) posit that there is evidence to show that not much has been done on firm-level acceptance of technology compared to individual-level (employee) technology acceptance using theories. There is the need to provide a theoretical understanding of what factors will determine firm employees' acceptance and use of marketing analytics. Hence, the theoretical perspectives discussed in this chapter will be valuable in guiding the empirical research of this study.

Unified theory of acceptance and use of technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most widely used theories in the study of technology acceptance and adoption. UTAUT, developed by Venkatesh et al. (2003), integrates eights theories. The development of the theory by Venkatesh et al., (2003) was done using data from four organisations on the factors that determine individual intentions to and actual use of information technology. Empirically, the validation of the assumptions of the theory found that the four main constructs of the theory, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, influence intention to use technologies (Venkatesh et al., 2012). This relationship among antecedents of technology acceptance and technology usage intentions has served as the basis for many empirical studies.

The theory also proposes that the intention to use technology affects the actual use of technology. This central assumption is undoubtedly drawn from the Theory of Planned Behaviour by (Ajzen, 1991). The theory of planned behaviour explains that the actual adoption of behaviour is influenced by the individual's intentions to pursue such a behaviour. In simple terms, the UTAUT theory is built on three main concepts, relating to individual reactions to using the technology, intentions to use technology, and actual use of technology (Venkatesh et al., 2003). The adoption of marketing analytics technology is proposed in this study to follow a similar pattern. The adoption of marketing analytics begins with firm employees' reactions towards the technology, intentions to use the technology, and the actual use of the technology.

Venkatesh and Zhang (2010) provide a concise summary of the UTAUT by stating that the theory integrates and refines existing models to demonstrate that the theory's constructs explain 70 per cent of the variance in technology use intentions. On the other hand, user characteristics, including gender, age, and experience, were examined as having the ability to alter the link between intentions to use technology and technology use. The focus of the theory on other factors such as gender, age, and experience provide a fair idea that this theory acknowledges the individual role of users in adopting technologies. This approach informs the treatment of user characteristics of age, gender, and experience as moderating factors.

The wide application of the UTAUT on innovative technologies places it better positioned to explain the marketing analytics phenomenon. The theory provides a clear focus for this study because it indicates the procedure and constructs to measure the acceptance and use of marketing analytics. The theory informs the focus on employees who are the users of the technology and not on organisation and the process they go through to develop marketing analytics technology.

Application of the UTAUT in technology acceptance research

A review of 22 empirical studies that have used the UTAUT from 2008 to 2020 found that the theory has widely been used to study the acceptance and use of innovative technologies. The technologies studied using the UTAUT include internet banking, mobile banking, e-commerce, electronic medical records, health information systems, social media, online tax filing, and big data. The study of Silva et al. (2019), Shin, Woo and Seo (2016), Shin (2016) and Cabrera-Sánchez and Villarejo-Ramos (2020) were identified as using the UTAUT to examine the acceptance and use of business analytics technology, which form the basis for the use of this theory in the context of marketing analytics. The details of the empirical studies that have applied the UTAUT theory are presented in Appendix E. From the review of studies that have used the UTAUT, the following observations are made:

1. The focus has been on the acceptance and use of technologies that organisations have adopted. This approach is in line with the proposition made by the UTAUT, which posits that the end-user of an organisations' technology must be the focus of research. Hence, the majority of the studies reviewed focused on organisation-based technologies.
2. The unit of analysis in these studies are the users that have adopted innovative technologies. Firm managers and employees are considered as the users of innovative technologies. The theory seeks to examine the level of acceptance and use of technologies by end-users. The studies reviewed used surveys to collect data from firm employees regarding their acceptance and use of technologies.
3. In the context of big data, business analytics, and marketing analytics, few studies exist that have used the UTAUT (Silva et al., 2019; Shin, 2016; Cabrera-Sánchez & Villarejo-Ramos, 2020). Since business analytics and marketing analytics technologies are becoming increasingly popular among firms, studies must be intensified on the acceptance and use of the system.

Technology Acceptance Model

The TAM was proposed by Davis (1985) in a doctoral thesis to test for the adoption of new-user information technology empirically. The model proposes that an individual's motivation to use a technology depends on the cognitive response made of the perceived usefulness and perceived ease of use, the affective response formed from the attitude towards using the technology, and behavioural response, which explains the actual system use (Davis, 1985). The TAM adopted its main constructs from the Theory of Reasoned Action by

Fishbien and Ajzen (1975), which proposes that the belief that inform the performance of a behaviour are classified into behavioural believes influenced by individual attitudes and normative beliefs, influenced by social norms. It is also imperative to note that the TAM proposes that attitude towards technology is created from an individual's perception of usefulness and ease of use of technologies (Davis, 1985). This fundamental assumption proposed by the TAM makes it very crucial for technology researchers to relate attitude to the study of acceptance of innovative technologies.

From the discussions, a very important construct in the TAM is the attitude of the technology user towards a specific technology. In Fishbien (1979) view, this attitude must be limited to the "attitude toward the behaviour" by linking it to belief and intentions and not the traditional term of attitude in a social system. This recommendation was followed by Davis (1985) by referring to attitude as the evaluation of a technology user associated with the system. From a theoretical position, Hale, Householder and Greene (2002) explain that attitudes must relate to the affective response towards performing some behaviour and not a generalised attitude. From this explanation, the attitude about technology adoption must be examined in the technological context.

The intention to use technology within an organisation can be explained by the employees' attitude toward that specific technology. This distinction of context-based attitude from a generalised attitude of a person in the social system is very important in understanding an individual's positive and favourable attitude toward a particular behaviour. From the TAM, attitudes towards the marketing analytics technology can affect the use of the technology since firm employees' attitude relates to the individual's beliefs towards the system. Therefore, the attitude towards marketing analytics can be influenced by the perception of usefulness and the perception of ease of use. Finally, the intentions to use marketing analytics can be influenced by the attitude towards the technology, thus forming one of the basic assumptions of this study.

A review of existing studies that have used the TAM and, for that matter, attitude as a construct has been presented in Appendix F. One significant study that makes a strong case for extending the UTAUT with attitude from the TAM is that of Dwivedi et al. (2019). The role played by an individual's attitude toward a technology explains whether there will be a favourable or unfavourable reaction towards the use of the system, hence the need to extend the UTAUT by considering this construct.

Commitment-Trust Theory

The commitment-trust theory explains that successful relationships require commitment and trust. In the view of Mukherjee and Nath (2007), the theory explains how trust and factors are very necessary for building and maintaining successful relationships. In marketing, the relationship between commitment and trust makes it essential for partners to invest in preserving the relationship and consider risk options as prudent due to the belief that business partners may not act opportunistically.

In the marketing context, Morgan and Hunt (1994) relied on this theory to conceptualise that perceived trust is a key variable in marketing relationships. In the context of organisational technologies, the perceived trust in partner providing technologies may lead to firms taking high-risk options and considering technology use as prudent due to the belief that technology service providers will provide accurate, reliable, and safe services. In the study of Yuan et al. (2019) and Cui, Mou, Cohen, Liu and Kurez (2020), the commitment-trust theory explains why the perception of trust of information technology and the commitment of information service providers to keep existing relationships will affect the intentions to use technologies. In marketing analytics, the perception that the analytics technology can be trusted will lead to use intentions. The trust of analytics technology is enabled through the commitment shown between the parties involved in the provision of the analytics system.

Diffusion of Innovation Theory

From the theoretical perspective of diffusion of innovation, Rogers (1995) refers to innovation as an idea regarded as new by an individual or organisation. Innovations are considered new, and therefore there is some level of uncertainty surrounding their adoption. The complex nature of business analytics tools such as big data and marketing analytics fits perfectly into this classification of innovation. Innovative technologies are seen as a way for businesses to stay relevant and competitive. From the technological Darwinism perspective, firms, in order to survive the fast-evolving technological world, must adapt quickly by introducing innovative technologies such as marketing analytics.

The diffusion of innovation theory by Rogers (1995) proposes that the adoption of innovation is determined by the characteristics such as relative advantage, complexity, compatibility, trialability, and observability. These factors form the basis for the development of the UTAUT by Venkatesh et al. (2003). Factors that promote the adoption of internet-based technologies include the individuals' perception of the innovation relating to the relative advantage it has over the previous technology, the compatibility with existing beliefs and values, and necessary infrastructure to support the innovation (Rogers, 1995).

Oliveira and Martins (2011) acknowledge the innovative characteristics of an individual or an organisation as an important determinant of the adoption of innovation. The diffusion of innovation theory proposes five categories of individuals at each stage of an innovation process (Cheng, Kao, & Lin, 2004). These are innovators, early adopters, early majority, late majority, and laggards, representing 2.5%, 13.5%, 34%, 34%, and 16%, respectively (Cheng et al., 2004). Doyle, Garrett and Currie (2014) describe these adopter groups:

Innovators: individuals who are likely to take a risk, enjoy being on the cutting edge, and are motivated to be a change agent. These individuals are likely to influence other potential adopters.

Early adopters: this group relies on information provided by innovators to make their decisions. These individuals are visionaries in their fields and are considered key decision-makers.

Early majority: this group is likely to adopt an innovation before the average individual. They are not leaders in their field but are ready to adopt a change and tend to adopt an innovation slower than the early adopters.

Late majority: this group is willing to adopt an innovation after an average member of society. They represent individuals who are sceptical about innovation and may need intense persuasion and encouragement.

Laggards: this group is the last to adopt an innovation. They are not willing to change and may act as resistance to innovation. They tend to prefer using traditional means to do things.

Agarwal and Prasad (1998) basing on the diffusion of innovation theory, developed the personal innovativeness in information technology construct as an important in studying individual behaviour towards innovative technology. Agarwal and Prasad (1998), developing the personal innovativeness in information technology construct, made the following observations:

1. Individuals are characterised as innovative if they are early to adopt technology and serves as the basis for classifying consumers into innovators and non-innovators.
2. Personal innovativeness in information technology is, therefore, a hypothetical construct and not an observable phenomenon.

The effect of personal innovativeness on intention to adopt marketing analytics is based on the assumption that individual firm employees attempt to pursue new ways of doing things by introducing business practices that present relative advantage over existing practices are likely to embrace innovations. The study applies this theory to test that whether the type of innovator (innovators, early adopters, early majority, late majority, and laggards) will influence the use of marketing analytics technology. As a result, the type of innovator, which means whether firm employees are early adopters or late adopters and how these classifications affect the acceptance of marketing analytics, must be studied.

Technology-Organisation-Environment (TOE) Framework

Technology-organisation-environment (TOE) framework by Tornatzky and Fleischer (1990) explains the factors affecting the adoption of technology in organisational context. The TOE framework proposes that technology adoption by organisations is influenced by technology factors, organisational context issues and environmental issues. This theory has informed researchers approach in assessing the factors determining the adoption of technologies by firms (Bhattacharya & Wamba, 2018; Cruz-Jesus et al. 2019; Oliveira & Martins, 2011). Similarly, studies on business analytics (see Appendix G) have recognised the potency of the TOE framework to explain the adoption of this technology (e.g., Kumar & Krishnamoorthy, 2020; Verma & Bhattacharyya, 2017).

It is very important to note that this study applied the TOE framework to examine the effect of the environment on acceptance to use marketing analytics technology. Kim, Hebeler, Yoon, and Davis (2018) posit that the framework explains that the environmental context refers to the arena in which a firm operates, such the government regulation, industry competition. In the context of marketing analytics, the environmental context issues related to the industry's competitiveness, the intensity of use of a particular technology, industry dynamics in terms of customer needs and wants (Germann et al., 2013). Considering the type of industry as a moderating factor in the study of marketing analytics adoption is explained by the environmental aspect of this theory. The environmental context of this theory is of concern for this study since firm employees use of marketing analytics technology can be influenced by the environmental conditions.

Expectancy Confirmation Theory

The expectancy-confirmation theory (ECT) attributed to Oliver (1980) seeks to understand satisfaction outcomes. Satisfaction, in the view of Oliver (1980), is seen as a function of expectation and perception of disconfirmation. The ECT ensures the examination of pre-purchase and post-purchase behaviour (Chou, Min, Chang, & Lin, 2010). Bhattacherjee et al. (2008) posit that the theory explains that the use of a product is initiated by the expectations communicated through marketing initiatives, information from prior users, media reports. The theory explains how consumers evaluate how the product's actual performance matches the expectations leading to satisfaction or dissatisfaction with the product (Bhattacharjee et al., 2008).

The contribution of this theory to this is study is that the continuance usage of marketing analytics by firm employees will be determined by the level of satisfaction with the technology. The theory explains that information systems satisfaction is a very important factor in predicting continuance usage intention (Hossain & Quaddus, 2012). This theory leads to the use of the user satisfaction construct and how it affects continuance usage in the context of marketing analytics.

Summary of Theories Used

The study took into consideration some technology acceptance theories and models in this chapter. These theories and models serve as the assumptions and underlying conditions in deciding the variables for this study. The theories and models and the study variables they explain are summarised in Table 5.

Table 5: The application of theories in technology acceptance studies

Technology Acceptance Variables	Theory	Studies
Performance Expectancy Effort Expectancy Social Influence Facilitating Conditions, intention to use technology, use of technology	Unified Theory of Acceptance and Use of Technology	Venkatesh et al. (2003)
Age, gender, and experience of Employee	UTAUT	Venkatesh et al. (2003)
Personal Innovativeness	Diffusion of Innovation Theory and Personal Innovativeness in Information Technology (PIIT)	Rogers (1995), Agarwal and Prasad (1998)
Attitude towards Technology	Technology Acceptance Model (TAM)	Davis (1985), Davis et al. (1989)
Perceived Trust	Commitment-Trust Theory	Morgan and Hunt (1994)
Marketing Conditions (Type of industry)	Technology-organisation-environment Framework	Tornatzky and Fleischer (1990)
User satisfaction, Continuance Usage	Expectancy Confirmation Theory	Oliver (1980)

Source: Author's construct, Twum (2021)

CHAPTER FOUR

CONCEPTUAL REVIEW

Introduction

This chapter provides a conceptual overview of all the variables used in this study to understand the factors influencing the acceptance and continuance usage of marketing analytics technology. The chapter offers scholarly explanations of the various technology acceptance concepts and variables. This chapter using the various technology acceptance theories, reviews pertinent literature on the application of these constructs and variables in studying acceptance of marketing analytics.

Factors Affecting Intentions to Adopt Marketing Analytics

Existing literature on technology acceptance has applied technology acceptance theories and models. Considering the limited research on marketing analytics acceptance, this chapter attempts to position this research under technology acceptance and use research domain. The review first focuses on how the UTAUT factors explain the adoption of technology intentions are very important in determining how the actual technology use behaviour will be performed.

This chapter also takes a closer look at the moderating effect of firm employee characteristics as a moderator of intentions to adopt marketing analytics. Further, the study acknowledges the influence of the type of industry as a moderating factor affecting antecedents of technology adoption intentions and intentions to adopt marketing analytics. The review closes with a critical look at how two main marketing concepts, namely user satisfaction and continuance usage, present an important avenue to promote marketing analytics technology.

Performance expectancy

Performance expectancy refers to the belief that using new technology will improve activity performance (Venkatesh et al., 2003). Rogers (1995) explain that some innovations are likely to diffuse when they are perceived as having a high rate of relative advantage over other ones. According to Venkatesh et al. (2003), this construct was developed using other constructs such as perceived usefulness, extrinsic motivation, relative advantage, and job fit.

Specifically, the development of the UTAUT found performance expectancy as the most important determinant of intention to use a technology (Venkatesh et al., 2003). From the TAM, perceived performance expectancy explains the perceived usefulness of technology (Im et al., 2011). Ratten (2014) also acknowledge that the perception of gaining an advantage from the use of technology is very crucial in deciding the intention to use the system.

Two main technology acceptance variables associated with performance expectancy are perceived usefulness and relative advantage. The relative advantage in using big data in the view of Shin (2016) and Cabrera-Sánchez and Villarejo-Ramos (2020), is an important predictor of intentions to use this technology. Chiu and Wang (2008) discuss the long- and the near-term usefulness of using technology and describe performance expectancy as near-term usefulness of using technology. An individual's assessment of the impact that innovative technology will have on the immediate performance of their functions will boost the likelihood that they will form an intention to use that technology.

The importance of this variable is evident in its use in numerous empirical studies on antecedents of intentions to use innovative technologies such as mobile-based communication by farmers (Engotoit, Kituyi, & Moya, 2016), health information technology (Kijsanayotin, Pannarunothai, & Speedie, 2009), fitness wearables (Reyes-Mercado, 2018), e-government (Alraja, Hammami, Chikhi, & Fekir, 2016; Kurfali, Arifoğlu, Tokdemir, & Paçin, 2017), cloud-based collaborative learning (Yadegaridehkordi, Nasir, Noor, Shuib, & Badie, 2018), big data (Shin, 2016). Despite the abundant use of performance expectancy to examine the intentions to adopt innovative technologies, there seems to be little research on how this variable affects intentions to adopt marketing analytics.

In business analytics studies such as big data, performance expectancy has been explained as using analytics technology to gain competitive advantage and business benefits (Shin, 2016). In-text mining system Demoulin and Coussement (2020) explain that the perceived usefulness (performance expectancy) of the system is attributed to output relevance (the judgement of employees about the ability of data mining information to meet the needs of the decision-maker) and output novelty (the judgement that information innovation provides the best value). Firm decision-makers are likely to choose text-mining systems that provide information that is relevant to the decision (Demoulin & Coussement, 2020). Therefore, the performance expectancy in using a text mining system is based on the perception that the system can provide unique and novel information for the business.

With artificial intelligence, Grover, Kar and Dwivedi (2020) refer to job-fit as the perception by a technology user that using the system will enhance their job performance. Job-fit is an important construct in the development of performance expectancy construct in UTAUT. The perception of employees that using artificial intelligence for product inspection will improve product delivery quality will influence the use of the technology (Grover et al., 2020). Grover et al. (2020) also used the construct perceived consequences to explain the decision to use a technology base on the feeling that they will gain maximum reward. In the context of artificial intelligence, the perception that firms will gain benefits to employees (job satisfaction, job flexibility) and the corporation will subsequently lead to an increase in the use of the technology (Grover et al., 2020).

Cabrera-Sánchez and Villarejo-Ramos (2020) propose that the performance outcome of using big data will influence user's intentions to use the technology. This view is supported by Baharuden, Isaac and Ameen (2019) that with a strong belief by an individual that big data analytics will have a positive impact on work performance, there will be a corresponding strong intention towards big data. In marketing analytics adoption, performance expectancy should be regarded as leading to an immediate improvement in the performance of marketing function. It is expected that marketing professional's expectations that the use of marketing analytics will enhance their gains in terms of marketing results will influence their intentions to adopt the technology.

Effort expectancy

The effort expectancy construct is about how easy an individual can use new technology (Venkatesh et al., 2003). Roger (1995) states that technological innovations that are considered simple are adopted rather than complex ones. This construct was developed from constructs, namely perceived ease of use (the degree a person perceived the use of the technology would be free of effort) and complexity (the degree a user perceives a technology is difficult to use and understand) (Venkatesh et al., 2003).

Effort expectancy has attracted research attention in technology adoption, including internet banking (Im et al., 2011), collaboration technology used by employees (Brown, Dennis, & Venkatesh, 2010), cloud-based technology (Yadegaridehkordi et al., 2018). These and many other studies provide empirical evidence that effort expectancy as a UTAUT construct enhances the likelihood that innovative technologies will be adopted. It is expected that the complexity of using marketing analytics may pose a challenge to using the technology. Marketers that perceive they possess the skills and ability to use marketing analytics in the performance of their marketing activities are likely to develop a positive attitude towards the technology. This view is supported in a study by Yoon, Jeong and Ghosh (2017) that firm employees are not likely to adopt business intelligence technology due to the system's complexity.

In a developing country context, this construct becomes a crucial factor since innovative technologies are now gaining prominence. This assertion supports the claim made by Im et al. (2011) that effort expectancy will be stronger in more individualistic economies than in developing economies. It is expected that marketing practitioners in developed economies are likely to perceive that marketing analytics will be easier to use in their marketing activities than their counterparts in developing economies. In the case of Ghana, the ease of use of marketing analytics technology is expected to be a challenge and, therefore, could not be the strongest predictor of intentions to use the technology.

In business analytics studies, effort expectancy, in the opinion of Shin (2016), explains data compatibility and normalised data with the functional processes of the firm. In deciding to use text mining systems, Demoulin and Coussement (2020) explain that the perceived ease of use (effort expectancy) of text mining systems is important in determining the intention to use the system. Text mining systems deemed accurate, complete, and can be interpreted lead to perceived ease of use (Demoulin & Coussement, 2020). It is expected that firm employees who perceive analytics systems to provide accurate, complete, and information that can be easily interpreted will perceive a positive effort expectancy.

Cabrera-Sánchez and Villarejo-Ramos (2020) propose that effort expectancy is an important predictor of intention to use big data since the perception of how easier it will be to use will encourage its use. The complexity of using big data analytics is a major issue of concern that needs to be considered in assessing employees' intention in using the system (Baharuden et al., 2019). Similarly, Grover et al. (2020) explained in the context of artificial intelligence technology that the complexity in using this technology refers to the difficulty in understanding and using it. Grover et al. (2020) posit that employees are more inclined to use the technology with less effort. These studies provide support for proposing that the perception of ease of use of marketing analytics technology will influence firm employees to use the technology.

Social influence

Social influence refers to an individual's perception that other people expect them to use new technology (Venkatesh et al., 2003). Rogers (1995) proposes that the innovative technologies that are likely to be adopted align with individuals' values and norms based on the use of the system by members in a social system. The construct was developed using social norms, social factors, and image (Venkatesh et al., 2003).

The UTAUT proposes that social influence exhibit much dominance in mandatory technologies rather than voluntary technologies (Venkatesh et al., 2003). Marketing analytics is a voluntary technology hence the effect of social influence on employees of firms to accept and use the technology may be low. Im et al. (2011) posit that social influence may play a key role in developing intentions to adopt technologies in societies where there is collectivism. The interpersonal relationships and networks of firm employees may serve as an impetus to promote marketing analytics.

The inclusion of the social influence construct has been studied in technologies including internet banking (Im et al., 2011), Uber mobile application (Min, So, & Jeong, 2019), open online courses (Wu & Chen, 2017). These studies acknowledge that referent groups and individuals play an important role in the diffusion of innovative technologies. These referent groups serve as individuals who advocate and encourage the use of innovative technologies. Referent groups in marketing analytics technology adoption may be marketing experts, marketing colleagues in the industry. In this case, the role of family and friends who do not have experience in using firm-level innovative technologies may not play a crucial role in promoting such technologies. The emphasis must be on social identity and group norms from the perspective of the marketing profession and practice in a particular industry.

Yoon et al. (2017) posit those important referents may explain the benefit of using a technology, which can influence the beliefs about a perceived outcome of technology use. Referent groups in business intelligence technology include coworkers and superiors (Yoon et al., 2017). Shin (2016) describes social influence in business analytics as the normative pressure exerted on firms to adopt analytics technology. In the context of artificial intelligence, Grover et al. (2020) propose that social factors determine how organisations perceive the technology and how they are influenced to use it to remain competitive.

Similarly, Demoulin and Coussement (2020) propose that top management support of text mining systems is a crucial factor in using technology. The use of analytics is possible through the support in terms of the encouragement of employees and advocating for the use of the system. Cabrera-Sánchez and Villarejo-Ramos (2020) propose that service employees are likely to be influenced by colleagues and superiors into developing the intention to use big data. Baharuden et al. (2019) assume that the intention to learn about big data is influenced by the social system for business managers.

Facilitating conditions

Facilitating conditions explain the existence of technical and organisational support to enable the use of a technology (Venkatesh et al., 2003). This definition fits perfectly into the adoption of technologies that organisations initiate. Factors and resources that an individual believes exist to support users using technology are termed facilitating conditions (Chiu & Wang, 2008). This support may be in the form of technical and non-technical (Chiu & Wang, 2008). This construct was developed using other constructs such as perceived behavioural control and compatibility (Venkatesh et al., 2003).

The implementation of marketing analytics is described in the literature as a process (Germann et al., 2013). In the UTAUT, this process may better be explained using the facilitating conditions. Venkatesh et al. (2003) explain that the facilitating conditions, in theory, relate to conditions that will make the use of technology easy, such as computer support. It is important to acknowledge that the deployment of marketing analytics is not a one-off disparate activity. Grubb (2018) describe the implementation of marketing analytics as a three-resource approach, which includes people, process and technology. Kumar and Sharma (2017) discuss the implementation of marketing analytics as a roadmap illustrating a series of activities a firm can adopt to deploy marketing analytics. These activities serve as a support firms provide for firm employees to help them accept and use innovative technologies.

Mahardika, Thomas, Ewing and Japutra (2018) posit that facilitating conditions represent technology adoption's external antecedents, including user's knowledge and resources. For instance, in the mobile banking sector, facilitating conditions can be resources such as network coverage, the operating system of mobile services (Mahardika et al., 2018). Shin (2016) provides a clear explanation of facilitating conditions in analytics to include issues of privacy, trust, cyber-security integrity, accuracy and reliability.

The existence of organismal support and resources in encouraging the use of marketing analytics has been acknowledged. Demoulin and Coussement

(2020) acknowledged the importance of firm resources, which serve as facilitating conditions for the adoption of innovative technologies. In the analytics context, a person's perception of the availability of resources and structure support can facilitate the use of the system (Demoulin & Coussement, 2020). Grover et al. (2020) refer to facilitating conditions in artificial intelligence adoption as environmental factors that ease the use of the technology within an organisation. These conditions include support for investments, availability of technology infrastructure, data availability, training of employees, and top management support. Germann et al. (2013) described the process leading to the deployment of marketing analytics as beginning with the commitment of firm resources to data gathering, analytics culture, and information technology infrastructure.

This study adopts the UTAUT as a basis to explain this phenomenon. The facilitating conditions, as explained by the UTAUT, involves the perceived behavioural control of using marketing analytics. The theory also acknowledges the existence of computer support systems and factors that will enable the use of the technology. In the study of intention to adopt big data, Lai et al. (2018) identified that resources in the form of IT equipment and professional employees could affect the adoption of the technology.

These assumptions are seen to be applied by Germann et al. (2013) in determining the factors that lead to the deployment of marketing analytics. Therefore, the development of data and information technology provides the technological resources that may lead to providing training and practice for an employee to acquire skills in analytics. Firms must ensure there exist qualified people who possess the required marketing analytics capabilities. As part of making marketing analysis an integral aspect of business processes, there is the need to promote a culture of marketing analytics. Germann et al. (2013) assert that providing the logic behind why and how marketing analytics is being pursued creates a norm regarding the commitment to using marketing analytics to make marketing decisions.

This process of adopting marketing analytics begins with the top management advocacy resulting from the development of intentions to adopt it. The intentions and advocacy for marketing analytics must be supported through the commitment of firm resources. Wedel and Kannan (2016) attribute the success of marketing analytics to building an organisational analytic culture as the basis for decision making using data and the continuous training and development of professionals.

Other Factors Affecting Intentions to Adopt Marketing Analytics

The study acknowledges the effect of other variables in the link between intentions to adopt a technology and technology adoption behaviour. Several studies have proposed that the intention to use technology could be affected by other important variables such as personal innovativeness, user attitude towards technology, and perceived trust, which become the centre of discussion of this review.

Attitude towards technology

The focus on the attitude of technology users in the study of acceptance of technology has been proposed since the cognitive and affective attitude of technology users affects the information system usage (Yang & Yoo, 2004). Dwivedi et al. (2019) also propose an extension of the UTAUT include user attitudes. Studies have also proposed an examination of the relationship between perceived usefulness (performance expectancy in UTAUT), perceived ease of use (effort expectancy in UTAUT) and user attitude towards a technology (Dwivedi et al., 2019; Yang & Yoo, 2004).

Attitude explains the negative or positive evaluation of a behaviour (Fishbien & Ajzen, 1975). Ajzen (1991) refers to the attitude toward a behaviour as an individual's favourable or unfavourable evaluation of behaviour. These definitions serve as the basis for conceptualising user attitude in the technology context (Davis et al., 1989). Attitude towards technology in the view of Davis et al. (1989) is explained by the salient beliefs about the consequences of performing the behaviour and the evaluation of the consequences of that behaviour. Dwivedi et al. (2019) recognise that the attitude of a technology user refers to the negative or positive feelings about performing a target behaviour.

Personal innovativeness in information technology

This study introduces innovation as a variable in marketing analytics adoption studies. Individuals regard innovations as ideas that are new and are likely to have perceptions of uncertainties (Rogers, 1995). The identification and adoption of innovation are associated with the innovativeness of individuals in organisations. The personal innovativeness in information technology construct proposed by Agarwal and Prasad (1998) has gained the attention of scholars.

The innovation culture of a firm in Lee, Chu and Tseng (2009) is one of the major issues affecting adopting new technologies to gain a competitive advantage. The assumption is that innovation culture ensures that employees within an organisation are more open to changes and are likely to accept new technologies leading to quick innovation diffusion. Lee and Runge (2001) argue that the innovativeness of a business is the most important determinant of technology adoption.

Apart from the innovativeness of businesses, the innovativeness of individuals in a firm is very important in the adoption and acceptance of technology. Agarwal and Prassad (1998) posit that personal innovativeness of individuals in firms is important to identify individuals who are likely to adopt innovative technologies. The consideration given to personal innovativeness will help the firm dedicate limited resources to individuals who can serve as change agents and opinion leaders to facilitate further diffusion of technology.

Agarwal and Prassad (1998) explain the perspective that individual personal traits will help understand the process of technology adoption. Personal innovativeness of information technology refers to the willingness to try new technology (Agarwal & Prassad, 1998). Personal innovativeness, which explains the willingness by an individual to try out any new technology, has been used to explain technology acceptance (Aloysius, Hoehle, & Venkatesh, 2016). Personal innovativeness in information technology is an individual characteristic that determines the difference in whether an individual will accept technology or not.

Perceived trust

This study also proposes that the role of trust in acceptance and use of marketing analytics. Researchers have integrated trust as an antecedent of technology acceptance and use into research models (Ha & Stoel, 2009; Kamal et al., 2020). Pavlou (2003) assert that technology-driven innovations are faced with the challenge of trust among users. Trust has catalysed valued and satisfying relationships between suppliers and customers (Pavlou, 2003). Trust in using business analytics technologies is important due to vulnerabilities related to information storage and sharing. Trust creates a belief that a party will behave in a socially responsible manner, which makes an individual expect that a party might not take advantage of the vulnerabilities of a relationship.

Pavlou and Fygenson (2006) posit that the uncertainty of technologies emphasise the importance of consumer trust. Trust is an important issue in information technology since the competence and integrity dimensions of getting information are critical (Pavlou & Fygenson, 2006). Therefore, trust in information technologies refers to the vendor's ability to provide valid, accurate, and timely information. In the context of big data, Shahbaz, Gao, Zhai, Shahzad, and Hu (2019) posit that firm involvement in big data is a risk, and also apart from just the trust issues, mistrusting the big data technology to provide valuable services without interruptions and data loss is likely to reduce adoption intention.

This study proposes that trust will affect the firm employee's intentions to use marketing analytics technology. It is expected that firm employees with low levels of trust for marketing analytics may not encourage them to use the system than firm employees with an orientation that marketing analytics tools may not pose any security and privacy threat to their business. The examination of trust will be one of the major contributions in the marketing analytics literature on how perceived trust towards marketing analytics tools can be enhanced to encourage firm employees' acceptance of the system.

Moderating Factors Affecting Technology Acceptance Intentions

The adoption of technology research takes into consideration some moderating factors. These factors are firm-level and external environmental factors. This study will focus on employee characteristics (age, gender, experience, and type of innovator) as moderating factors in the UTAUT model. Manager characteristics are considered important factor in technology adoption due to the role a manager's orientation and perception about a technology plays in promoting technology adoption. This study also focuses on the type of industry as a moderator of the relationship between intentions and actual use of marketing analytics.

Moderating role of employee characteristics on intentions to use technology.

Using the upper echelon theory by Hambrick and Mason (1984), Chuang, Nakatani and Zhou (2009) argue that the characteristics of employees of firms influence the adoption and use of technologies. It is, therefore, relevant to acknowledge and investigate the role played by top management in the adoption of marketing analytics tools for firms. Germann et al. (2013), using the upper echelon theory, explain that firms reflect managers and that the experiences and willingness to commit resources to initiate a marketing analytics system is a key driver of marketing analytics adoption. The UTAUT proposes that employee characteristics such as age and gender influence the intentions to accept adopt a technology. The intention to use marketing analytics technology is likely to be influenced by the orientation of employees in relation to their level of experience, age, and gender.

Moderating effect of type of innovator group

The type of innovator group has been the focus of researchers to examine how the different segments of technology users adopt a technology (see Chiu, Fang & Tseng, 2010; Tzou & Lu, 2009). From the Diffusion of

Innovation Theory by Rogers (1995), there are five categories of innovation groups: innovators, early adopters, early majority, late majority, and laggards. The type of innovator group in these studies have been treated as moderators to examine the differences in the intentions to use innovative technology.

In measuring the effect of adopter group on technology adoption, Tzou and Lu (2009) and Chiu et al. (2010) did not use all the five categories to perform the moderation analysis but grouped them under early adopters, early majority, and late adopters; and early users and potential users respectively. For the purpose of this study, the approach adopted by Tzou and Lu (2009) seems appropriate as they argued that from a marketing perspective, the five categories of innovators might fall under two main subgroups (i.e., innovators and non-innovators) or two main subgroups, namely early adopters, and late adopters. This study adopts these two categories of type of innovators to examine the difference in how they perceive marketing analytics technology.

Intentions to use Marketing Analytics Technology

A stream of research focuses on using intention to adopt technology as a dependent variable (Venkatesh et al., 2003). This research direction is not surprising since Ajzen (1991) assert that an individual's intention to perform a given behaviour is a central factor in the theory of planned behaviour. In this study, the intention of firm employees to adopt marketing analytics is used as the dependent variable, which explains an individual's acceptance to adopt a technology. The definition of intention to adopt technology is derived from the theory of planned behaviour proposed by Ajzen (1991). Intentions to perform a behaviour explains how hard an individual is willing to try and how much effort they put in to perform a behaviour. A general rule stated by Ajzen (1991) is that a strong intention to perform a behaviour will lead to a more likelihood of the performance of the behaviour. Hence, the motivation to perform a behaviour (intention) and the ability to perform the behaviour are important predictors of behaviour achievement (Ajzen, 1991).

This study focuses on the intention to use marketing analytics since marketing analytics in Ghana is still in its infancy. Many technology adoption studies due to the infant stage of innovative technologies in their respective countries opt to use intention to use as the main dependent variable (e.g. Ferri, Spanò, Ginesti, & Theodospoulos, 2020; Pan, Ding, Wu, & Yang, 2019; Sheel & Nath, 2020). Similar to the work of Kalinic and Marinkovic (2015), this study describes the intentions to use marketing analytics as an individual's subjective probability that he or she will use a technology (marketing analytics).

Behavioural intentions in business analytics research are referred to as the decision to use the technology (Shin, 2016). Using the work of Shin (2016), this study defines intentions to use marketing analytics as to how hard an employee is willing to use marketing analytics technology. Therefore, the intentions construct in this study does not mean a future behaviour but how hard firm employees are willing to use marketing analytics.

Consequently, the intention to use technology has become the major dependent variable for studies using the UTAUT to study the acceptance of technology-based services (Im et al., 2011; Raza, Shah, & Ali, 2019). In analytics technology acceptance studies, such as that of Silva et al. (2019), Queiroz and Pereira (2019), and Cabrera-Sánchez and Villarejo-Ramos (2020), the intention to use big data is regarded as an important predictor of the use of big data. The use of marketing analytics technology is affected by the motivation (intention) of firm employees to use the system due to their perception of trust, attitudes, personal innovativeness, performance expectancy, effort expectancy, social influence, and facilitating conditions.

Actual Use of Marketing Analytics Technology

Usage behaviour has been a dependent variable in technology acceptance studies (Venkatesh et al., 2003). From the development of the UTAUT, the actual use of the technology system used for the study was measured based on the duration of use. Davis (1989) refers to the actual use of technology based on the frequency. The actual use of technology can explain the consistent and regular use of a system. Davis (1989) considers this variable as a subjective measure of the use of technology. On this basis, studies assessing the actual use of innovative technologies have adopted subjective measures (see Siyam, 2019).

Kim, Park and Lee (2007), from a subjective perspective, measure actual usage as the usage frequency of the technology and usage times. A review of studies by DeLone and McLean (2003) found that studies have referred to system use as the subjective measure of the frequency of use, time of use, number of accesses, usage patterns, and dependency. These measurements capture the approach used by Davis (1989) to measure the actual use of technology. Therefore, the measure of actual use of organisational technology can be examined from the subjective perception of firm employees regarding the usage rate, the usage to perform a task, usage patterns, and dependency. The dependency of marketers on using marketing analytics to perform their tasks will be used to measure the actual use of the technology.

In marketing analytics research, Germann et al. (2013) explain that actual use of marketing analytics relates to the use of the system to make marketing decisions and perform marketing activities linked to pricing, promotions, sales forecasting, segmentation and targeting, etc. In the context of this study, the actual use of the technology variable is measured using the function that firm employees perform with marketing analytics.

Moderating Effect of Type of Industry on Actual Use of Marketing Analytics

This study considers the effect of external environmental factors that influence the adoption of marketing analytics. These factors serve as moderators between the relationship between intentions to adopt marketing analytics and actual use. The moderators considered by scholars include the type of industry, level of competition, the prevalence of marketing analytics, and the level of changing customer needs (Germann et al., 2013). This approach of using environmental factors as moderators of the business analytics adoption studies is similar to that of Lai et al. (2018) and Germann et al. (2013). The focus of this study, however, is on the moderating effect of the type of industry.

The type of industry has been of interest for researchers in investigating technology acceptance (Hernández-Ortega et al., 2006). Type of industry has been acknowledged as a moderating factor in the adoption of marketing analytics due to the firm performance implications in an industry. This approach is useful in determining the specific industries that are likely to adopt technology earlier due to the importance of the technology in that industry.

User Satisfaction of Technology

The concept of customer satisfaction underpins user satisfaction of technology. In the view of Oliver (1980), customer satisfaction is a result of customers' satisfaction with a product assessed through the subjective comparison between their expectations and perceptions. Using the expectancy-confirmation model, Oliver (1980) explains that satisfaction is a result of an initial expectation and a perception of the actual performance of a product. The evaluations that are poorer than expected will lead to a negative disconfirmation (dissatisfaction), and outcomes that the better than expected create positive disconfirmation (satisfaction).

An evaluation process of a product as to whether it meets the expectations of customers creates customer satisfaction (Slack, Singh, & Sharma, 2020). Customer satisfaction measures the overall satisfaction with the performance of the product of an organisation. Organisations want to satisfy customers since the ultimate goal of businesses is to gain benefits from customers satisfaction, such as customer loyalty and positive word-of-mouth (El-Adly, 2018).

The concept of user satisfaction of information technology emerged more than three decades ago. Melone (1990) acknowledged the development of the user satisfaction of information services from the studies of Bailey and Pearson (1983), Baroudi and Orlikowski (1988). Although there is no consensus on the definition of user satisfaction in the context of information technology and information services, Melone (1990) states a common notion that it relates to the technology user providing some form of evaluative response. Therefore, Melone (1990), citing Ives, Olson and Baroudi (1983), refer to user satisfaction as the extent to which technology users perceive the system meets their information requirements and needs.

The examination of user satisfaction of using technology is aimed at the desire of managers to improve the productivity of information systems (Bailey & Pearson, 1983). Baroudi and Orlikowski (1988) posit that measuring how satisfied a user is with a particular technology represents a way of assessing the success and effectiveness of an information system. Doll and Torkzadeh (1988) advocate for increased usage and user satisfaction of computer systems during the initial implementation stage of technology adoption. This focus makes a case for a shift from the concentration on measuring the performance implications of using technology to ensuring the technology meets the user requirements and expectations.

In the technology context, Kim et al. (2007) refer to customer satisfaction as the overall degree of satisfaction with the system provided in a specific transaction. In the context of this study, user satisfaction explains the degree to which marketing analytics users are satisfied with the system and how well it meets their expectations. User satisfaction of information technology services must be explained from the marketing theory point of view (Sun, Fang, Lim, & Straub, 2012). Sun et al. (2012) posit that user satisfaction is attained from service quality, a construct proposed by Parasuraman, Zeithaml and Berry (1985). This focus is needed because information services are regarded as intangible services provided by service providers to customers. It is also worth noting that information service users are not just the receivers of services but are active co-producers.

Dalcher and Shine (2003) explain that satisfaction produces more predictive behaviour than intentions even though intentions is a common approach to measure actual future behaviour. It will be efficient to predict future information technology use using user satisfaction as this affects behavioural responses of users. Similarly, Mahmood et al. (2000) have previously stated that the level of end-user satisfaction with information technology has a likely effect on ensuring the system's success. Wixon and Todd (2005) also posit that the inclusion of user satisfaction in technology acceptance studies is important in predicting the value of technology as it offers an opportunity to generate feedback about information systems.

Continuance Usage of Technology

The literature on continuance usage of technology can be traced to the concept of customer loyalty. Bhattacherjee et al. (2008) developed the continuance usage construct in the context of technology from the expectation disconfirmation theory by Oliver (1980), which explains that an initial expectation of the performance of a product is evaluated against the actual performance. The evaluation of the product performance in the view of Bhattacherjee et al. (2008) will either lead to satisfaction or dissatisfaction. For satisfied customers, they are expected to continue using the product and dissatisfied customers may stop using it.

Information continuance usage refers to the decision of technology users to continue using the system in the long run (Bhattacherjee, 2001). From the information technology continuance model, Bhattacherjee et al. (2008) conceptualised that perceived usefulness and user satisfaction of information technology will affect continuance intention to use technology. The extension of the TAM model by Roca and Gagné (2006) explains that user satisfaction explains the continuance usage of technology. Bhattacherjee et al. (2008) also posit that continuance usage of information technology is influenced by user satisfaction, which is an evaluative affect resulting from users' transactional experience.

CHAPTER FIVE

EMPIRICAL REVIEW AND CONCEPTUAL FRAMEWORK

Introduction

This chapter performs a review of the literature on existing findings of the research objectives of this study. The source of these empirical reviews is scholarly papers on the subject matter in academic journals that provide evidence of the relationship between constructs proposed in this study. The empirical review serves as the basis for formulating the hypotheses used to develop the conceptual framework.

Performance Expectancy and Intentions to Use Marketing Analytics

Empirical studies have paid much attention to understanding the effect of performance expectancy on intentions to use innovative technologies. Ratten (2014) found a positive relationship between performance expectancy and adoption intention in China and the USA in a cloud computing study. Slade et al. (2015) also found that performance expectancy is the second strongest predictor of intention to adopt remote mobile payment. Other studies have found performance expectancy to predict intentions to use technologies such as enterprise architecture (Hazen, Kung, Cegialski, & Jones-Farmer, 2014) and e-government services (Kurfali et al., 2017). On the other hand, this variable was found not to be a predictor of student technology adoption by Attuquayefio and Addo (2014).

The development of the performance expectancy construct using the diffusion of innovation theory considers the importance of relative advantage and demonstrability (Venkatesh et al., 2003). As expected, empirical studies have found that the performance expectancy perception is a predictor of intentions to use analytics technology (Cao et al., 2019; Cabrera-Sánchez & Villarejo-Ramos, 2020; Demoulin & Coussement, 2020; Jaklič, Grublješič, & Popovič, 2018; Okcu et al., 2019; Shin, 2016; Sun et al., 2019; Yoon et al., 2017). Based on the empirical studies identified, this study proposes that performance expectancy has a positive and significant relationship with intentions to adopt marketing analytics. It is expected that the perception of employees that marketing analytics will enhance the performance of their marketing function will influence them to use the system.

Effort Expectancy and Intentions to Use Marketing Analytics

The empirical review sought to establish that effort expectancy perception of marketing analytics will influence intentions to use the system. Kang (2014) asserts that studies have shown that the low level of effort to learn and understand a new technology tends to increase the adoption rate of the technology. With mobile learning and networking apps, Thomas, Singh and Gaffar (2013) and Chua, Rezaei, Gu, Oh and Jambulingam (2018) respectively found that effort expectancy has a significant and positive relationship with behavioural intentions to use these technologies. Slade et al. (2015), however, did not find a significant statistical relationship between effort expectancy and intentions to adopt remote mobile payment.

In the literature, some studies have focused on how effort expectancy affects intentions to use big data despite the limited studies on marketing analytics. Studies have found effort expectancy to have a significant effect on intentions to use analytics technology (Cabrera-Sánchez & Villarejo-Ramos, 2020; Okcu et al., 2019; Shin, 2016; Shorfuzzaman et al., 2018). Yoon et al. (2017), Demoulin and Coussement (2020), and Jaklič et al. (2018), on the other hand, found that effort expectancy does not predict intentions to use the technology. The reason for this result may be that the perception of individuals that business intelligence technology will improve their work performance is enough motivation to use the technology and may not give much importance to how complex the technology is (Yoon et al., 2017).

From the preceding discussions of existing studies, effort expectancy as a construct in examining factors affecting the intentions of employees to adopt marketing analytics is justifiable. The study proposes that positive perceptions about the ability of firm employees to use marketing analytics technology will influence their intentions to use the systems. It is expected that the understanding from firm employee position that marketing analytics will be easier to use to enhance marketing effort will lead to their intentions to use the technology.

Social Influence and Intentions to Use Marketing Analytics

The effect of social influence on technology acceptance has been widely examined. The study of Slade et al. (2015) acknowledges that social influence is the most important determinant of intentions to use remote mobile payment. Thomas et al. (2013) also found that social factors have a significant and positive relationship with behavioural intentions to adopt mobile learning. Similarly, mobile banking adoption behaviour was found to be influenced by social influence (Zhou, Lu, & Wang, 2010). On the other hand, some studies report an insignificant relationship between effort expectancy and intention to use (Attuquayefio & Addo, 2014; Ratten, 2014; Yoon et al., 2017). These studies may explain that the pressure from other individuals will not have a greater influence on firm employees to use marketing analytics systems.

It is worth reporting that some studies in the context of analytics, such as Jaklič et al. (2018), Demoulin and Coussement (2020) and Cabrera-Sánchez and Villarejo-Ramos (2020) found that social influence has a significant direct relationship with intentions to use business analytics. These studies acknowledge that individuals are likely to develop the intention to use business analytics technology when peers and management support it. This result is supported by Germann et al. (2013) and Sun et al. (2019) that top management influence the intention to use big data by performing activities, thereby enhancing the diffusion process of the technology, by encouraging others within the organisation to accept innovative technologies. This study proposes that marketing analytics adoption can be promoted through the advocacy efforts of managers and employees.

Facilitating Conditions and Intentions to Use Marketing Analytics

A considerable number of studies have revealed the significant effect of facilitating conditions on intentions to use innovative technologies such as telemedicine (Kamal et al., 2020), healthcare wearables (Wang, Tao, Yu, & Qu, 2020), and 3D printing (Holzmann, Schwarz, & Andretsch, 2020). A study by Kwon et al. (2014) found that the existence of facilitating conditions that are necessitated through the data usage experience and data quality leads to the intention to adopt business analytics. The initial trigger to adopt business analytics as a valuable resource for firms must be supported by top-level managers due to the resources needed to sustain the initiative.

In the business intelligence context, requisite skills and resources, and organisational learning climate, aspects of the facilitating conditions construct are proposed to have a positive and significant relationship with motivation to learn and use the technology. Cabrera-Sánchez and Villarejo-Ramos (2020) found that facilitating conditions is a predictor of intentions to use big data. Cabrera-Sánchez and Villarejo-Ramos (2020), Cao et al. (2019), Behl, Dutta, Lessmann, Dwivedi and Kar (2019) and Sun et al. (2019) reveal that the availability of management support, data, and technology facilities will catalyse the use of analytics technology. The study of Germann et al. (2013) also found that analytics culture, analytics skills, data, and information technology contribute to the deployment of marketing analytics technology among fortune 1000 companies in the US. These studies though limited, provide empirical evidence of the role played by facilitating conditions in influencing intentions to use marketing analytics.

Perceived Trust and Intentions to Use Marketing Analytics

Trust in information technology systems is proposed as an important determinant of intention to use innovative technologies. In mobile commerce, Yadav, Sharma and Tarhini (2016) found that perceived trust has a significant effect on usage intention. In cloud-based applications, Chen and Nakayama (2016) provide evidence of the important role of perceived trust on the usage intention. Trust in service (technology) and trust in service providers were found to be predictors of intentions to use mobile payments in the study of Manrai and Gupta (2020).

Shahbaz et al. (2019) found among health care employees that perceived trust in big data information systems positively affects intentions to use the technology. Perceived trust is very important in the context of big data analytics since the adoption of the technology is a risky one. Madhlangobe and Wang (2018) found that trust does not have a significant relationship with the intention to use big data analytics. Despite this result, studies cited earlier demonstrate that perception of trust by firm employees allows for the use of technologies since they do not want to be at risk. In the context of marketing analytics, employee's perceptions about the security of firm and customer data will determine whether they will use the services of analytics service providers. This study proposes that trust in marketing analytics services will promote the intention to use the technology.

Personal Innovativeness and Intention to use Marketing Analytics

Empirical studies reviewed have found that personal innovativeness of firm employees influence technology adoption. Lu et al. (2005), Xu and Gupta (2009), Lu (2014) and Hwang (2014) show how important personal innovativeness construct is in understanding technology acceptance. In the view of Aloysius et al. (2016), individuals with a high level of personal innovativeness are more likely to use new technologies than users with low personal innovativeness. In the business analytics literature, Shorfuzzaman et al. (2018) acknowledge that personal innovativeness influences end-user perceptions relating to the usefulness and ease of use of analytics systems.

Despite the little empirical evidence on the effect of personal innovativeness on intentions to use marketing analytics, this study relies on empirical studies in other technology contexts such as mobile learning (Shorfuzzaman et al., 2018), mobile-store (Aloysius et al., 2016), mobile commerce (Lu, 2014) to propose that personal innovativeness will influence marketing analytics acceptance intentions. These arguments imply that firm employees' innovativeness in technology will affect their willingness to try a marketing analytics system. Therefore, it is expected that firms that are likely to lead in the acceptance of marketing analytics are those with innovative employees.

Attitude towards Marketing Analytics and Intentions to Use the Technology

This study reviews existing literature that seeks to examine the effect of user attitude towards technology on user intentions. Verma et al. (2018), in the context of big data analytics, found that perceived ease of use and perceived usefulness have a positive and significant relationship with attitude towards big data. A study by Wang, Li and Zhao (2017) on big data in the health sector found that perceived usefulness is significantly related to attitude towards the system. It is, therefore, expected that performance expectancy and effort expectancy will influence the attitude of marketing analytics technology use.

In the literature, attitude towards big data technology has a positive and significant relationship with behavioural intention to use big data analytics systems (Verma et al., 2018). Wang et al. (2017) also found that attitudes towards big data in the health sector significantly influences usage intentions of the system. From the empirical studies focused on business analytics, this study proposes that attitude towards marketing analytics will predict the intention of users to use the system.

Moderating Effect of Employee Characteristics on Intentions to use Marketing analytics

This study proposes that firm employee characteristics play an important role in influencing the intention to use marketing analytics technology. From the theoretical perspective of Venkatesh et al. (2003), firm employees age, gender, and experience with technology moderates the relationship between antecedents of technology acceptance and usage intentions. From the UTAUT, some moderating effects of user characteristics on the relationship between UTAUT technology acceptance constructs and intentions were ascertained. First, the effect of performance expectancy on intentions to use technology was stronger for men and young workers (Venkatesh et al., 2003). Second, the effect of effort expectancy on intentions to use technology was stronger for women, older workers, and those with limited experience (Venkatesh et al., 2003). Third, social influence on intentions to use technology is stronger for women, older workers, and those with limited experience. Finally, the UTAUT did not find any worker's age, gender, and experience to be a moderator of the relationships between facilitating conditions and intentions to use a technology (Venkatesh et al., 2003).

There have been contradictory findings on the moderating effect of demographic factors on intentions to use technologies. In a developing country context, Baker, Gahtani and Hubona (2007) found that age and gender were not significant predictors of intentions to use technologies. Pan and Jordan-Marsh (2010) also found that age and gender did not significantly affect intentions to use technology when applied on a predictive model with all the four UTAUT constructs. Despite the contradictory results, this study based on the moderating effects in the UTAUT proposes that firm employee characteristics will moderate the relationship between UTAUT constructs and user intentions.

Moderating Effect of Type of Innovator on Intention to Use Marketing Analytics

This study reviews empirical studies to conclude that the type of innovators that exist in firms may play a key role in affecting the intentions to use marketing analytics technology. The study of Tzou and Lu (2009) found that the category of innovator (early adopters, late adopters) influences the adoption of technology. Tzou and Lu (2009) found that early adopters of technology tend to score higher in terms of all the constructs used to study the adoption of technology. Chiu et al. (2010) found that early technology users exhibit higher performance expectancy and effort expectancy than potential users. From these existing studies, this study proposes that early adopters will demonstrate a higher intention to use marketing analytics than late adopters.

Effect of Intention to use Marketing Analytics and Actual Use

Empirical studies on the effect of intention to use technology on actual technology use are informed by technology acceptance models (e.g., TAM, UTAUT). Studies have applied the technology acceptance models to test the proposition that behavioural intention is the most important determinant of actual use of technology. Similarly, Martins, Oliveira and Popovič (2014) found that to explain internet banking usage, the most important predictor to consider is behavioural intention. Consequently, researchers have found that intentions to use information system technology predict actual use (Dwivedi et al., 2019; Venkatesh et al., 2003). One profound empirical study is that of Venkatesh et al. (2012), which found that behavioural intention is a predictor of actual technology use. Based on the empirical results and the TPB perspective, this study proposes that the behavioural intention of firm employees to use marketing analytics will lead to the actual use of the system.

Moderating effect of Type of Industry on Actual Use of Marketing Analytics

The empirical review also presents some existing studies on the moderating effect of market conditions (type of industry) on the relationship between intentions by firm employees to use marketing analytics and actual use. The adoption of technology, based on antecedents of technology adoption, can be affected by the industry in which an organisation operates (Hernández-Ortega et al., 2006). Hernández-Ortega et al. (2006) found that industry type significantly affects acceptance to use online business management applications by firms. Similarly, Oliveira and Martins (2009) used the service industry as a control for determining the adoption of information control.

The study of Cao et al. (2019) considered the type of industry to examine the sustained competitive advantage of marketing analytics. The study found that type of industry did not have a statistically significant effect on using marketing analytics (Cao et al., 2019). Despite the mixed findings, this study proposes that the type of industry a firm operates in will serve as a moderator between intentions and actual use of marketing analytics.

The effect of Actual use on User satisfaction

This study also hypothesised that the actual use of marketing analytics technology affects user satisfaction with the technology. In the context of electronic patient records, Maillet, Mathieu and Sicotte (2014) found that actual use influences user satisfaction. Isaac, Abdullah, Ramayah and Mutahar (2017) also found that the actual use of internet systems influences user satisfaction among public sector employees. The use of innovative technologies will lead to end-users identifying the satisfaction in using the system. From the empirical studies cited, this study proposes that firm employees' actual use of marketing analytics systems will predict the perception of user satisfaction.

The effect of User Satisfaction on Continuance Usage

Studies on the relationship between user satisfaction and continuance usage follow the proposition of the information system success model by DeLone and McLean (2003). Al-hawari and Mouakket (2010) in the e-learning context, Hadji and Degoulet (2016) in the information system context, and Garg and Sharman (2020) in the electronic training context found that user satisfaction predicts retention of the system. The continuance use of marketing analytics by firm employees will depend on the level of satisfaction they derive from using the system. This study proposes that firm employees will discontinue marketing analytics technology if they perceive the system does not meet their expectations and needs but are likely to continue using it if their needs and expectations are met. The study hypothesises that user satisfaction of marketing analytics will have a significant effect on continuance usage.

Conceptual Framework

The conceptual framework developed to guide this study is based on the literature review of key theories, concepts, variables, and empirical studies. The conceptual framework shows the relationships that exist among the variables. The framework depicts four main structural paths of the relationships between technology acceptance antecedents, intentions to use, actual use, user satisfaction, and continuance usage of marketing analytics. The main structural paths and moderating variables also proposed are based on the review of pertinent literature. The framework is depicted in Figure 1.

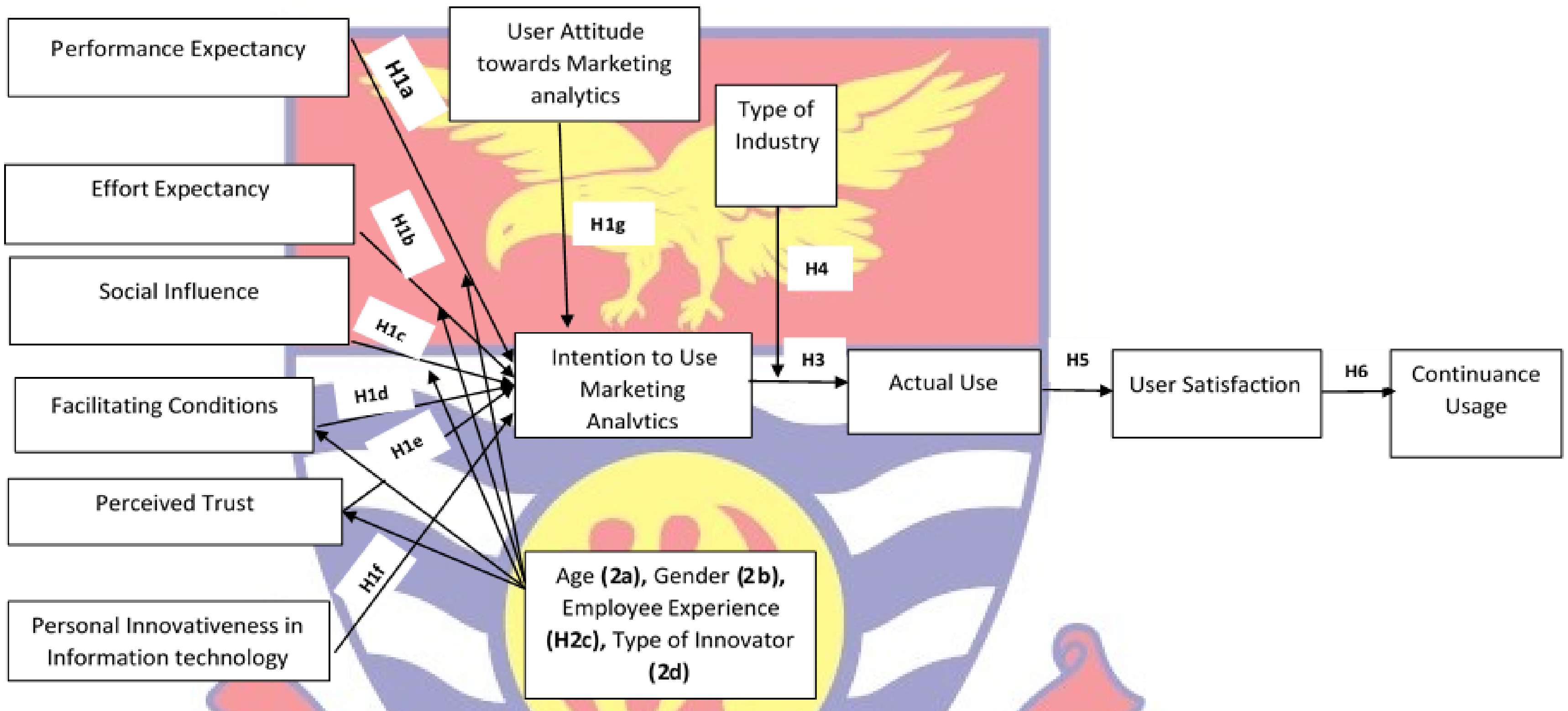

Figure 1: Conceptual framework

Source: Author's construct, Twum (2021)

CHAPTER SIX

RESEARCH METHODS

Introduction

From the earlier chapters, this research acknowledges the use of technology acceptance theories to explain the factors affecting the intentions to use, actual use, user satisfaction and continuance use of marketing analytics technology. This chapter takes a look at the research methodology guiding the empirical aspect of the study. The chapter contains essential components explaining the methods used in conducting the study. The study's methodology comprises of research philosophy, research approach, research design, research population, sample and sampling technique, research instrumentation, data collections, data analysis.

The basic components of research methodology in business research include research approach, research design, sampling technique and sample size, data collection, and data analysis (Saunders, Lewis & Thornhill, 2009). These fundamental elements of the research were followed to present details on the research methodology.

Research Philosophy/Paradigm

This study adopted positivist and constructivist philosophies due to the use of both quantitative and qualitative methods. The quantitative aspect of this study supports a positivist paradigm because the study sought to objectively test research hypotheses using theories and models of technology acceptance. Johnson and Onwuegbuzie (2004) explain that positivism involves the use of methods and procedures that seek to confirm or falsify theories. In this study, the study of the proposed relationships between constructs is informed by testing hypotheses of existing theories in the context of marketing analytics. On the other hand, the study also adopted a constructivist paradigm to conduct the qualitative study. Lee (2012) explain that a constructivist paradigm assumes that there are multiple realities that can be investigated through subjective means. This study, therefore, relied on the subjective responses from study participants in organisations with different realities to understand the factors influencing the use of marketing analytics.

Apart from positivist and constructivist paradigms, other philosophies have been proposed by researchers, such as postpositivism (Guba & Lincoln, 1994) and pragmatism (Feilzer, 2010; Mertens, 2012). In the view of Mertens (2012), pragmatism assumes that a researcher must use a method that fits a particular research question. This study adopted the postpositivist paradigm since it seems more appropriate in explaining the method adopted. It enables the collection of quantitative-oriented data and qualitative-oriented data on the same research question and then puts the two in a conversation to aid in deeper understanding generated from patterns found in the approaches (Martens, 2012).

A Postpositivism paradigm begins with testing of key hypotheses and including qualitative methods to understand a phenomenon (Guba & Lincoln, 1994). An important assumption in this study is that a postpositivist study relies mainly on using quantitative approaches to test hypotheses and supporting the quantitative data with qualitative data. Therefore, this study uses quantitative methods to test the hypotheses indicating the factors affecting intentions to use marketing analytics while supporting these findings with qualitative data.

Research Approach

The research approach of a study can be classified as quantitative and qualitative research (Amaratunga, Baldry, Sarshar, & Newton, 2002). A research approach is determined by the research philosophy/paradigm guiding the study. Quantitative research is based on how clear one is about the theory at the beginning of the research (Saunders et al., 2009). This approach is referred to as a deductive approach since the research design tests hypotheses based on theories. This approach is in line with a positivist paradigm (Brand, 2009; Creswell, 2009; Kankam, 2019), which proposes that reality is objective.

On the other hand, in an inductive research approach, the research does not begin with a theory and does not seek to test hypotheses. The inductive approach is linked to an interpretivist paradigm (Chandra & Shang, 2017; Johnson & Onwuegbuzie, 2004; Sobh & Perry, 2006) that perceives reality as subjective and can be understood through human experience. Saunders et al. (2009) assert that the deductive approach owes more to positivism and induction to interpretivism.

This study adopted a quantitative deductive approach and followed the sequential stages proposed by Robson (2002) as cited in Pathirage, Amaratunga and Haigh (2007) to include a hypothesised relationship between variables, operationalising the study variables, testing the hypotheses, and analysing the results with theory. Specifically, this study adopts a correlational analysis for the quantitative study. Compared to a causal relationship approach, which includes a categorical variable and provides better evidence of cause and effect, correlational studies involve quantitative variables and determine the relationship among variables to aid predictions (Johnson, 2001). This study adopts variables from technology acceptance theories and how these variables predict the intentions to use marketing analytics.

On the qualitative approach, Baxter and Jack (2008) posit that this approach adopts a constructivist paradigm which recognises that truth is relative and depends on an individual's perspective, thus leading to a close collaboration between the researcher and the participant. This research approach also enables researchers to investigate complex phenomena with their context (Baxter & Jack, 2008). A qualitative approach has been used by researchers in conducting studies relating to technology acceptance (Hart & Sutcliffe, 2019; Renaud & Biljon, 2008).

On the qualitative approach, this study follows the approach that enables the researcher to identify patterns and themes and make interpretations based on the relationships identified (Leech & Onwuegbuzie, 2007). As a result, this approach does not seek to generate theories but to answer why and how and seems appropriate in answering process-oriented questions. The implication is that in technology acceptance studies, a qualitative approach can be useful in explaining why the use of these technologies and how these technologies are used. In the context of this study, the qualitative approach attempts to address why marketing analytics technologies are accepted and used.

Apart from the quantitative and qualitative approaches, mixed methods approach has become a dominant form of research (Creswell, Plano Clark, Gutman, & Hanson, 2003; Johnson et al., 2007). In the view of Feilzer (2010), the use of mixed methods strives for the integration of quantitative and qualitative research strategies. Johnson, Onwuegbuzie and Turner (2007), citing Denzin (1978), state that mixed methods approach embraces triangulation, which is a combination of methodologies in the study of the same phenomenon. Triangulation may take the form of data triangulation (use of data from different sources) and methodology triangulation (using multiple methods to study a research problem).

In business research, the use of mixed methods approach has gained acceptance by scholars (Cameron & Molina-Azorin, 2011). It is worth acknowledging that mixed methods apply triangulation to research, thereby emphasising the use of multiple research designs (Harrison III, 2013). Morse (1991) identified two types of methodological triangulation, namely simultaneous and sequential mixed methods. The simultaneous mixed method makes use of quantitative and qualitative methods with little interaction between the data collection, but the findings complement each other (Morse, 1991). On the other hand, the sequential mixed methods approach starts with an approach (quantitative) and later follows with another (quantitative) to explain the findings (Cameron, 2009).

This study adopted the sequential mixed methods approach. The mixed methods, therefore, enables the confirmation or corroboration of quantitative and qualitative data through triangulation. In this study, the quantitative data and qualitative data are collected separately, and a different set of data is obtained. The analysis of the data is finally triangulated to ascertain how they collaborate each with other.

In conducting explanatory sequential mixed methods studies, Creswell et al. (2003) identified that the following approach could be used: 1) begin with collecting quantitative data using surveys and follow with interviews, 2) the quantitative data is analysed statistically followed by the analysis of the qualitative data, 3) the quantitative and qualitative data are discussed jointly in the discussion section to identify areas where the results collaborate or overlap.

Research Design and Strategy

The research can be exploratory, descriptive, and explanatory (Saunders et al., 2009). This study adopted an explanatory approach for both quantitative study and qualitative study. The quantitative study employed an explanatory research approach using a survey to determine how antecedents of adopting technology affect intentions to use marketing analytics. Saunders et al. (2009) state that explanatory studies seek to subject data to statistical tests such as correlation to have a good view of the relationship between variables. This study sought to test the proposed relationship between study variables using hypotheses and testing of theories.

Surveys as a research strategy are associated with a deductive approach and a common strategy in business and management research (Saunders et al., 2009). Saunders et al. (2009) posit that a survey strategy allows for collecting quantitative data from a large population using questionnaires that can be analysed quantitatively to indicate the relationship between variables and produce models of these relationships. This approach brings to bear the use of confirmatory survey research, which focuses on theory testing using well-defined variables, models, and propositions (Forza, 2002).

Concerning the time horizon, this study adopted a cross-sectional design. Olsen and St George (2004) explain that cross-sectional surveys usually use data collected just once from study respondents. This approach makes it difficult to establish causality, but rigorous analysis using regression could help make some causal inferences, which is a significant strength of longitudinal studies (Saunders et al., 2009).

An explanatory case study was adopted for the qualitative research design to explain the presumed causal links (see Baxter & Jack, 2008). The qualitative data from case studies aim to identify similar themes to explain factors influencing the use of marketing analytics. The study adopted a cross-case analysis, which involves comparing and contracting selected cases (Onwuegbuzie & Leech, 2007). In this instance, multiple cases represent thematic analysis across cases to ensure a thorough investigation and understanding of the phenomenon.

In the view of Baxter and Jack (2008), a qualitative case study is an approach that uses a variety of data sources, which is aimed at understanding a phenomenon from more than one source. An advantage of a qualitative case study is to ensure closer collaboration between the researcher and the study participant and help understand contextual conditions relevant to studying the phenomenon under study (Baxter & Jack, 2008).

In this study context, multiple respondents (firm employees) from different organisations were used to understand the factors influencing the acceptance of marketing analytics technology. The use of multiple cases is aimed at understanding the factors influencing marketing analytics acceptance from the perspective of firm employees in organisations.

Since this study adopted a mixed methods approach, the design employed was explanatory sequential mixed methods. According to Cameron (2009), explanatory sequential mixed methods design is where quantitative data is collected first and followed with qualitative data. The triangulation, therefore, entails the researcher mixing the data between the two phases. In this study, the survey was first collected from firm employees who use marketing analytics technology. Another study using interviews with firm managers who use marketing analytics was done to collect the qualitative data. Ultimately, both the quantitative and qualitative studies sought to establish a relationship between variables, hence, the use of an explanatory design.

Research Population

In this study, the population comprise firm employees who use marketing analytics technologies in Ghana. Despite having over 7037 registered companies limited by guarantee, and 18,139 companies limited by shares (Registrar-General's Department, 2020), it is important to note that not all these companies in Ghana may use marketing analytics technology. It is crucial to note that an important aspect of this study is that the unit of analysis is not the firms but users of marketing analytics technology (firm employees). Therefore, the study population is not firms in Ghana but the end-users of marketing analytics technology. As a result, firm employees that work for organisations that have marketing analytics technologies in place are classified as the population for this study.

Since the phenomenon under investigation relates to the use of advanced big data analytics in marketing such as Hadoop and SAP, it was necessary to identify the study population (firm employees) that use these systems. It is, however, difficult to ascertain the users of marketing analytics in Ghana. Following the approach used by scholars, the focus of such studies has been on firm employees of reputable firms that possess the characteristics of using these advanced analytics systems (e.g., Cao & Duan, 2017; Germann et al., 2013;

Verma et al., 2018). Germann et al. (2013), for instance, focused on Fortune 1000 companies in the US. Cao and Duan (2017) also focused on valued manufacturing companies in the UK that have the capability to use big data. This study, following this approach, considered focusing on using the employees of Ghana Club 100 companies as the study population.

The Ghana Club 100 is a list of companies considered leaders in their respective industries such as banking, telecommunications, hospitality, insurance, manufacturing, etc. (Ghana Investment Promotion Center, 2019). The companies included in this list are limited liability companies in Ghana and have demonstrated growth and profitability in the past three years. The companies that are listed represent those that are rated higher in their respective industries. According to the Ghana Investment Promotion Center (2021), one of the methodologies that are used in ranking is the growth in the marketing of the company. Therefore, employees of firms that are ranked very high in terms of marketing performance in Ghana were considered as the population.

The use of firm employees in the Ghana Club 100 as the population has been adopted in technology acceptance studies in Ghana (Okpattah, Chisenga, & Addo, 2014; Senyo, Addae & Adam, 2015; Senyo, Effah & Addae, 2016). A study by Appiah-Adu, Okpattah, and Djokoto (2016) justified using the employees of Ghana Club 100 firms in their study of technology capability because it is made up of leading firms from different operational sectors and has a good mix of local and foreign firms.

The study population are firm employees (marketing officers, sales and distribution officers, digital media employees) of Ghana Club 100 companies currently performing marketing activities using marketing analytics technology.

This population, based on the description of Barratt et al. (2015), is a hidden population since it is difficult to determine the sample frame and cases for data collection. The users of marketing analytics technology in Ghana are difficult to determine since there is no data to identify the users of the technology. In the case where a study is conducted to determine the population among employees of Ghana Club 100, the users of the technology in firms that are not part of Ghana Club 100 will not be captured. Therefore, one major limitation of this study is the inability to determine the total population of the study.

Sampling Technique

This study adopted a non-probability sampling. This decision is in line with Saunders et al. (2009) recommendation that when it is not possible to statistically select a sample at random in market research where there is no sampling frame, non-probability sampling can be used to subjectively select a sample. It is important to note that this study focuses on users of a service (technology), and there may not be a complete list of firm employees who use the systems. Guarte and Barrios (2006) propose that the unavailability of a complete list of technology users makes it market research, making the use of probability sampling appropriate.

Using the contacts (emails, telephone numbers, postal addresses) provided by the Ghana Investment Promotion Center, the researcher contacted managers of firms included in the Ghana Club 100 using the mailing address provided. The mailing addresses can be assessed on Ghana Investment Promotion Center (2019) magazine available on https://gipc.gov.gh/wp-content/uploads/2020/09/GC100-2018-EDITION.pdf. This approach is supported by studies on analytics (Germann et al., 2013; Cabrera-Sánchez &

Villarejo-Ramos (2020), where researchers use mailing to communicate with firm managers.

The initial communication was sent to contact persons in Ghana Club 100 companies indicating the scope and objective of the study. A consent form (see Appendix H) was sent to firm employees to describe the kind of marketing analytics the study is interested in and to ensure firms included in the study have employees using the technology. This initial attempt is to ensure employees in companies on the Ghana Club 100 list have been contacted and also to identify the companies that use marketing analytics technology.

The result of identifying the study sample led to the identification of 25 firms in the Ghana Club 100 that indicated they use some form of marketing analytics. Therefore, the entire study mainly focused on 25 firms in Ghana that were identified as using marketing analytics technology. The researcher indicated in the initial contact that firms that use marketing analytics must distribute the consent form to their employees that use the systems. The employees of these 25 firms who responded to the consent forms sent were used as the main source of sampling in their respective organisations. The study adopted purposive sampling for the qualitative data collection and convenience sampling for the quantitative survey.

Unlike purposive sampling that is qualitative, convenience sampling can be adopted in a quantitative approach (Etikan et al., 2016; Teddlie & Yu, 2007). The rationale for using convenience sampling is that some studies have cases that appear to be almost finite and may not be possible to include every subject (Etikan et al., 2016). In this study, it is difficult to obtain a sample frame or a list of users of marketing analytics technology in Ghana. Convenience sampling is effective to select respondents who meet the inclusion criteria. The use of this approach is evident in scholarly studies on the use of marketing analytics (Cao et al., 2019; Cao & Tian, 2020; German et al., 2013). Therefore, this study adopted convenience sampling to select study participants for the quantitative study.

Following the approach used by Verma et al. (2018), the study adopted a respondent-driven sampling method by asking study respondents to recruit other study respondents. In this study, the 25 contact persons who accepted to be part of this study were used as the first respondents. They were asked to recruit as many as other study participants in their organisation who use marketing analytics technology.

Using this approach is quite similar to snowballing sampling techniques, which demands that an initial study respondent contact other individuals who are later contacted by the researcher (Heckathorn, 1994). In the case of snowballing, the researcher does not have access to a large number of study respondents. Respondent-driven sampling has access to a large number of respondents who know other potential study respondents. The co-workers are also users of marketing analytics technologies; therefore, they represent the study sample. The use of respondent-driven sampling arises when there is a small size of the target population and the difficulty to locate members of the target population (Salganik & Heckathorn, 2004). Using this approach is justified because, in an organisational setting, people are connected in a network of relationships (Salganik & Heckathorn, 2004).

A purposive sampling technique was used to select study participants for the qualitative study. This is because Sarstedt, Bengart, Shaltoni and Lehmann (2018) explain that purposive sampling uses the researcher's expertise and judgement based on an assessment of respondents that are perceived to be appropriate to analyse the effect being studied. The study again relied on the 25 firms identified as using marketing analytics in Ghana. Purposively, the study, therefore, included digital media managers, marketing managers, and sales and distribution managers who use marketing analytics. Purposively, the researcher selected study participants across the telecommunications, banking, hospitality, fast-moving consumer goods sector, and manufacturing sectors. This approach is to ensure there is information collected on the use of marketing analytics across different sectors.

In order to gain access to these study participants, the telephone numbers of firm managers of the 25 companies identified as users of marketing analytics systems among the Ghana Club 100 were used to inquire about managers responsible for marketing analytics. This exercise led to the identification of six firm managers who were willing to be part of the study after consent forms (see Appendix H) were sent to them. These firm managers selected, apart from being users of marketing analytics are in charge of the use of the technology in their department or unit. This technique is needed to select respondents who have the most information on the topic (Guarte & Barrios, 2006) and will be willing to provide information by virtue of their experience (Etikan, Musa, & Alkassim, 2016).

Sample Size Selection

This study also determined the sample size for the quantitative study and qualitative study. This study provides a justification for the sample size used for the quantitative aspect of this study. Hair Jr, Sarstedt, Hopkins and Kuppelwieser (2014) explain that sample size can affect many aspects of the structural equation model, such as parameter estimates, statistical power, and model fit. Scholars have proposed that a sample of 200 is appropriate (e.g. Hoe, 2008) for structural equation modelling studies. Hair Jr et al. (2014) proposed that the minimum sample size of a PLS structural question model must be equal to or larger than the following two conditions:

(1) ten times the largest number of formative indicators used to measure one construct;

(2) ten times the largest number of inner model paths directed at a particular construct in the inner model.

From the rule of thumb in selecting a minimum sample size for PLS studies, this study must have 70 study participants as the minimum sample size. This is informed by the number of inner model paths directed at a particular construct in the model. In the model, the intention to use the marketing analytics construct is predicted by seven (7) constructs. Following the explanation by Cao and Tian (2020) that there is no agreed method for selecting sample size based on online surveys, therefore, the rule for selecting sample size for a structural equation model forms the basis for selecting the sample size.

The studies on the use of marketing analytics also serve as justification for selecting a sample size for this study. A similar study by Germann et al. (2013) on the use of marketing analytics to improve marketing performance used 212 firm employees. A study by Verma et al. (2018) on the factors affecting the acceptance of big data analytics used 150 data analytics employees as the sample size.

Considering a response rate of 23.25 per cent in the study of German et al. (2013) and 84 per cent response rate in the study of Rahman, Hossain, Muniem and Fattah (2021) demands that additional data above 70 is collected from respondents. Cao et al. (2019) explain that the completion rate of non-probability sampling surveys is important. Out of 252 surveys submitted, 213 were usable. Following the approach by Cao et al. (2019), the response of 213 from study participants is higher than the minimum sample size of 70. Therefore, the minimum sample size of this study was met.

The study also justifies the use of the sample size for the qualitative study. The main issue in determining the sample size of a qualitative study is data saturation (Blaikie, 2018; Guest, Bunce, & Johnson, 2006). Following the approach Marshall, Cardon, Poddar and Fontenot (2013) recommended, this study sought to attain data saturation by introducing new study participants until the data set was complete. It is not enough to refer to the study of Eisenhardt (1989) that qualitative study sample size can be between 4 to 10 cases, but there is a need to justify the selection of sample cases (Guest et al., 2018). In a study to justify the saturation point of a qualitative sample, Guest et al. (2018), using a study from Ghana and Nigeria, performed an analysis on data saturation to recommend that a sample of 6 to 12 is appropriate to attain saturation.

Methodologically, qualitative studies on technology acceptance have used six respondents to generate insightful results (see Oppong, Singh, & Kujur, 2020). Verma and Bhattacharyya (2017) used five firm managers who have adopted big data analytics in a qualitative study to understand the adoption of analytics in emerging economies. It is expected that generating qualitative insight from six firm managers from different organisations on a theme is adequate to collect adequate information. This study justifies the use of six study participants for the qualitative aspect of this study from the preceding discussions.

Data Sources and Instruments

This study relied on primary data. The researcher, in this case, uses data collected from the field from study participants. The study adopted primary data due to the main study objective, which is to identify the factors that influence the acceptance and use of marketing analytics from the perspective of firm employees. The source of data, therefore, is based mainly on the responses of study participants on the phenomenon under consideration.

With the qualitative study, this study used telephone interviews with firm managers. In the view of Sturges and Hanrahan (2004), qualitative researchers generally use face-to-face interviews in conducting in-depth interviews. It is proposed that for short and structured interviews, telephone interviews can be used (Sturges & Hanrahan, 2004). The use of telephone interviews is justified when there is a need to ensure the interviewer safety, limited to hard-to-reach respondent groups, sensitive topics, and cost of accessing respondents (Sturges & Hanrahan, 2004).

During the Covid-19 pandemic, many organisations have imposed restrictions on the movement of people in office spaces and have instituted social distancing. These made it very difficult to use face-to-face interviews with firm managers. Therefore, telephone interviews were used to conduct interviews with study respondents. The nature of the study, which used unstructured interview questions, makes it even possible to use telephone interviews.

The instrument used to collect the qualitative data is an interview guide. The interview guide in Appendix B has 13 questions. The interview guide was developed using theories on technology acceptance. The questions include issues relating to the perception of the usefulness of marketing analytics, the ease of use of marketing analytics, the influence from others to use marketing analytics, the facilities and support to use marketing analytics, the trust of analytics systems, the attitude of firm employees to use analytics, perception of personal innovativeness, the actual of analytics, the level of satisfaction of analytics, and the continuance usage perception of marketing analytics.

The study adopted the use of an online survey questionnaire to collect data from study participants for the quantitative study. Specifically, google forms were sent to firm employees via emails. The study resorted to the use of online surveys due to some reasons. First, using electronic means to conduct surveys are increasingly common, and the results from this survey can be the same as paper-based surveys (Andrews, Nonnecke & Preece, 2003). Online surveys can be used to collect data measuring particular variables. Second, online surveys provide the opportunity to conduct studies in situations where it is practically and financially unfeasible to access the study population (Andrews et al., 2003). This view is also expressed by Wright (2005) that is online surveys help to have access to samples that are difficult to access; it saves time since it allows a researcher to reach many people in a short time and ensure quicker data entry. Unlike paper-based surveys, where the cost per response is very high, online surveys are very cost-effective. Third, the Covid-19 pandemic has rendered the use of paper-based surveys not appropriate due to social distancing and lockdown restrictions. Firms at the time of conducting this study had restricted the movement of their employees and visitors in their premises. Consequently, studies have adopted online surveys during the Covid-19 pandemic (Al-Okaily, Alqudah, Matar, Lutfi & Taamneh, 2020; Shehzadi et al., 2020).

In online surveys, there is usually the option of self-selection, where invitations are posted at multiple online sources (Andrews et al., 2003) or are sent directly to study participants. This approach, therefore, does not allow for the use of random sampling (Andrews et al., 2003). The inability to use random sampling for online surveys makes this study adopt a non-probability sampling approach. The online survey mainly made use of Likert scales. The Likert scale is very important for marketers in measuring the perception and attitude of individuals (Albaum, 1997). A typical use of the Likert scale is to measure how an individual likes or dislikes a product. Likert scales are a self-reported way of collecting data. Blunch (2008) maintains that self-reported scales are considered as interval or continuous variables when it employs at least five possible values, and the variables have a normal distribution.

The first part of the survey questionnaires (see Appendix A) includes questions on age, gender, experience in using analytics technology, position, type of industry, and type of innovator. The second aspect of the survey questionnaire contains questions measuring the various constructs, namely performance expectancy, effort expectancy, social influence, facilitating conditions, perceived trust, personal innovativeness, attitudes, intentions to use, actual use, user satisfaction, and continuance usage, included in the structural equation model. The interval Likert scales responses used in this study ranged from 1 (least agreement) to 5 (strong agreement).

Operationalisation of Variables

The survey questionnaire uses an interval Likert scale measure to collect data for quantitative analysis. The variables used in the conceptual framework were used to develop questions (items). All the research items were adapted from existing scales that have been verified and used for empirical studies. The scales were adopted because they have been validated and also applied by numerous studies.

The antecedents of the intention to adopt marketing analytics were developed using the UTAUT theory items from the study of Venkatesh et al. (2003). Performance expectancy variables are made of four (4) indicator items generally on the usefulness of marketing analytics in performing marketing functions. Effort expectancy is also measured using four (4) indicator items on how easily marketing employees can learn and use the technology. Social norm is measured using four (4) indicator items on the influence of other individuals and organisation on the use of marketing analytics. The facilitating conditions variable is measured using four (4) indicator items on the availability of resources, knowledge, and systems support to ensure marketing analytics is adopted.

The intention to use marketing analytics scales were adapted from the intention to use technology scales by Venkatesh et al. (2003). This variable was measured using three (3) indicator items from the UTAUT model. The items measuring the actual use of marketing analytics was adopted from Germann et al. (2013). These items relate to the use of marketing analytics technology for marketing decision making and performing marketing activities such as pricing, promotions, sales forecasting, and segmentation and targeting.

The questions measuring personal innovativeness were adapted from the study of Agarwal and Prasad (1998). These questions measure the level of innovativeness in terms of willingness to try new technologies. The perceived trust towards the marketing analytics technology was measured using three indicator items adapted from Pavlou (2003). The perceived trust variable measures the trustworthiness of marketing analytics retailers and software that comes with it. User attitude towards marketing analytics was measured using four items adapted from the study of Venkatesh et al. (2003).

Gender as a moderating variable was measured as a dummy (1 or 2) in line with the study of Venkatesh et al. (2003). The experience of study participants was measured using a dummy 1 or 2 to indicate the level of user experience with marketing analytics technology as proposed by Venkatesh et al. (2003).

Age was measured in years by grouping respondents into younger and older workers, which is in line with the study of Morris and Venkatesh (2000). The age responses provided in years were later classified in groups using intervals of five (i.e., 23-27, 28-32) in line with technology studies such as Zuiderwijk, Janssen, and Dwivedi (2015). Also, using the digital natives (users up to 45 years) and digital immigrants (users above 45) classification, this study classified young technology users as digital natives and older technology users as digital immigrants (see Hoffman, Lutz, & Meckel, 2014). Technology researchers use respondents who are 45 years and above as older technology users and those below 45 as young users (Hoffman, Lutz, & Meckel, 2014; Swindle, Ward, Whiteside-Mansell, Bokony, & Petit, 2014). These two groups formed the basis of the assessment of the effect of age.

User satisfaction was measured from the study of Jiang. Klein, and Carr (2002). These items measure the reliability, relevance, precision, completeness, and overall satisfaction of the marketing analytics technology. The continuance usage variable items were measured using three items relating to intention to continue using marketing analytics for decision making and performance of marketing-related responsibilities. These scales were adopted from the study of Bhattacharjee et al. (2008).

Procedure for Quantitative Data Collection

The study adopted a two-phase data collection approach. The first phase of data collection was done using an online survey. This approach follows the use of online surveys by marketing analytics researchers (e.g., Germann et al., 2013; Verma et al., 2018) to reach out to firm employees. This activity was performed from April to July 2021. The 25 firm managers identified in the initial investigation to identify firms that use marketing analytics helped in identifying the study respondents to send the survey questionnaire to.

The researcher ensured the potential study participants had agreed to be part of this study by providing a consent form to them. The potential study participants were assured of confidentiality. The survey questionnaires were sent to 25 firm managers of the Ghana Club 100 identified by the researcher as using marketing analytics technologies to be completed. The survey was sent to the emails of the study participants. After the 25 study participants had submitted a response, they were encouraged to send the survey to other qualified study respondents in their organisations. This instruction was indicated in the survey questionnaire. The responses provided by the study participants were recorded using google forms, which enabled the researcher to receive the responses directly. In all, 252 participants responded to the survey.

Procedure for Qualitative Data Collection

From the initial identification of 25 companies that indicated they use marketing analytics, an attempt was made to contact senior marketing, sales and distribution, and digital media communication managers. This was done using telephone and email addresses provided to the researcher by the Ghana Investment Promotion Center. Out of the 25 organisations, the researcher was able to agree with six firm managers to be part of the study.

The firm managers who agreed to be part of interviews with the researcher were sent a copy of the interview guide on issues of interest to the researcher since there was an opportunity to conduct a face-to-face interview due to the COVID-19 pandemic. Before the interviews, a consent form was sent to the study participants detailing the confidentiality of the data to be collected from them.

The interviews commenced after consent was secured from study participants. The study conducted the interviews over the telephone. The researcher made the telephone calls based on agreed appointments with study participants. The study participants were informed about a need to record these interviews for the purposes of transcription and analysis. The mobile phone device used for the interviews aided in the recording. The interviews lasted about 30 minutes.

Qualitative Data Analysis

The analysis of the qualitative data is discussed next. This section discusses the data analysis approach, processing procedure, data validation, and analytical procedure and tool.

Qualitative data analysis approach

The analysis of the qualitative data is discussed next. This section discusses the data processing procedure, data validation, and the analytical procedure and tool.

Data processing for the qualitative study

The consent sought from study participants enabled the researcher to record the telephone interviews, thus enabling these recorded responses to be transcribed to Microsoft Word document. The transcribed data were saved to represent data from the six respondents. These files were edited to ensure they were grammatically correct. The responses provided were subjected to validation and were subsequently extracted to MAXQDA software.

Validation of qualitative data

This study supports the recommendation by researchers that validation of qualitative data is relevant as a way of having confidence that the account narrated in qualitative data is accurate (Pyett, 2003). More importantly, Patton (1990) explains that qualitative studies use reliability and validity to ensure rigour in sampling, the collection of data, analysing data, triangulation of data, and theories.

Pyett (2003) states that an important validity measure is the researcher's interpretation and assessment of the study participants understanding of the situation. The assumption is that it is not enough to accept anything that the study participant says without subjecting it to detailed analysis (Pyett, 2003). The qualitative data was subjected to verification and validation by checking the notes from the field data (Cobos et al., 2016). The transcribed responses were sent back to the study participants to confirm the responses they had provided during the interview. Following the recommendation by Pyett (2003), the qualitative data was subjected to the researcher's theoretical insight and contextual information to build an understanding of the study participants perspective. The qualitative data were reviewed by two academics in management information systems and an academic in marketing.

Performing thematic analysis of qualitative data

The analysis of the qualitative data followed the approach proposed by Miles and Huberman (1984). The first significant component apart from data collection is data reduction. Data reduction, according to Miles and Huberman (1984), entails data coding and summaries. The data reduction is performed by using the identified themes from the theoretical issues expected by the researcher to group the data. In the view of Brain and Clarke (2012), thematic analysis demands that the researcher must first be aware of the theoretical issues, which guides the coding and analysis of the data. Following the approach proposed by Brain and Clarke (2012), the thematic analysis was performed by understanding the data, developing codes, looking for themes, revising the themes redefining the themes, and producing a report.

In qualitative data analysis, this study adopts the use of MAXQDA since this qualitative software allows for the collection of quantitative and qualitative data for triangulation (Kuckartz, 2010). This software can allow for the collection of data collected using questionnaires and interviews. The use of

MAXQDA enabled the researcher to perform a first-round coding to extract the data based on the main constructs (Cobos, Mejia, Ozlurk & Wang, 2016). The second coding using the MAXQDA enabled the organisation of emergent sub-themes as used by Cobos et al. (2016).

In qualitative studies, data coding is part of the analysis since it sharpens, sorts, discards, and enables the organisation of data in the form that can be used for conclusions. The coding is also supported with summaries and paraphrasing. This stage is followed by data display, thus putting it in organised form (Miles & Huberman, 1984). This step enables the organisation of the data as compared to narrative texts. In this case, the researcher organised the major qualitative findings using a table. The final stage of the qualitative analysis is drawing meaning from the displayed, reduced data based on patterns and propositions (Miles & Huberman, 1984).

Quantitative Data Analysis

This section of the study describes how the quantitative data analysis was performed. As stated earlier, this study adopted a quantitative approach; hence the analysis was performed using quantitative analytical tools. The analytics tools used are Statistical Package for Social Science (SPSS) version 22.0 and SmartPLS version 3 by Ringle, Wende and Becker (2015). The testing of the hypothesised relationships was done using partial least squares structural equation modelling. The analysis of demographic data was analysed using SPSS. This section includes the use of structural equation modelling to ensure reliability and validity, the development of a structural path model showing the relationship between study variables, and the testing of hypotheses using bootstrapping. These steps in structural equation data analysis are discussed in this chapter.

Data processing of quantitative study

The data from the online survey are extracted and saved as Microsoft excel. The responses in Microsoft excel was converted to quantitative form to enable an analysis of the data. There were some missing responses in the data set. The researcher deleted the data set for 39 respondents, which were deemed inadequate for further data analysis. In the end, data from 213 study participants were retained for further analysis. The responses on the demographic questions were exported to SPSS, and the responses of questions on the Likert scale measuring study variables were converted to numeric form to ensure they could be exported to SmartPLS for further analysis. There were no missing values for the data set.

In using SmartPLS, the excel data set must be converted to .csv file format and exported. Following the steps in data processing explained by Wong (2013), the names of the indicators (e.g. PE1, PE2, EE1, EE2) were placed in the first row of the Excel spreadsheet and also ensured that no "string value" (e.g. words or single dot) were used in the cells. The research items that serve as indicators for the constructs were labelled as PE1, EE1, SI1, FC1, PT1, PIIT1, ATT1 in that order to ensure the building of the structural equation model and easy identification of the indicators.

Structural equation modelling

The first is the measurement model, which seeks to specify the relationship between constructs and their observed indicators. This analysis includes analysis to ensure the validity and reliability of indicators measuring study constructs. The second model is the structural model, which measures the relationship between the study constructs. This analysis performs a statistical test to show the predictiveness of constructs. Structural Equation Modelling (SEM) is a second-generation multivariate data analysis method that is used to test theoretically supported models (Wong, 2013). In marketing research, Wong (2013) states that SEM is used by marketers to visually examine the relationship between variables in an attempt to prioritise marketing efforts and resources to deliver superior customer service. SEM is important in showing how various marketing variables are connected to each other, hence helping in identifying marketing issues to dedicate resources to ensure a particular outcome is achieved. Wong (2013) asserts that this approach is helpful to measure unobservable, difficult to measure latent variables, thus enabling marketers to resolve business problems.

According to Wong (2013), Partial Least Squares (PLS) is one of the widely used approaches of structural equation modelling, which uses analysis of variance carried through SmartPLS. Hair, Ringle, and Sarstedt (2011) provide some rules of thumb for selecting PLS-SEM, such as if the goal is, predicting key target constructs, extending an existing structural model, using formative constructs, modelling a complex structural path with many constructs and indicators, using smaller sample size, using non-nominal data, etc. These assumptions make the use of PLS worth considering. In the case of this study, all these assumptions apply to the study, and therefore, the PLS-SEM approach is regarded as appropriate to study firm employees in Ghana who use marketing analytics, which may present skewed data because the study participants are few.

Reliability and validity of research items

The study, following the recommendation of Hair et al. (2011), performed reliability and validity tests. Using Structural Equation Modelling, the study that uses a reflective model will conform to the reliability and validity test proposed by Hair, Sarstedt, Ringle and Mena (2012). In the view of Wong (2013), a reflective model in PLS is when the indicator items are pointing away from the latent variable.

Indicator reliability

As proposed by Hulland (1999), the indicator reliability is assessed to examine the loadings of a measure with their respective construct. The rule of thumb used in PLS research is that each item loadings must be 0.7 or more, which explains that there is more shared variance between the latent variables and its measure than error variance (Hulland, 1999). This study uses this test of reliability to examine the loadings of items of various latent variables. A loading of above 0.7 will be accepted for further analysis since the study adopts a reflective model.

Internal consistency reliability

According to Wong (2013), Cronbach's alpha measures internal consistency reliability and have limited use in PLS. In PLS, composite reliability is a standard measure of construct reliability. Götz, Liehr-Gobbers and Kraff (2010) state that it is important to ensure that all the indicators come together to measure the study construct adequately. This measure explains how well the assigned indicators measure a construct. According to Hair et al. (2012), internal consistency, as proposed by Nunnally and Bernstein (1994), should have a value of 0.7 as a benchmark. This benchmark has been proposed and supported by a number of researchers such as Bagozzi and Yi (1988); hence this study uses 0.7 as a measure of internal consistency reliability.

Convergent validity

The Average Variance Extracted (AVE) is evaluated to assess convergent validity (Wong, 2013). Götz et al. (2012) propose that an AVE of more than 0.50 is acceptable for the validity test since the indicators of a construct accounts for more variance. In this study, all AVEs must be above 0.5, which is the acceptable threshold for convergent validity to be confirmed.

Discriminant validity

Discriminant validity test is done to ensure there is dissimilarity in the various constructs used in a study (Götz et al., 2012). This test enables a researcher to determine that a construct in a structural model is different from other constructs. The test is performed using the Fornell-Lacker criterion. The criterion states that the squares root of the AVE of the constructs must be larger than the correlation values among the other constructs (Fornell & Larcker, 1981). In this study, discriminant validity for all the constructs was attained.

Analysis of proposed hypotheses

The quantitative study analysis follows a number of steps. The first issue is analysing the demographic profile of respondents. The second aspect is performing statistical analysis to achieve the study objectives. The demographic data and descriptive analysis were done using SPSS. The demographic data entails details about firm employee's age, gender, role in the organisation, number of years working in the organisation. The descriptive analysis using mean scores and standard deviation seeks to analyse each question asked the study participants. The mean scores are the average of responses asked respondents using the Likert scale. The mean scores determine the general perception of respondents on the various indicators used to measure the study's variables.

As stated earlier, the analytical tool used for this structural equation modelling is the SmartPLS. The PLS approach, according to Henseler (2017), is performed using four main steps:

Step 1: the iterative PLS algorithms produce a proxy as a linear combination of the observed indicators for each construct. These indicators are determined to have as much variance with the constructs. The first thing to report on is explaining the target endogenous variables variance (Wong, 2013). In this study, the items measuring the intentions to use marketing analytics and other constructs such as user satisfaction and continuance usage are estimated.

Step 2: the next step involves correcting for attenuation if the model contains factors. The measurement error of proxies, proxy correlations, which are underestimations of factor correlations, are determined. The aim of this is to use PLS to address the issue of what would be the correlation between study constructs in the presence of random measurement error. The proxy correlations are assigned to generate a major output called a consistent correlation matrix.

Step 3: This step involves the estimation of the model parameters. The analysis will also report on the path coefficients. According to Wong (2013), path coefficients lower than 0.1 (i.e. 0.003) imply that the relationship between the variables used has no statistical significance. This approach leads to concluding that any hypothesised path relationship between variables in the model that records a path coefficient higher or equal to 0.1 is regarded as having a statistical significance. There are four main relationships to be examined in this study.

Step 4: the final step in PLS is applying bootstrapping to generate inference statistics for all model parameters. The hypothesised relationships that meet the requirement (t statistics larger than 1.96) mean the hypothesised relationship is supported. In contrast, t-statistics less than 1.96 for hypothesised relationships in the model are deemed not supported.

Moderation analysis

Moderation analysis is relevant to this study because of the need to examine the moderation effect of age, gender, experience, type of innovator and industry type. The moderation test was done using multi-group analysis (MGA) in PLS. The multi-group analysis in PLS is done to compare the significance levels of the relationships across groups of data (Sarsteft, Henseler & Ringle, 2011).

This analysis means that the survey questions must capture responses on each of the moderating factors. The main objective of this analysis is to determine whether there is a difference in how the UTAUT antecedents influence intentions due to the moderators. The age of respondents, gender, level of experience, type of innovator, and type of industry were all categorised using two groups to aid in performing the moderation test. Through a bootstrapping approach, a p-value of less than 0.05 signifies a moderation effect.

Multicollinearity and common method bias assessment

The study ensured that the predictor variables that express a linear relationship do not explain the same variance in the dependent variable. This analysis is important to this study to ensure the statistical significance of variables is not reduced. A detailed PLS-SEM analysis would include a multicollinearity assessment (Wong, 2013). This analysis is done to determine the tolerance or the Variance Inflation Factor (VIF).

The rule of thumb is that a VIF of 5 or lower is acceptable to avoid a problem of collinearity. Hair, Risher, Sarstedt and Ringle (2019) acknowledge that a VIF value of 5 and higher indicate a problem of collinearity. In PLS, Wong (2013) proposes that to resolve the problem of collinearity, variables could be eliminated, merged into one, or simply have a higher-order latent variable developed. In this study, it was ensured that all the VIF values were below 5.

The study also ensured there was no common method bias in the measurement method. Kock (2015) acknowledges that common method bias may occur in structural equation studies as these studies use indicators that are derived from questionnaires. A common method bias occurs when the instructions at the top of a questionnaire may influence other responses, thus leading to a common variance (Kock, 2015). In this study, the independent and dependent variables included in the same questionnaire are likely to generate a common method bias. An analysis to detect standard method bias is, therefore, needed. This test was done by using Harman (1960) one-factor exploratory factor analysis. According to Podsakoff, MacKenzie, Lee, and Podsakoff (2003), a common method bias is detected when the variance of the first factor is above 50 per cent.

Total effect size analysis

There is a need to perform a detailed discussion on the effect size of the exogenous latent variables on the endogenous latent variables. Wong (2013) explains that the extent to which the f^2 effect size of the exogenous latent contributes to the R^2 of the endogenous variable enables researchers to assess the magnitude of or the strength of the relationship between the latent variables. This analysis is done to examine the importance of the effect size to examine the overall contribution of the research study. The rank order of the predictor variables in explaining the dependent variables in the structural model is usually the same as the size of the path coefficients and the f^2 effect size. Hair et al. (2019), citing Cohen (1998), state the rule of thumb for analysing effect size is 0.02 for small, 0.15 for medium, and 0.35 for large effect size.

Importance-performance map analysis

The importance-performance map analysis in SmartPLS produces a matrix or a map that indicates path coefficient estimates of constructs (Ringle & Sarstetd, 2016). This analysis uses the total effect of a construct to indicate how important the construct is in forming a target construct (Martilla & James, 1977). The objective of this analysis is to identify the constructs with the higher total effect but have a lower performance in predicting the target construct. The analysis will be based on examining the variables with higher importance values and lower performance. An attractive feature of this analysis is that the result can be graphically presented to enable easy interpretation (Martilla & James, 1977). The analysis will show to managers that variables with lower performance but with higher importance must be targeted first to improve the performance of the target construct. Martilla and James (1977) assert that this will reduce the difficulty managers find to understand the practical significance of research findings expressed using statistical terms.

Predictive relevance of variables

Apart from the effect size of the latent variables, the predictive relevance is another important aspect to examine in the inner model (Wong, 2013). This analysis is done by using Stone-Geisser's (Q^2) values. This is done using the blindfolding procedure in SmartPLS (Hair et al., 2019). In performing this procedure, Hair et al. (2011) propose that care must be taken to ensure that the number of valid observations must be between 5 to 10. The structural model has a predictive relevance when the Q^2 value is greater than zero (Hair et al., 2011). In this study, Q^2 values higher than 0.025 depict a small predictive relevance, while Q^2 values higher than 0.50 means a large predictive relevance of the PLS structural model.

Ethical Considerations

This study in data collection considered some ethical issues. First, ethical clearance was applied to seek approval from the university awarding the degree. As proposed by Saunders et al. (2009), before data collection commences, ethical approval must be secured. Ethical approval was sought from Institutional Review Board (IRB) and granted before data collection commenced. Consent forms were also sent to study participants to explain the research and gain their approval. As proposed by Saunders et al. (2009), the study ensured the privacy of participants, voluntary participation, maintenance of the confidentiality/anonymity, and objectivity of the researcher.

Chapter Summary

The study adopted a mixed methods approach, thereby doing this research using both positivist and interpretivist approaches. This decision emanates from the reliance on a postpositivist philosophy to guide this study. The study, therefore, used quantitative and qualitative approaches to collect and analyse the data. With the quantitative study, data from firm employees who use marketing analytics technology were included in the survey. The study also performed an in-depth interview with six firm managers regarding the use of marketing analytics technology.

From the quantitative perspective, this study relied on convenience sampling to select study respondents since users of marketing analytics technology seem to be a hidden population, while purposive sampling was used to select participants for the qualitative data collection. The data collected from the survey were analysed using SmartPLS 3 by Ringle, Wende and Becker (2015). This software allows for the use of structural equation modelling to establish the relationship between factors that affect technology acceptance and outcome variables used in the study. On the other hand, MAXQDA, was used for interview coding, and thematic analyses guided the data analysis.

A very important aspect of the methodology is the application of explanatory sequential mixed methods, where the quantitative data collection is supported by using qualitative data. The chapter uses triangulation to collaborate or contrast the qualitative data and the quantitative data explaining the various proposed hypotheses. It is important to note that the quantitative data collection and analysis proceeds the qualitative data collection and analysis, which is a major feature of an explanatory sequential mixed methods approach.

The study, however, encountered a number of methodological limitations. First, the focus of the research was only in Ghana and, therefore, the findings could not be the basis for generalisation in other developing countries. The study adopted a cross-sectional design using study participants who had already used marketing analytics technology. On the other hand, a longitudinal study could aid in studying the acceptance process of marketing analytics. The use of convenience sampling also resulted in using study participants available to the researcher, thus, making the study findings not very suitable for generalisation.

CHAPTER SEVEN

PRESENTATION OF RESULTS

Introduction

The chapter presents empirical evidence to address the issues discussed in the theoretical and conceptual chapters of this study. The chapter presents findings in accordance with the research objectives proposed in the introduction chapter of this study. The chapter presents the results of the quantitative study and the results of the qualitative study. The study first presents the profile of respondents and descriptive analysis for the quantitative study and later that of the qualitative study. With the quantitative study, the chapter presents the age, gender, experience in using marketing analytics technology, position in the organisation, type of innovator, and type of industry, and type of analytic system used.

The qualitative study considered issues such as position in the organisation and type of industry. The study presents the descriptive analytics of study variables using mean and standard deviation. The reliability and validity results of the various constructs used in the study are presented. The study relied on both quantitative and qualitative studies to discuss the proposed hypotheses. The study used SmartPLS 3 to analyse the quantitative data and MAXQDA to analyse the qualitative data. The chapter presents the structural model assessment to show the various path relations to depict the conceptual framework in the literature review. The mediation and moderation test were also presented in the chapter.

Profile of Respondents of Quantitative Study

The profile of the 213 quantitative study respondents is presented in Table 6. The results about the background of study participants have been organised based on gender, age, position in organisation, previous use of marketing analytics, type of marketing analytics used, and the industry type.

Table 6: Profile of Respondents

Profile of respondent	Frequency	Percentage
Gender of Respondent		
Male	142	66.67
Female	71	33.33
Age of Respondent		
23 – 27	9	4.23
28 – 32	14	6.57
33- 37	28	13.15
38-42	88	41.31
43 -47	48	22.54
48-52	18	8.45
53 and above	8	3.75
Position in Organisation		
Sales and Distribution	79	37.09
Digital and Media	42	19.72
Marketing	92	43.19
Previous Experience with Marketing Analytics		
Yes	68	31.92
No	145	68.08
Marketing Analytics Used		
Hadoop	56	26.29
Google Analytics	60	28.17
Semrush	12	5.63
SAP	32	15.01
Distributor Management System	53	24.09

Source: Field Survey, Twum (2021)

Table 6, continued: Profile of Respondents

Profile of respondent	Frequency	Percentage
Frequency of Use of Analytics Technology		
Seldom	43	20.19
Once a month	94	44.13
Several times a week	58	27.23
Daily	18	8.45
Type of Innovator		
Early Technology Adopter	86	40.38
Late Technology Adopter	127	59.63
Industry		
Services	142	66.67
Manufacturing	71	33.33

Source: Field survey, Twum (2021)

The study sample comprises 142 males and 71 females, representing 66.67% and 33.33%, respectively. On the age of study respondents, 41.31% of study respondents were between the age of 38 to 42. There were 48 respondents between the age of 43-47, representing 22.54%. The study recorded 28 respondents who are between the age of 33-37. The study also had 14 respondents who were 28-32 years old. The least represented age groups were those between the age of 23-27 (9%) and 52 years and above (8%). The profile of respondents also indicated that 92 study participants are marketing officers for their organisations. There were 79 employees who were sales and distribution managers. The study also included 42 employees responsible for digital and media management for their organisations.

The profile of respondents also showed that 145 study participants indicated that they had not previously used marketing analytics technology apart from the use of it in their current organisations. On the other hand, 85 study respondents indicated they have experience using the system before. The study recorded more late adopters of technology (127) than early adopters (87). The study also sought to examine the marketing analytics systems used by study participants for their marketing functions. The study results found that Distributor Management System, Hadoop, Google Analytics, SAP, and Semrush are the analytics systems their organisations subscribe to. The profile of respondents also indicated that 142 respondents work in the service sector, while 71 respondents work in the manufacturing sector.

Quantitative Descriptive Statistics

The descriptive analysis of the factors affecting intention to use technologies seeks to address research objective one. In explanatory studies, which involves using the perception of studies participants for statistical analysis, it is expected that a descriptive analysis is performed before any further analysis (Pallant, 2011). It is, therefore, expected that before the data is subjected to further statistical analysis (correlation, regression), the data is analysed using descriptive statistics to measure for central tendency such as mean and standard deviation. The descriptive analysis describes the extent to which the study participants agree with the statements in the study questionnaire. Pallant (2011) also indicated that using descriptive statistics enables a researcher to obtain a measurement of study variables. The descriptive statistics of this study are presented in Tables 7 to 17.

Perception of performance expectancy of marketing analytics

The study considered assessing the perception of firm employees on the performance expectations of using marketing analytics technology. Using descriptive analysis, the study sought to examine the expectation that marketing analytics will be useful to marketing tasks, accomplishing marketing tasks quickly, increasing marketing productivity, and raising marketing task output. To do this analysis, four research items were used to measure the perception of firm employees relating to the performance expectancy of marketing analytics. The results are presented in Table 7.

Table 7: Employees' Perception of Performance Expectancy of Marketing Analytics

Study Items	Mean	STDEV
I would find the marketing analytics system useful in my job	3.48	1.01
Using the marketing analytics system enables me to accomplish tasks more quickly	3.35	1.06
Using the marketing analytics system increases my productivity	3.69	0.94
If I use the marketing analytics system, I will raise my marketing task	2.98	0.59

Source: Field survey, Twum (2021)

The research item that received the lowest mean is the question on "If I use the marketing analytics system, I will raise my marketing task". The majority of the study participants indicated that they perceive marketing analytics has the ability to raise their marketing task to a large extent. The highest mean (3.69) for the performance expectancy variable question was recorded for the question "using the marketing analytics system increases my productivity". The study participants were of the opinion that the use of marketing analytics increases their marketing productivity. The study participants also indicated a moderate agreement to the question on the perceived usefulness of marketing analytics to their jobs.

Perception of effort expectancy of marketing analytics

The study aimed at assessing the perception of firm employees on the perceived ease of use (effort expectancy) of marketing analytics technology. As indicated in Table 8, four research items were presented to study participants to examine their views on the understanding of using the technology, the ease of gaining skills to use the technology, the perception that the system is easy to use, and how easy is it to learn to use the system. In general, all the questions measuring this variable received agreement from the study participants.

Table 8: Employees' Perception of Effort Expectancy of Marketing Analytics

Study Items	Mean	STDEV
My interaction with the marketing analytics system would be clear and understandable	3.79	0.91
It would be easy for me to become skillful at using marketing analytics	3.68	0.95
I would find the marketing analytics system easy to use	3.95	0.85
Learning to operate the marketing analytics system is easy for me	3.81	0.91

Source: Field survey, Twum (2021)

The highest mean recorded (3.95) was for the question "I would find the marketing analytics system easy to use". This result is an indication that most of the study participants perceive that the marketing analytics technology deployed by their organisations can easily be used. The study also recorded moderately higher means for questions on how interaction with the system will be clear and understandable (3.79) and for the question on ease of learning to use the marketing analytics technology (3.81). The least mean recorded for this variable was on whether the users of the marketing analytics technology would easily become skilful in using the system (3.68).

Perception of the effect social influence on the use of marketing analytics

The study also sought to examine how people who have a social relationship with firm employees influence their intentions to use marketing analytics. To measure the level of social influence in using marketing analytics, the study presented study participants with four questions relating to how people who influence them think they should use marketing analytics technology. From the results in Table 9, in general, the study participants indicated that they perceive people expect them to use the marketing analytics system. The highest mean recorded was 3.99 was on the question "People who influence my behavior think that I should use the marketing analytics system".

Table 7: Employees' Perception of Social Influence in Using Marketing Analytics

Study Items	Mean	STDEV
People who influence my behavior think that I should use the marketing analytics system	3.99	0.75
People who are important to me think that I should use the marketing analytics system	3.84	0.81
The senior management of this business has been helpful in the use of the marketing analytics system	3.88	0.82
In general, the organisation has supported the use of the marketing analytics system	3.86	0.84

Source: Field survey, Twum (2021)

This was followed by the question on "the senior management of this business has been helpful in the use of the marketing analytics system", which recorded a mean of 3.88. The least mean (3.84) recorded for this variable is on the question "people who are important to me think that I should use the marketing analytics system". This shows that marketing analytics technology may not be promoted by important people in social relations. The study participants indicated the influence usually comes from the senior management members in their organisations.

Perception of facilitating conditions supporting the use of marketing analytics

The study examined the extent to which the organisation provides support and resources for the use of marketing analytics. The study asked respondents to provide answers to four questions relating to resources necessary to use marketing analytics, the provision of necessary knowledge to use the marketing analytics, ensuring there is compatibility with other information systems, and available of resource persons to assist in the use of marketing analytics technology. From the results in Table 10, the highest mean recorded (3.95) was on the question on "the system is compatible with other systems I use". This result was followed by the question on "a specific person (or group) is available for assistance with marketing analytics system", and the question on "I have the knowledge necessary to use the marketing analytics system".

Table 10: Employees' Perception of Facilitating Conditions in Using Marketing Analytics

Study Items	Mean	STDEV
I have the resources necessary to use the marketing analytics system	3.86	0.84
I have the knowledge necessary to use the marketing analytics system	3.90	0.88
The system is compatible with other systems I use	3.96	0.83
A specific person (or group) is available for assistance with marketing analytics system	3.90	0.88

Source: Field survey, Twum (2021)

The least mean (3.86) recorded was on the resources necessary to use the marketing analytics. This means that the study participants indicated that they agree they have the knowledge required to use the marketing analytics system.

Perceived trust in using marketing analytics

The study aimed at understanding the perceived level of trust for marketing analytics technology. Five questions indicated in Table 11 were asked the study participants on the trust in the reliability, security, and competency of the marketing analytics system. On the question to examine the overall trust study participants have for marketing analytics technology, the study participants indicated they perceive the marketing analytics technology can be trusted.

Table 8: Employees' Perception of Trust of Marketing Analytics

Study Items	Mean	STDEV
The marketing analytics technology would be competent in delivering in a timely manner	3.42	1.03
I trust the marketing analytics system to be reliable	3.68	0.96
I trust the marketing analytics system to be secure	3.38	1.02
Overall, I trust the marketing analytics system	3.60	0.95
In general, I trust I trust the information provided by the marketing analytics system	3.59	0.93

Source: Field survey, Twum (2021)

The highest mean (3.68) for this variable was on a question was on "I trust the marketing analytics system to be reliable". This is an indication that the study participants were of the view that marketing analytics technology can be relied on for accurate and reliable information for decision making. The least recorded mean was on the issue of whether the marketing analytics was secured (3.38). Respondents indicated they were not sure about the security of the marketing analytics technology but did not indicate the systems pose a security threat to their organisations.

The level of personal innovativeness in information technology

The usefulness of the personal innovativeness of technology users has been acknowledged in the literature as an important factor in technology acceptance, hence demanding this study to examine the extent to which study participants possess these characteristics. The descriptive analysis presented in Table 12 was performed on four questions measuring personal innovativeness. The highest mean (3.96) recorded was on the question "among my peers, I am usually the first to try out new information technologies". This result is an indication that study participants are generally willing to try out new technologies as compared to others.

Table 9: Employees' Perception of Level of Personal Innovativeness in Information Technology

Study Items	Mean	STDEV
If I heard about a new information, I would look for ways to experiment it	3.94	0.77
Among my peers, I am usually the first to try out new information technologies	3.96	0.74
In general, I am not hesitant to try out new information technologies	3.88	0.80
I like to experiment with new information technologies	3.81	0.77

Source: Field survey, Twum (2021)

The study also found that study participants are willing to look for ways to experiment with new technologies (3.94). Among the study participants, there exists a moderate personal innovativeness, thus showing that they are willing to try or experiment with innovative technologies (3.81). The questions asked did not result in very high mean scores.

Attitude towards marketing analytics

The study sought to assess the attitude of firm employees towards marketing analytics. The study participants were examined base on their perception of whether using marketing analytics is a good idea as compared to traditional marketing. This assessment is important because the attitude of technology users can be favourable or unfavourable. The questions examined are presented in Table 13.

Table 10: Employees' Perception of Attitude towards Marketing Analytics

Study Items	Mean	STDEV
Using the marketing analytics system is a good idea	3.81	0.83
The marketing analytics system makes work more interesting	3.89	0.84
Working with the marketing analytics system is fun	4.03	0.74
I like working with the marketing analytics system	3.86	0.82

Source: Field survey, Twum (2021)

The study generally found that study participants possess favourable attitude towards marketing analytics. The least mean (3.81) recorded was on the question "using the marketing analytics system is a good idea". The study participants indicated they perceive the use of the marketing analytics system as interesting and fun (3.89, 4.03). They also indicated they like working using the system (3.86).

Intentions to use marketing analytics

The study sought to find out from firm employees whether they have the intention to use the marketing analytics system. To achieve this, three questions found in Table 14 were asked in the survey.

Table 11: Employees' Perception of Intentions to Use Marketing Analytics

Study Items	Mean	STDEV
I intent to use the marketing analytics system in the next months	3.99	0.71
I predict I would use the system in the next months	3.97	0.73
I plan to use the marketing analytics system in the next months	3.00	1.08

Source: Field survey, Twum (2021)

The results of this survey resulted in the highest mean of 3.99 for a question on the intention to use the system in the next months. The lowest mean recorded was for the question on the plan to use marketing analytics in the next month (3.0).

Perception of actual use of marketing analytics

The study sought to examine the use of marketing analytics technology by study participants. The use of marketing analytics was measured based on its deployment to support decision making, pricing decisions, promotions, sales forecasting, and segmentation and targeting. The mean and standard deviation scores are presented in Table 15.

Table 12: Employees' Perception of Actual Use of Marketing Analytics

Study Items	Mean	STDEV
I use marketing analytics-based insights to support decisions	3.81	0.83
In my marketing duties, I back my arguments with analytics-based facts	3.42	1.03
I use marketing analytics to support pricing decisions	3.68	0.96
I use marketing analytics to support promotions decisions	3.68	0.83
I use marketing analytics for sales forecasting	3.58	0.82
I use marketing analytics for segmentation and targeting	3.88	0.83

Source: Field survey, Twum (2021)

The study found that marketing analytics is used to support decision making by organisations. Study participants were of the view that marketing analytics play a role in marketing decision making and also aid in performing promotional, pricing, sales forecasting, and segmentation decisions.

User satisfaction with marketing analytics

The study sought to examine the level of satisfaction with the use of the marketing analytics technology from the perspective of users of the technology. The descriptive analysis in Table 16 was done to assess the perception of study participants about their satisfaction of the reliable output of the technology, the relevance of the data provided, the precision of the output information, the completeness of the output, and the overall satisfaction. The highest mean (3.92) was recorded for the question on "there is precision of output information from the marketing analytics system".

Table 13: Employees' Perception on Level of Satisfaction with Marketing Analytics

Study Items	Mean	STDEV
The output information from the marketing analytics system is reliable	3.85	0.88
There is relevant output information (to intended function) from the marketing analytics system	3.82	0.83
The output information from the marketing analytics system is accurate	3.79	0.82
There is precision of output information from the marketing analytics system	3.92	0.75
There is completeness of the output information from the marketing analytics system	3.84	0.80
Overall, I am satisfied is the experience with the marketing analytics system	3.85	0.83

Source: Field survey, Twum (2021)

The lowest mean (3.79) was recorded for the question on the accuracy of the information output. On the question of the overall level of satisfaction with the system, the study participants indicated they are satisfied with the technology.

The continuance usage of marketing analytics

The study examined the perception of study participants regarding the continuance usage of marketing analytics technology. Three questions indicating the continuous use of marketing analytics technology to perform marketing task, decision making and job responsibilities were assessed. In Table

17, the highest mean (4.03) was recorded for the use of the intentions to continue using the technology to perform more marketing job responsibilities.

Table 14: Employees' Perception of Continuance Usage of Marketing Analytics

Study Items	Mean	STDEV
I intent to continue using the marketing analytics system for my job	3.98	0.73
I intent to continue using the marketing analytics technology for more decision making	3.91	0.80
I intend to continue using the marketing analytics system for more of my job responsibilities	4.03	0.74

Source: Field survey, Twum (2021)

The study participants also indicated that they would continue to use the system for making marketing decisions (3.91). In general, study respondents indicated they would continue to use them for their marketing activities.

Qualitative Analysis Results

The second part of the demographic and descriptive analysis is focused on the profile of respondents for the qualitative interview and the summary of the responses provided by study participants. The Table 18 presents the job role and sector of the study participants. The summary of the responses of the study participants is presented in Table 19.

Profile of Respondents for Qualitative Study

The study participants used for the collection of qualitative data through interviews are presented in Table 18. In all, six firm managers who use marketing analytics technologies to perform marketing and sales functions are involved in in-depth interviews to examine the factors influencing acceptance and use of the system. Two of the respondents are in the manufacturing sector and, four firm managers are in the services sector. These firm managers are responsible for their organisation marketing, sales and distribution. In all six firm managers responsible for sales, marketing and sales, digital media, and media and advertising were used in this study.

Table 15: Profile of Study Participants for Qualitative Study

Respondent	Position	Industry
Respondent 1 (RES1)	Sales Director	Telecommunications
Respondent 2 (RES2)	Marketing and Sales Manager	Hospitality (Hotel)
Respondent 3 (RES3)	Digital Media Manager	Banking
Respondent 4 (RES4)	Sales and Distribution	Manufacturing (Fast Moving Consumer Goods Market)
Respondent 5 (RES5)	Media and Advertising Manager	Telecommunication
Respondent 6 (RES6)	Marketing Manager	Manufacturing (Fast Moving Consumer Goods Market)

Source: Field survey, Twum (2021)

Descriptive Results of the Qualitative Data

The study used the qualitative data to provide results to address research objectives. A descriptive analysis of the study variables is presented qualitatively. The analysis is performed by indicating the responses provided by the study participants. The study, following the recommendation of Miles and Huberman (1984) performed data reduction and also data display. In Table 19, the summary of results from the interview of firm managers is presented. The summary is based on the responses of each study respondent.

Qualitative Results for Objective One

The qualitative results obtained from interviews with study participants on what factors influences the intentions to use marketing analytics are presented in this section. The study participants were asked to provide an answer to what influences their intention to use marketing analytics in their respective organisations. A number of themes emerged from the interviews, which forms the basis for the analysis of results.

Usefulness of the technology

From the study responses presented, the interview with study participants revealed a number of issues relating to the performance perceived usefulness of marketing analytics. First, the responses from all study participants indicated that the use of marketing analytics technology provides a relative advantage over using traditional means of performing marketing tasks in a number of ways. The study results indicated that marketing analytics technology has some usefulness depending on the industry.

The first theme identified is the use of marketing analytics for the management of sales and revenue. The study respondents (RES1, RES6) in the telecommunication and manufacturing sector provided evidence of the use of marketing analytics for tracking sales and revenue. In the telecommunication sector, a study respondent (RES1) commented that:

"…we use real-time sales tracking dashboards to monitor sales trends on a regular basis"

The usefulness of marketing analytics in tracking sales is collaborated by a study participant in the manufacturing sector. Analytics systems are crucial in tracking of goods and stock, route management, and tracking sales. A study participant in the manufacturing sector (R6) commented that:

"…the system is a web-based system placed at the premises of the distributor … the sales representatives are able to record whom the distributor sells to and at what price…the salesmen also use these hand-held devices to manage their route"

Another theme identified is the use of marketing analytics for the management of customer databases. The study participants (R1, R2, R3, RE4, R5) indicated that they use marketing analytics to manage customer databases, thus helping in segmentation and customer profiling. RES1 commented that:

"… my organisation perceives that marketing analytics helps to understand customer behaviour….we use the national population data, from the Ghana Statistical Service as base to profile consumers"

Another respondent in the hospitality sector indicated that the analytics systems are useful in management of customer database. A study respondent (RE2) stated that:

"…we are able to take a closer look at what customers are requesting for and the kind of service they need in real-time…we are able to come up with services such as no-refundable, and room-only services because we see in advance the kind of client"

Under the usefulness perception, another theme identified is the use of marketing analytics for digital marketing communications (RES3, R6). In the banking sector, technology plays a major role in managing digital communications. RES (3) commented that:

"...we use marketing analytics in managing our website and social media communications…we ensure there is monitoring of organic social media use such as comments, shares, reports...we use analytical tools to monitor communication feedbacks such as digital ask, posts, and people coming into our branches"

In the fast-moving consumer market, manufacturing firms use analytics systems to perform marketing communications to their distributors. RES6 commented that:

"*…we can also run promotions in the distributor analytics system …. It enables the distributors to have knowledge of any sales promotions and information we share"*

Another theme identified is the use of marketing analytics to gather intelligence about customers and the market. The study respondents (RES2, RES3) provide insight into how the use analytics systems to understand the market (competitors and customers). In the hospitality sector, marketing analytics aids in the monitoring of competitor offerings and customer segmentation. RES2 commented that:

"…the analytics systems allow us to analyse what is happening in the industry…we are able to detect the activities of our competitors such as when the prices and promotions they are offering"

The usefulness of marketing analytics to gather intelligence is also collaborated by a study respondent in the banking sector. RES3 commented that:

"…we are able to monitor the social media and digital media behaviour of current and potential clients… we can observe the marketing communication materials accessed by target audience and the behaviour of target audience"

From the results obtained from the qualitative study, the intentions to use marketing analytics technology is influenced by the performance expectations in relation to the accomplishment of marketing activities. The perception by firm managers that marketing analytics technology will enhance the performance of their marketing tasks will affect their intentions to use the system. The themes identified include, marketing communications, managing customer database, market (customer, competitor) intelligence, and sales tracking.

The ease of use of the system

On the attainment of the research objective of what factors influence intentions to use marketing analytics, the qualitative data provided some insights into how the ease of use influences the use of the system. Generally, the systems that are in place in the view of study participants are not too complex to use. A reason for this is that firms usually prepare for the use of these systems through training. The study participants admitted that even though the systems are not common to them, the training they go through enables them to easily use the systems. Therefore, the common theme that is present in the responses is that the systems become easy to use because of training. Another theme is the level of technological skills present (self-efficacy) present among firm employees. Finally, the complexity of the systems (procedures and features) is another crucial issue affecting the use of the technology.

The results indicate that initially, the effect of ease of use on intentions to use marketing analytics will be high at the initial stages of acceptance of the technology. This view is expressed by RES2, RES4, and RES5. A manager (RES2) of a company in the hospitality sector stated that:

"…some of the analytics systems are not easy to use at the beginning…I personally do not like using complex technologies such as these"

Another study participant explained that learning to use the systems depends on the training regime, which means the systems are not easy to use. RES5 also commented that:

"yes, some of the systems are difficult to learn and use …however, it depends on who is taking you through the training"

The second theme is related to the self-efficacy of the study participants. Generally, study respondents indicated they have the ability to use the marketing analytics systems (RES1, RES3, RES5, RES6).

A study participant (RES1) commented that:

"for me, it is easy to use…you do not need an IT background to use…you have to just follow the instructions, and it is user friendly"

The self-efficacy of firm employees is key in the use of marketing analytics. From the telecommunication sector perspective, a firm manager RES5 stated that:

"…if you have existing skills in other analytics, it may be easier to learn new ones.

A major issue of concern to study participants regarding ease of use of marketing analytics technology is training. RES5 also commented that:

"...when you look at the trained personnel…yes we do have a lot of personnel who have software and analytics skills…we also have people who can train others on how to use the software"

A firm manager (RES5) again stated that:

"…every analytics developer also has new features, so there is the need to go through some training from the developers...for open-source analytics such as Hadoop it may be easy to learn"

Another respondent from the manufacturing sector expressed an opinion that training to use the system is key. RES4 commented that:

"the analytics team usually take other team members through how we generate the analytics results for instance, after generating the micro-market characteristics, we meet with the sales and distribution team to take them through how they analyse their activities and what they should be learning"

From these results, it can be deduced that having the right information technology training, coupled with employees with adequate analytical skills, could make it easier to use marketing analytics.

Participant's perception of the effect of social influence

The social influence on the intentions to use marketing analytics was seen to be limited because the study participants perceive the technology to be work-based and may not be used due to the influence from friends and relatives. The important individuals that are likely to influence firm employees are colleagues that use the systems and their superiors. These individuals are crucial in ensuring the use of the systems due to the social pressure they pose.

Study respondents in their responses indicated that the influence from managers and colleagues may actually have some impact on their intentions to use marketing analytics systems. Therefore, two main themes are very relevant in providing social influence on the use of marketing analytics. In the banking sector, the study participant expressed confidently that social influence is not very crucial in influencing the use of marketing analytics. RES3 commented that:

"…my personal relationship with informational relationship digital managers in the banking sector is the option that makes me get encouragement and advise to use analytics"

The use of marketing analytics in the hospitality sector may be influenced by the pressure from competitors. A manager (RES2) commented that:

"…every firm in the industry use the systems, and that is what puts pressure on us to also use them"

The view opined by RES3 in the banking sector is supported by that of a respondent in the manufacturing sector. RES6 stated that:

"I think the use of analytics is more of a company directive… the systems are industry-specific and has a common group of people who use it and also influence me"

Another important social issue in the use of marketing analytics is what other important competitors and experts are doing about marketing analytics. In the hospitality sector, a manager (RES2) commented that:

"…in our industry, every marketing professional use analytics for their job…there is always a pressure on you to also use the systems for your work"

The systems are novel in the developing country context; therefore, the expectation is that other analytics users are in the best position to influence others to use the systems. An important finding is that compliance from other analytics users and top managers in an organisation or industry is key in the diffusion of marketing analytics. The pressure from competitors in the industry also affects the use of marketing analytics. The technology is not common to other members of the population, which makes social influence from friends and family have a lesser effect on the intention to use the system.

Participant's perception of the influence of organisational support

The support needed to enable the use of marketing analytics was found to be very important to study participants. The interviews conducted revealed that analytics technologies availability through firm investments in resources, support from the analytics service providers and departments, and analytics skills are very crucial. The respondents also indicated there are some challenges with the use of analytics.

Some firm managers acknowledged some challenges in terms of facilities and investments in marketing analytics. RES3 commented that:

"...not all banks in Ghana are doing very well with the use of marketing analytics...I am aware some banks do not have budgets to develop their own marketing analytics capabilities, and there are few banks with analytics managers due to little skills and expertise"

Apart from issues of lack of investments and resources, most of the firm managers who use marketing analytics acknowledged the influence of organisational support on intention to use the technology. The main theme that is detected is the investment in analytics systems by firms. The study respondents (RES1, RES3, RES2, RES6). A manager (RES6) of a manufacturing firm commented that:

"…we have analytics administrators at our distributor ends to assist in management…we provide all forms of Information systems such as internet systems, computers…we see this as a form of investment"

The availability of information technology systems provides the use of marketing analytics; RES2 commented that:

"…we have over the years provided information technology systems to firm employees…the marketing team has very modern information technology facilities"

Another important issue is the existence of an analytics department or support team dedicated to helping users. RES5 and RES6 strongly supported this notion. RES5 stated that:

"…there is an analytics department in the organisation that provide our needs and ensure all employees use the systems effectively"

Apart from support from the firm analytics department, analytics service providers also play a crucial role in supporting firm employees to use marketing analytics. RES6 provided an in-depth response regarding the support from analytics service providers. RES6 commented that:

"…the analytics service provider always includes new features based on our needs…they also provide training to our staff"

The study participants indicated there are some shortfalls in this regard in their industries. The firms the study participants work for, however, indicated that firms provide the resources needed to use some form of marketing analytics. It is worth indicating that some facilitating conditions identified include the dedication of a marketing budget for analytics, top management strategy to use analytics, investments in competent analytics experts, provision of information technologies, support from analytics service providers, and integration of analytics into the information management systems.

Participants' perception of the influence of the trust of marketing analytics

The trust of marketing analytics systems was not a major challenge preventing firm employees from using marketing analytics. The study participants indicated that the analytics systems are reliable and provide accurate information to inform decision making. The security and privacy issues about the analytics stems are also protected through contractual agreements with system providers. There are also verification and procedures that make the system safe to use.

On the intention to use marketing analytics technology due to the perceived trust of data protection, study participants were of the view that the systems are safe. In the manufacturing sector, RES4 commented that:

"the system is very safe. We have passwords and verification systems. There are legal agreements between the system developers. The legal agreement makes it difficult for the developer to share the data and also marketing manager is also prevented from doing so"

Another response confirms this perception. RES2 also stated that:

"the systems are usually secure. I have not experienced any hacking into our systems. There is a contract between our hotel and system providers. I feel secured because there are legal obligations of parties in using the systems"

On the perception that of the accuracy and reliability of data from marketing analytics technology, study participants indicated they trust the data provided by the system. In the banking sector, RES3 stated that:

It is very timely because it gives real time information; for example, if you need data for as far as three months ago it can give u very fast. A look at customers who have are using our banking app to perform banking transactions and what kind of transactions.

Participants' perception of the influence of personal innovativeness

The perception of study participants about their level of personal innovativeness was also high. Most of the study participants indicated they are willing to try new technologies. two comments provided by the study participants confirm the importance of personal innovativeness on the intentions to use marketing analytics technology. It is important to note that personal innovativeness may help in initiating the use of marketing analytics. The qualitative results indicate that firm employees have high levels of personal innovativeness and, therefore, possess the willingness to use marketing analytics technology. Employees may even serve as the source of generating the idea to use a particular innovative technology.

A study respondent in the banking sector expressed that personal innovativeness is an important drive for the intentions to use marketing analytics technology. RES3 stated that:

"I believe I am a very innovative technology user. Am always looking for new technologies to work with. I can say it is because of my innovative nature that has made my bank to use certain analytics systems that others do not use".

Another respondent (RES2) in the hotel industry indicated that he is usually the one to introduce his organisation to certain innovative technologies. RES2 commented that:

"I have always been the one to initiate the use of a new technology. I am very must interested in looking for new technologies that have been introduced and see how they can be applied to my work"

Participants' perception of the influence of attitude

The attitude of firm managers towards marketing analytics technology is favourable. The study participants were of the view that the analytics systems use in marketing is a good way to enhance decision making. The study participants indicated that analytics will enhance the marketing discipline in developing economies since decision making would be supported by data. The responses were mainly on issues of how exciting it is to use marketing analytics systems. In the FMCG market, a respondent indicated that the use of marketing analytic is a good idea and makes marketing fun. RE4 stated that:

"the system use is very fun. We sometimes put play book on the system. Product adverts been run by the company can be shown to customers and distributors. These are fun functions"

Another response by RES6 confirms the importance of attitude towards the use of the technology. The study participant stated that:

"for me personally I like the marketing analytics system and will make marketing performance to improve a lot. I think it makes the marketing discipline very effective"

Qualitative Results of Objective Two – Effect of Intentions on Actual Use of Marketing Analytics

The qualitative study results were analysed to assess the influence of intentions and actual use of marketing analytics. Inferences are drawn from the responses on the intentions and actual use of the technology by study participants.

Participants' perception of intention to use marketing analytics

The willingness to try to use marketing analytics technology, which is a measure of intentions to use the technology for marketing practice, showed how important this is in influencing the actual use of the technology. The intentions to use the systems is as a result of the willingness to help their organisations to integrate customer data in the information system (RES1, RES5, RES6). Another theme that was identified is the effect of firm analytics culture (RES2, RES4). In the telecommunication sector, for instance, a study respondent (RES1) commented that:

"*when I first joined the organisation, I was tasked to migrate most of the customer data onto our analytics systems"*

The intentions by technology users to use the system and how it translates into actual use was also expressed by another firm manager. Respondent (RES6) in the manufacturing sector started that:

"the sales officers and our distributors were anticipating to use the analytics system for some time., we started by investing in the gadgets and information technology systems…I can say before we all started using the system the organisation ensured all users have the skills to use the system.

The qualitative data explains that when employees become aware of the need to use marketing analytics, and they have the resources to perform this behaviour, it will influence them to use the systems.

Participant perception of actual use of marketing analytics

The study participants provided details of how they use marketing analytics in their respective industries. The use of the system differs depending on the nature of marketing. All study participants indicated they actually use marketing analytics for their marketing activities. The systems are used for sales and revenue tracking (RES1, RES6), segmentation and customer profiling (RES2, RES4, RES5), and marketing communications (RES3). In the telecommunications sector, study participant (R1) indicated that:

"we use marketing analytics technology to perform sales and revenue tracking and forecasting…the use of analytics enables us to see every day how the company is performing in real-time…we use dashboards to generate our reports and do our presentations to management"

In the banking sector, a study respondent (R3) provided insight into how the systems are used to manage digital communications on social media. R3 commented that:

" analytics technologies are used to monitor the effectiveness of our marketing communication across many platforms…we can see in real-time the impact of marketing communications on the target market…we usually rely on metrics such as the number of shares, visits, and enquiries"

Another respondent in the manufacturing sector indicated that:

"analytics systems are used to control our entire sales and distribution systems…our record-keeping has been upgraded from manual to technology-based…systems provide the data for forecasting decisions"

Inference can be drawn that organisational analytics culture and the willingness to use the systems to perform marketing duties, influence the actual use of marketing analytics.

Qualitative Result of Objective Three – The Effect of Actual use and User Satisfaction.

From the earlier results indicating all firm actually use marketing analytics, the study sought to examine whether the actual use of the systems will translate to satisfaction with the systems. All the study participants (RES1, RES2, RES3, RES4, RES5, RES6) who use the systems indicated they are satisfied with the use of marketing analytics systems.

The level of satisfaction was related to a number of themes including, timely and accurate data and reports (RES1, RES4), quicker marketing decision making (RES2), effective marketing communications (RES3), effective sales management (RES4, RES6), and monitoring customer behaviour (RES5).

Perception of participants on level of satisfaction of marketing analytics

The interview also sought to examine the level of satisfaction and willingness to continue using the marketing analytics system. The level of satisfaction of using the technology is related to the accuracy and reliability of the systems. The ability of the system to provide very fast and timely data is key. Study participants were very satisfied with the use of marketing analytics for many sales and marketing activities.

In the telecommunications sector, a study participant expressed satisfaction with the use of marketing analytics technology. RES1 commented that:

"the analytics systems we use provide timely and accurate data and report. The systems provide very good data depending on how you use the systems"

A study respondent (R4) in the manufacturing sector commented that:

"the analytics systems have modernised our sales routing plan. The sales managers are able to supervise the whole network in real-time. So far, the data provided by the sales force and retailers have been accurate and reliable"

Qualitative Result of Objective Four- The Influence of User Satisfaction on Continuance Usage

The qualitative results also indicated the perception of firm managers about the use of marketing analytics systems in the long term. It is also clear that all study participants (RES1, RES2, RES3, RES4, RES5, RES6) who indicated they are satisfied with the marketing analytics systems also indicated they would continue to use the systems in the long term.

Participant perception of continuance usage

The study participants all indicated they are willing to continue using the marketing analytics systems in future. The responses (RES1, RES2, RES3, RES4, RES5, RES6) indicate that firm employees are willing to use the system for marketing decision making and management in the long term. The study respondents indicated analytics is now part of their job and serves as a means of performing marketing functions. In the manufacturing sector, R6 commented that:

"there is no indication I and other marketing professionals in this organisation will stop using the analytics systems we have…as a multi-national organisation, the use of analytics is part of our work and decision making"

The perception of continuance usage of analytics was also indicated by a manager in the hotel sector. RES2 stated that:

"i will continue to use the analytics systems because in the hospitality sector I cannot do without it…most of the transactions are done using online platforms that are integrated with our analytics systems"

The Summary of the Descriptive Statistics of the Qualitative Results

Following the approach proposed by Miles and Huberman (1984), the various responses provided by the study participants were presented using a table to fulfil data reduction requirements in qualitative studies. The summary in Table 19 provides details of the perception of firm managers on the various questions. These responses are organised under themes. The summary of the responses can be examined in relation to another theme, thus indicating the relationship between variables.

Table 16: Summary of Qualitative Data Results

THEMES	RES1	RES2	RES3	RES4	RES5	RES6
Performance Expectancy	Sales Management Customer Database	Customer Management Database Competitor Intelligence	Digital marketing communications Customer Intelligence	Customer intelligence Customer database	Customer profiling and Customer management database	Sales Management Customer Database
Effort Expectancy	Less Complex system Self-efficacy	Complexity of the systems Training is key	Good configuration and following the steps Self-efficacy	Training and learning	Less Complex systems Training	Less Complex system Self-efficacy
Social Influence	Compliance pressure from superiors and other employees	Competitive Pressure Compliance by others	Competitive Pressure Networking with other analytics managers in the industry	Firm level compliance pressure	Influence from employees	Compliance pressure from superiors and other employees

Source: Author's construct, Twum (2021)

Table 19, continued: Summary of Qualitative Data Results

THEMES	RES1	RES2	RES3	RES4	RES5	RES6
Facilitating Conditions	Firm top management strategic initiate direction The investment in analytics infrastructure.	Investments to provide Information technology infrastructure.	Marketing budget for analytics.	Analytics experts and analytics skills culture.	Compatibility and integration of analytics to other firm systems. Analytics department support	Firm top management strategic initiate direction. The investment in analytics infrastructure
Trust of System	The contractual agreements with system vendors	The systems are usually not vulnerable to hacking and security breaches.	The systems can provide accurate and timely data	The systems have passwords and verification systems to protect firm and customer data.	The key to trusting the systems is by putting in the right data. The results or output generated depends on the manner the data was generated.	The contractual agreements with system vendors

Source: Author's construct, Twum (2021)

Table 19, continued: Summary of Qualitative Data Results

THEMES	RES1	RES2	RES3	RES4	RES5	RES6
Personal Innovative ness	From an engineering and information technology background, using new technologies is a passion.	Very innovative in terms of trying new technologies and has initiated a number of technologies in the organisation.	Usually, among the first three to use a new technology among my friends and colleagues.	Usually, the first among my colleagues to use new technologies.	Not very technologically inclined. There is a fair use of new technologies.	From an engineering and information technology background, using new technologies is a passion.
Attitude	The marketing analytics systems are preferred over the traditional marketing decision making systems.	The use of marketing analytics systems is interesting. It makes marketing tasks easier.	The analytics system is a good idea and makes the marketing job exciting.	Marketing analytics is exciting and fun.	Firm employees are very interested and comfortable using the marketing analytics system.	The marketing analytics systems are preferred over the traditional marketing decision making systems.
Intentions	The intention to use marketing analytics is informed by the integration of customer data into our information systems.	The competitiveness of the industry and the culture of using analytics makes me willing to always use the systems.	The use of marketing analytics tools is part of my job in the sector in which I work. There is a need to try every time to use the systems.	The analysis systems are many and with different features, but I try to use as many systems as possible.	The analytics systems are now integrated with operations, and employees try to use them often.	The intention to use marketing analytics is informed by the integration of customer data into our information systems.

Source: Author's construct, Twum (2021)

Table 19, continued: Summary of Qualitative Data Results

THEMES	RES1	RES2	RES3	RES4	RES5	RES6
Actual Use	The systems are used on a regular basis to inform the firm about sales and revenue patterns.	The systems in the hotel sector are used for segmentation, pricing, and offering services base on the type of customer. Competitor monitoring is also done with the system.	The systems are used to manage digital media communications and measure communication impact.	The analytics systems are used to manage customer databases and offer services to clients	The identification of customer needs and classifications. Monitoring customer behaviour.	The systems are used on a regular basis to inform the firm about sales and revenue patterns.
User Satisfaction	The systems provide timely and accurate data and report.	The systems have made decision making very fast and effective	The marketing communications task has been enhanced through analytics	The systems aid in managing sales routes nationwide. The data generated are accurate.	The ability of the systems to provide real-time service usage is a good thing.	The systems provide timely and accurate data and report.
Continuance Usage	Analytics are needed for survival and competitiveness	High prevalence of analytics in the industry	Employee committed to continuing to use marketing analytics.	The systems will be used so far as the firm continues to invest in the systems.	High prevalence of marketing analytics in the industry.	Analytics are needed for survival and competitiveness

Source: Author's construct, Twum (2021)

Assessing the Measurement Model of Partial Least Squares Modelling

The study sought to assess the measurement to ensure it met all the criteria used for a reflective model. This involves analysing the reliability and validity of study indicators and constructs. These analyses were performed using the rules of thumbs, which serve as guidelines for using PLS.

Reliability and validity of constructs

To ensure the reliability of research items, Hair et al. (2019) propose that indicators measuring a construct in the structural model must be 0.60 for exploratory study and 0.70 for research that relies on established constructs. An explanation for this is that the indicator explains more than 50 per cent of the indicator's variance. This study used established constructs from existing studies and therefore performed a reliability test using a minimum value of 0.70 for the indicators. All indicators that did not meet this requirement were deleted from the structural model. The indicators were given labels such as PE1, EE1, SI1, FC1, PT1, ATT1, PIIT1 to enable easy coding and analysis. The eleven indicators deleted from the final model are PE4, EE4, PT4, PT5, ATT4, IT3, ATU1, ATU4, ATU5, US5. The outer loadings of the indicator that were used in the final structural model are presented in Table 20.

Table 17: Outer Loadings and VIF

Items	Loadings	Inner VIF	VIF
	0.800		1.650
Actual Use	0.775	1.000	1.596
	0.726		1.111
	0.846		1.713
Attitude	0.879	2.254	2.227
	0.867		1.994
	0.863		1.924
Continuance Usage	0.865		2.008
	0.857		1.756
	0.845		1.753
Effort Expectancy	0.872	2.056	1.856
	0.715		1.263
	0.738		1.458
Facilitating Conditions	0.854	2.385	2.205
	0.870		2.583
	0.869		2.360
Intention to Use	0.910	1.000	1.999
	0.937		1.999
	0.763		1.511
Performance Expectancy	0.835	1.416	1.670
	0.740		1.189
	0.825		2.121
Personal Innovativeness	0.872	2.271	2.468
	0.896		2.849
	0.843		2.082
	0.844		1.749
Perceived Trust	0.874	1.424	1.818
	0.820		1.637
	0.826		2.127
Social Influence	0.866	2.504	2.406
	0.846		2.073
	0.816		2.018
	0.867		4.106
User Satisfaction	0.850	1.000	2.667
	0.854		3.270
	0.865		2.612
	0.901		4.644

Source: Field survey, Twum (2021)

Apart from the use of outer loadings to check for reliability, the indicators measuring the constructs were also subjected to a collinearity test to determine the tolerance or the Variance Inflation Factor (VIF). Using the rule of thumb of deleting values that are equal to 5 or higher (see Ringle & Sarstedt, 2019), the indicators that were maintained meet this criterion. Apart from collinearity, Kock (2015) propose that common method bias must be checked. As recommended by Kock (2015), all the inner VIF values used for checking common method bias in PLS SEM were below 3.3. The use of the one-factor test proposed by Harman (1960) is also appropriate to test for common method bias. The first factor accounted for 33.091 per cent variance, which is less than the 50 per cent threshold proposed by Podsakoff et al. (2003).

In assessing reliability, the internal consistency reliability test was performed by using the composite reliability. Hair et al. (2019) state that, unlike composite reliability, Cronbach's alpha, which are also another measure of composite reliability produces lower values. Cronbach alpha is seen as a less accurate assessment for reliability since the values are unweighted (Hair et al., 2019). Following the recommendation by Hair et al. (2019), outer loadings higher than 0.95 may be as a result of undesirable response patterns that must be deleted. Composite reliability between 0.70 and 0.95 was maintained for further analysis.

The next step was to ensure convergent validity was met. In a reflective measurement model assessment, the constructs are assessed to ensure their validity. Unlike the reliability test that takes a look at the indicators, a validity analysis focuses on the extent to which a construct converges to explain the variance of its items (Hair et al., 2019). According to Hair et al. (2019), the metric that measures convergent validity is Average Variance Extracted (AVE). The AVE is the square of the outer loading of the indicators on a construct. The acceptable level of the AVE is 0.50 or higher (Hair et al., 2019). The analysis performed in Table 21 proved that all the constructs included in this study met convergent validity.

Table 18: Construct Reliability and Validity

	Composite Reliability	AVE
Actual Use	0.811	0.589
Attitude	0.898	0.747
Continuance Usage	0.896	0.742
Effort Expectancy	0.854	0.662
Facilitating Conditions	0.901	0.697
Intentions	0.920	0.853
Perceived Trust	0.883	0.716
Performance Expectancy	0.823	0.609
Personal Innovativeness	0.919	0.739
Social Influence	0.905	0.704
User Satisfaction	0.938	0.753

Source: Field survey, Twum (2021)

Table 19: Fornell-Larcker Criterion

	ATU	ATT	CUA	EE	FC	IT	PT	PE	PIIT	SI	US
Actual Use	**0.768**										
Attitude	0.715	**0.864**									
Continuance Usage	0.519	0.629	**0.862**								
Effort Expectancy	0.564	0.638	0.458	**0.814**							
Facilitating Conditions	0.339	0.329	0.391	0.332	**0.835**						
Intentions	0.535	0.651	0.697	0.495	0.415	**0.923**					
Perceived Trust	0.746	0.435	0.398	0.445	0.264	0.415	**0.846**				
Performance Expectancy	0.310	0.423	0.397	0.435	0.400	0.433	0.192	**0.781**			
Personal Innovativeness	0.642	0.676	0.515	0.628	0.354	0.529	0.499	0.381	**0.860**		
Social Influence	0.404	0.410	0.435	0.367	0.751	0.412	0.314	0.392	0.398	**0.839**	
User Satisfaction	0.630	0.663	0.684	0.485	0.409	0.726	0.530	0.412	0.525	0.448	**0.868**

Source: Field survey, Twum (2021)

The study also assessed discriminant validity. The Fornell and Larcker (1981) criterion was used to examine the discriminant validity. The results in Table 22 indicates that the shared variance of all the constructs was not larger than their AVEs (in bold). This implies that the study constructs met discriminant validity. The study, in an attempt to ensure discriminant validity has been met also performed the Heterotrait-Monotrait (HTMT) test. Hair et al. (2019) states that the HTMT compares the mean average of the constructs measuring a target construct in the model. HTMT has a threshold value of 0.90 for structural models (Henseler et al., 2015). From the study results in Table 23, discriminant validity was met since all the values were below 0.90.

Table 20: Heterotrait-monotrait (HTMT) Ratio

	ATU	ATT	CUA	EE	FC	IT	PT	PE	PIIT	SI	US
Actual Use											
Attitude	0.826										
Continuance Usage	0.689	0.757									
Effort Expectancy	0.789	0.810	0.584								
Facilitating Conditions	0.450	0.393	0.466	0.418							
Intentions	0.703	0.776	0.842	0.625	0.499						
Perceived Trust	8.029	0.534	0.488	0.576	0.316	0.501					
Performance Expectancy	0.434	0.553	0.526	0.600	0.515	0.573	0.255				
Personal Innovativeness	0.824	0.788	0.602	0.778	0.414	0.615	0.588	0.488			
Social Influence	0.529	0.483	0.513	0.460	0.874	0.489	0.378	0.493	0.464		
User Satisfaction	0.799	0.756	0.780	0.578	0.462	0.830	0.620	0.514	0.581	0.503	

Source: Field survey, Twum (2021)

Assessing the Structural Model

The study evaluated the PLS-SEM results in assessing the structural model by including the coefficient of determination (R^2), the blindfolding-based cross-validated redundancy measure Q^2, f^2 effect size to assess the relevance of path relationship, and the statistical significance.

The structural model coefficients

The coefficients are derived from measuring series of regression equations to examine the relationship between study variables. These correlations were recorded since the VIF for the indicators were below values of 5. The coefficients in Table 24 for the relationship between technology acceptance factors, namely attitude (0.449), effort expectancy (0.014), performance expectancy (0.132), facilitating conditions (0.173), perceive trust (0.122), personal innovativeness (0.050), were positively related with intentions to use marketing analytics. There is a negative relationship (-0.018) between social influence and intentions to use marketing analytics. The was also a positive relationship between intentions to use marketing analytics and actual use (0.535) and between user satisfaction and continuance usage (0.684).

Table 21: Relationship between Study Constructs

	Intentions	Actual Use	Continuance Usage
Attitude	0.459		
Effort Expectancy	0.014		
Facilitating Conditions	0.173		
Performance Expectancy	0.132		
Personal Innovativeness	0.050		
Social Influence	-0.018		
Perceived Trust	0.122		
Intentions		0.535	
User Satisfaction			0.684

Source: Field survey, Twum (2021)

The coefficient of determination

The coefficient of determination R^2 measures the variance, which is explained in each of the endogenous construct(s) (Hair et al., 2019). This is referred to as the in-sample predictive power. R^2 values of 0.75, 0.50, and 0.25 represent substantial, moderate, and week explanatory power (Hair et al., 2019). In Table 25, the R^2 of 0.499 represents a moderate explanatory power of antecedents of intentions to use marketing analytics on intentions. 49.9 per cent of the variance in intentions to use marketing analytics technology is explained by performance expectancy, effort expectancy, social influence, facilitating conditions, perceived trust, attitude, and personal innovativeness.

The study found that an R^2 of 0.287 was recorded for the relationship between intentions to use marketing analytics and actual use of marketing analytics. This implies that 29.7 per cent of the variance in the actual use of marketing analytics is predicted by behavioural intentions to use marketing analytics. The explanatory power is, therefore, regarded as weak. The study found that actual use explains 39.7.5 percent of user satisfaction of marketing analytics. An R^2 of 0.467 explains that 46.7 per cent of the variance in continuance usage of marketing analytics technology is explained by user satisfaction. This result is an indication that there is a moderate explanatory power of user satisfaction on continuance usage of marketing analytics.

Table 22: Summary of Coefficient of Determination

Constructs	R Square (R^2)
Actual Use	0.287
Continuance Usage	0.467
Intentions	0.499
User Satisfaction	0.397

Source: Field survey, Twum (2021)

Assessing the effect size of study constructs

In the analysis of the data, the attempt was made to assess how the removal of a certain predictor will affect the R^2 of an endogenous construct. According to Hair et al. (2019), the f^2 effect size metric is used to explain this. The f^2 effect sizes reported in the Table 26 depict that when attitude ($f^2 = 0.179$) is deleted, it will represent the greater effect on intentions to use marketing analytics. This result shows how attitude towards technology is important for developing intentions to use the technology. This represents a medium effect size since the rule of thumb states that values higher than 0.02, 0.15, and 0.35 depict small, medium, and large effect sizes (Cohen, 1988). The study found that facilitating conditions, performance expectancy, and perceived trust recorded a small effect of 0.025, 0.025, and 0.021 respectively on intentions. The effect size of social influence, effort expectancy, and personal innovativeness were not significant; therefore, these constructs were found to have little effect on intentions to use marketing analytics technology.

Table 23: The Effect Size of Study Constructs

Constructs	Intentions	Actual Use	User Satisfaction	Continuance Usage
Intentions		0.402		
Attitude	0.179			
Actual Use			0.659	
User Satisfaction				0.877
Effort Expectancy	0.000			
Facilitating Conditions	0.025			
Perceived Trust	0.021			
Performance Expectancy	0.025			
Personal Innovativeness	0.002			
Social Influence	0.000			

Source: Field survey, Twum (2021)

The f^2 effect sizes of 0.402 and 0.877 for intentions and user satisfaction, respectively indicate these constructs have a large effect on the actual use and continuance usage constructs. This means that the removal of intentions construct from the model will have the largest effect on actual use, while the removal of user satisfaction will have the greatest effect on continuance usage.

Assessing the predictive power of the model

The assessment of the predictive power of the path model is also done by calculating the Q^2 value (Hair et al., 2019). The blindfolding procedure in this study found that all the Q^2 values are greater than 0. The Q^2 value for actual use (0.156) indicates a small predictive relevance on user satisfaction. The study also found that a Q^2 of 0.340 indicates that user satisfaction has medium predictive statistical relevance on continuance usage. The factors predicting the intentions to use marketing analytics recorded a Q^2 of 0.398. This result indicates that is a medium predictive relevance of the antecedents of technology acceptance on the intentions to use marketing analytics.

Table 24: The Predictive Level of Constructs

Constructs	Q^2 (=1-SSE/SSO)
Actual Use	0.156
Continuance Usage	0.340
Intentions	0.398
User Satisfaction	0.296

Source: Field survey, Twum (2021)

The statistical significance of the various path relationships proposed in this study was analysed using the bootstrapping approach. Table 27 indicates the statistical significance of the exogenous constructs on the endogenous constructs in the path model. The assessment of the critical t-values was based on a 1.96 significance level and a p-value less than 0.05.

The importance-performance of indicators

The study performed an analysis on the importance-performance of indicators to identify the constructs with higher importance value and lower performance values. From the analysis, the indicator that falls under this criterion is *Attitude*. Figure 2 shows that the *Attitude* has the highest importance (0.434) but with a small performance value (69.890). Attitude towards marketing analytics construct was found to have a higher importance value than all other constructs but recorded a lower performance value. This is an indication that firm managers must target user attitudes first to improve the intention to use marketing analytics.

Table28: Importance-Performance Indicator

	Construct Total Effect for Intentions (Importance)	Construct Performance for Intentions
Attitude	0.434	69.890
Effort Expectancy	0.013	70.155
Facilitating Conditions	0.159	71.345
Perceived Trust	0.096	62.673
Performance Expectancy	0.113	63.087
Personal Innovativeness	0.051	69.709
Social Influence	-0.017	70.141

Source: Field survey, Twum (2021)

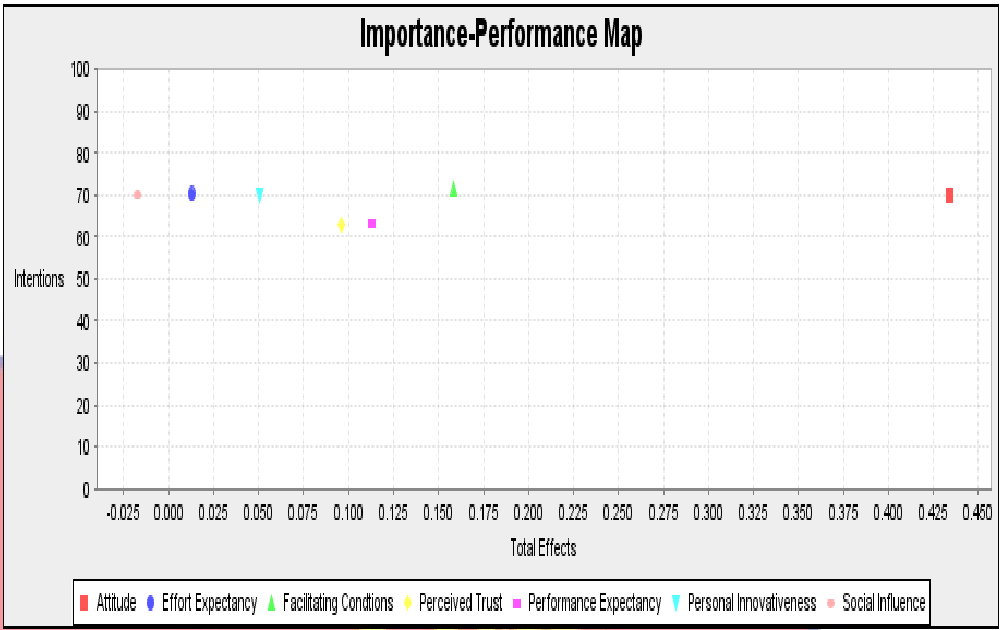

Figure 2: Important-Performance Map
Source: Author's construct, Twum (2021)

The level of statistical significance

The study examined the relationship between study constructs by performing hypotheses testing using bootstrapping in PLS. Two main indicator values, namely the t-statistics and p-values, were used to determine the level of predictive of study constructs on endogenous constructs in the model. A t-statistics of 1.96 and a p-value less than 0.05 was used to determine a significant relationship. The analyses were performed based on the proposed research hypotheses. The structural model has been presented to show the various paths and relationships in Figure 3. Since this study used mixed methods, the quantitative results will be supported by the qualitative results. The responses to questions by the qualitative study participants will be used to provide further explanation for the quantitative results of the hypotheses. This fulfils the triangulation approach adopted for this study.

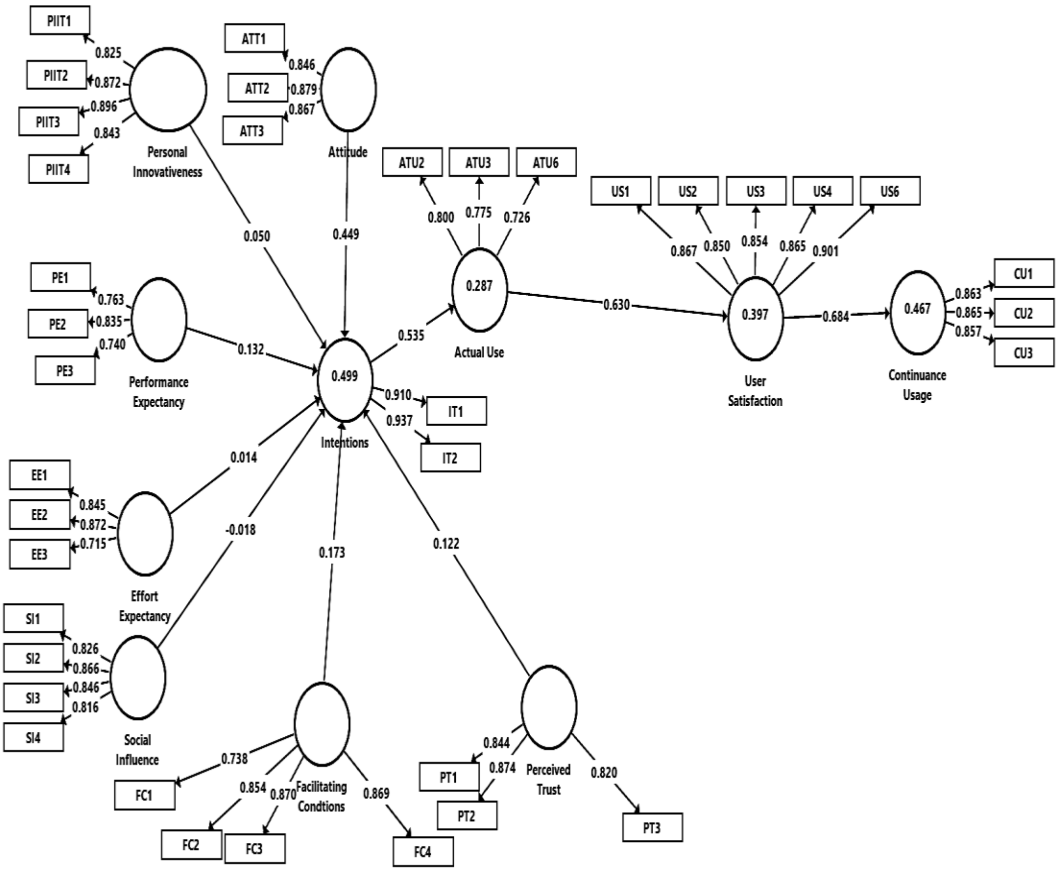

Figure 3: Structural PLS Model

Source: Author's construct, Twum (2021)

The first hypothesis (*H1a*) sought to examine the relationship between performance expectancy and intentions to use marketing analytics technology. The results of this study support the hypothesis that performance expectancy is statistically significant with intentions to use marketing analytics. The results show that the t-statistics (2.501) is higher than 1.96, and p-value (0.012) is less than 0.05.

The hypothesis (*H1b*) on the statistical relationship between effort expectancy and intentions to use marketing analytics technology was not supported. The results found a t-statistic of 0.186 and a p-value of 0.853, indicating there is no statistical significance. This result indicates that despite the positive relationship between effort expectancy and intentions to use marketing analytics, this construct may not be a very important predictor of intentions.

The findings of the study did not support the hypothesis (*H1c*) that social influence has a statistical significance relationship with intentions to use marketing analytics. A t -statistics of 0.229 and a p-value of 0.819 indicate that there was no statistically significant relationship between the constructs.

The hypothesis to examine the relationship between facilitating conditions (*H1d*) and intentions to use marketing analytics was supported. The results indicating a t-statistic of 2.006 and a p-value of 0.045 meant that there is a statistically significant relationship between facilitating conditions and intentions to use marketing analytics.

The study found a statistically significant relationship between perceived trust and intentions to use marketing analytics. A t-statistics of 2.188 and a p value of 0.029 indicate that perceive trust has a statistically significant relationship with intentions to use marketing analytics technology. The hypothesis (*H1e*) was supported.

The hypothesis (*H1f*) proposing a statistically significant relationship between personal innovativeness and intentions to use marketing analytics technology was not supported. The relationship between PIIT and intentions to use marketing analytics recorded a t-statistics of 0.577 and p value of 0.564. The t -statistics was less than 1.96 and the p-value is higher than 0.05.

The study examined the relationship between attitude towards marketing analytics and intentions to use marketing analytics. The study supports the hypothesis (*H1g*) that attitude has a statistically significant relationship with intentions to use marketing analytics. The study recorded a t-statistics of 5.807

and a p-value of 0.000. This construct recorded the strongest prediction of the intentions to use marketing analytics.

The Moderating Effect of Characteristics of Firm Employee

To achieve research objective one, the study analysed a number of moderators, including age, gender, the experience of the employee, and type of innovator, on the relationship between the UTAUT constructs and intentions to use marketing analytics as depicted in the model. The analysis presented was performed using the Multi-Group Analysis in SmartPLS3.The analysis was performed to examine the different effects of the antecedents of technology acceptance and intentions to use marketing analytics due to age, gender, experience, type of innovator, and type of industry.

The effect of age

Age as a moderator between UTAUT antecedents of technology acceptance and behavioural intentions to use marketing analytics was analysed. The difference in age of respondents did not result in a significance difference on how most of the antecedents of intentions to use marketing analytics technology predicts intentions. The p-value of attitude (0.900), effort facilitating conditions (0.620), perceived trust (0.124), performance expectancy (0.137), personal innovativeness (0.997), social influence (0.641) indicate that age does not influence the relationship between these constructs and intentions to use marketing analytics.

The study, however, found that the age of firm employees moderates the effect of effort expectancy on intentions to use marketing analytics. The hypothesis (*H2a*) that age moderates the relationship between UTAUT constructs and intentions to use marketing analytics was only supported for this construct. A p-value of 0.022 is an indication that there is a difference in how effort expectancy affects intentions to use marketing analytics due to age. From the analysis, the difference is higher among older users of technology. The effect of effort expectancy on intentions to use marketing analytics is higher among older users than younger users.

Table 29 Age as Moderator

Proposed Relationships	Total Effects-diff (Young - Old)	p-value
Attitude -> Intentions	-0.015	0.900
Effort Expectancy -> Intentions	-0.352	0.022
Facilitating Conditions -> Intentions	0.088	0.620
Perceived Trust -> Intentions	0.171	0.124
Performance Expectancy -> Intentions	0.189	0.137
Personal Innovativeness -> Intentions	-0.002	0.997
Social Influence -> Intentions	-0.081	0.641

Source: Field survey, Twum (2021)

The effect of gender

Gender as a moderator between technology acceptance factors and behavioural intentions to use marketing analytics was examined. The study hypothesis (*H2b*) that gender moderates the relationship between antecedents of technology acceptance and intentions to use marketing analytics was not supported. The gender of study participants was found not to influence any of the relationships proposed in the path model. The results indicating p values greater than 0.05 for all relationships moderated by gender implies that gender does not result in a difference among study participants in terms of intentions to use marketing analytics.

The effect of experience

The experience of firm employees in using analytics technology as a moderator on the relationship between technology acceptance factors and intentions to use marketing analytics was analysed. The study results indicate that there is no statistical difference in intentions to use marketing analytics technology due to the experience of firm employees in using other analytics technologies. The results indicating p values higher than 0.05 implies that the hypothesis *(H2c)* was not supported. The analysis revealed that the effort of effort expectancy, facilitating conditions, and personal innovativeness on intentions is stronger among users who had not experienced in using marketing analytics. On the other hand, the effect of attitude, perceived trust, social influence, and performance expectancy on intentions was stronger among users who had experienced using analytics.

The effect of type of innovator

The study sought to use the type of innovator (early adopters versus late adopters) to examine the differences in the intentions to use marketing analytics. The study hypothesis (*H2d*) that the type of innovator moderates the relationship between factors affecting technology acceptance and intentions to use marketing analytics was supported for effort expectancy (p-value = 0.023). Although it was not hypothesised, the study found that type of innovator serves as a moderator between the relationship between perceived trust (p-value = 0.046) and use intention.

The effect of effort expectancy, performance expectancy, perceived trust, personal innovativeness, and facilitating conditions on intentions was higher among early adopters of technology innovation than late adopters. The p-values greater than 0.05 for the other constructs (attitudes, social influence, personal innovativeness, facilitating conditions, performance expectancy) indicates that type of innovator does not influence the relationship between these variables and intentions to use marketing analytics technology. It is worth noting that the effect of attitude towards technology, effort expectancy, and social influence on use intentions was stronger among late adopters of innovative technologies than early adopters of technology.

Table 25: Type of Innovator as Moderator

Relationships	Total Effects-diff (Early Adopters- Late Adopters)	p-Value
Attitude -> Intentions	-0.016	0.906
Effort Expectancy -> Intentions	*-0.357*	*0.023*
Facilitating Conditions -> Intentions	0.154	0.390
Perceived Trust -> Intentions	*0.217*	*0.046*
Performance Expectancy -> Intentions	0.165	0.193
Personal Innovativeness -> Intentions	0.026	0.874
Social Influence -> Intentions	-0.084	0.646

Source: Field survey, Twum (2021)

The Statistical Effect of Intentions on Actual of Marketing Analytics

To achieve research objective two, the relationship between intentions to use marketing analytics and the actual use of marketing analytics was analysed. The findings confirm that hypothesis (*H3*) that there is a statistically significant relationship between intentions and actual behaviour. The study recorded a t-statistics of 10.574 and a p-value of 0.000.

The moderating effect of type of industry

As part of research objective two, the study proposes that the relationship between intentions to use marketing analytics and actual is moderated by the type of industry. The study sought to test a hypothesis (H4) to examine the type of industry as a moderator of the relationship between intentions and actual use of marketing analytic. The result revealed that the type of industry (service versus manufacturing) is not a predictor of the difference in the actual use of marketing analytics. A p-value of 0.985 is an indication that there is no effect of the type of industry and the use of marketing analytics technology.

Even though it was not hypothesised, the type of industry moderates the relationship between perceived trust and intentions. This relationship is stronger for users in the service sector. The moderation test reveals that the effect of attitude, facilitating conditions, perceived trust, and performance expectancy on intentions were stronger among users in the services sector. On the other hand, the effect of effort expectancy, personal innovativeness, and social influence on intentions was stronger in the manufacturing sector than in the service sector.

Table 26: Type of Industry as Moderator

	Total Effects-diff (Service Vrs Manufacturing	p-Value
Perceived Trust -> Intentions	0.239	0.029
Intentions -> Actual Use	0.004	0.985

Source: Field survey, Twum (2021)

The Effect of Actual Use and User Satisfaction of Marketing Analytics

To achieve objective three, the study examined the relationship between actual use and user satisfaction of marketing analytics. The relationship between the actual use of marketing analytics was statistically significant with user satisfaction with the technology. The study results indicate that a t -statistics of 14.166 and a p-value of 0.000.

The Relationship between User Satisfaction and Continuance Usage of Marketing Analytics Technology.

The study found that the relationship between user satisfaction of marketing analytics and continuance usage of marketing analytics was statistically significant. The study recorded a t-statistics of 17.640 and a p-value of 0.000, indicating that there is a statistically significant effect of user satisfaction in continuance usage of marketing analytics, thus supporting H6.

Summary of Hypothesised Relationships

Table 32 presents a summary of the result of all hypothesised relationships in the structural model. The findings that support the proposed hypotheses are indicated as supported, and those that were not supported are indicated as such.

Table 27: Summary of Results

	Hypothesised Relationships	T Statistics	P Values	Decision
H1a	Performance Expectancy -> Intentions	2.501	0.012	Supported
H1b	Effort Expectancy -> Intentions	0.186	0.853	Not Supported
H1c	Social Influence -> Intentions	0.229	0.819	Not Supported
H1d	Facilitating Conditions -> Intentions	2.006	0.045	Supported
H1e	Perceived Trust -> Intentions	2.188	0.035	Supported
H1f	Personal Innovativeness -> Intentions	0.577	0.564	Not Supported
H1g	Attitude -> Intentions	5.807	0.000	Supported

Table 32, continued: Summary of Results

H2a	Effort Expectancy × Age -> Intentions		0.022	Supported
H2b	UTAUT × Gender -> Intentions		>0.05	Not Supported
H2c	UTAUT × Experience -> Intentions		>0.05	Not Supported
H2d	Effort Expectancy × Type of Innovator-> Intentions		0.023	Supported
H3	Intentions -> Actual Use	10.574	0.000	Supported
H4	Intentions × Type of Industry -> Actual Use		0.985	Not Supported
H5	Actual Use -> User Satisfaction	14.166	0.000	Supported
H6	User Satisfaction -> Continuance Usage	17.640	0.000	Supported

Source: Field survey, Twum (2021)

Chapter Summary

The study results showed that most of the proposed relationships in the model were statistically significant. The qualitative results also aided in understanding the proposed relationships. The qualitative results provided evidence that firm managers have the intention to use marketing analytics. The results showed that social influence to use analytics might not be obtained from the general public. The results indicated there are some challenges with investments and facilities to enhance the use of analytics. On the other hand, the qualitative results show firm managers actually use the systems to perform marketing functions leading to the high level of satisfaction. The qualitative study also found that study participants are willing to continue using marketing analytics.

The results reported on the relationship between UTAUT constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions and also included three new constructs to the model, namely perceived trust, personal innovativeness, and attitudes, on intentions to use marketing analytics technology. In relation to objective one, the findings reveal that apart from effort expectancy, social influence, and personal innovativeness, the other constructs are predictors of intentions to use marketing analytics.

A moderating analysis of the effect of firm employee characteristics was performed to achieve objective one. The study also found that the gender and experience of firm employees does not play a crucial in affecting the nexus between the UTAUT antecedents of technology acceptance and intentions to use marketing analytics. The relationship between effort expectancy and intentions to use marketing analytics was moderated by the age of firm employees. To address objective two, the study reported that intentions to use marketing analytics is a predictor of actual use. The study also revealed that the type of industry does not influence the relationship between intention and actual use of marketing analytics technology. The study in achieving objective three and four, the study found that the actual use of the technology was a predictor of user satisfaction. The study also found that user satisfaction predicts continuance usage of marketing analytics technology.

CHAPTER EIGHT

DISCUSSION OF FINDINGS

Introduction

This chapter provides a discussion of the empirical findings in the previous chapter. The previous chapter presented empirical results on the various hypothesised relationships, while this chapter seeks to relate the findings to existing empirical studies and compare the results of the qualitative and quantitative studies. The discussions are mainly aimed at analysing the findings of this current study as against empirical studies. The discussions are based on the research objectives and research hypotheses in the introductory chapter. This chapter uses the mixed methods approach to perform the discussion of the findings.

Research Objective One - Antecedents of Intentions to Use Marketing Analytics

This chapter discusses the results of research objective one, which focuses on investigating the factors affecting intentions to use marketing analytics. The study proposed a number of hypotheses that the UTAUT factors have the efficacy of predicting the intention to use marketing analytics. The study, therefore, proposed that UTAUT constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions have a positive and significant relationship with intention to use marketing analytics.

A detailed literature review found that some scholars such as Agarwal and Prasad (1998) and Dwivedi et al. (2019) have proposed the inclusion of other factors as factors predicting intentions to use innovative technologies. As a result, this study introduced attitude towards innovative technology, perceived trust and personal innovativeness as constructs to examine the intention to use marketing analytics. Therefore, six hypotheses were analysed, and the results were presented in the previous chapter. The chapter, therefore, discusses these findings concerning existing empirical studies on factors determining intentions to use innovative technologies. This chapter presents an opportunity to triangulate the results of the quantitative and qualitative studies.

The relationship between performance expectancy and intentions to use marketing analysis

The study results found that performance expectancy has a statistically significant relationship with intentions to use marketing analytics technology. This hypothesised relationship was formulated based on abundant empirical studies that exist in the consumer context (Kurfali et al., 2017; Ratten, 2014; Slade et al., 2015) and in the organisation context (Hazen et al., 2014).

More importantly, this study findings support that of many empirical studies that have found that performance expectancy is a predictor of intentions to use business analytics technologies (Cabrera-Sánchez & Villarejo-Ramos, 2020; Jaklič et al., 2018; Okcu et al., 2019; Shin, 2016; Sun et al., 2019). The performance expectations of using marketing analytics as a business analytics tool must be regarded as an important predictor of the use of the system. The performance expectancy construct was the second strongest predictor of intentions to use marketing analytic.

The qualitative results provide enough justification that the expectations of firm managers relating to the ability to enhance marketing function will influence the use of the system. Some of the performance expectations identified include managing customer database, gathering market intelligence, managing marketing communication, generating customer data, segmentation and customer profiling, automation of sales, which are necessary for influencing firm employees to use marketing analytics.

From a theoretical perspective, the perception of firm employees that using a marketing analytics system will enable them to accomplish their marketing tasks more quickly is very important in influencing their intentions to use the systems. Venkatesh et al. (2003) provide a clear explanation that end-users of technologies are influenced to use technology mainly because the system will enhance their performance and productivity. The result of this study contributes to the literature confirming that performance expectancy predicts intentions to use marketing analytics in a developing country context.

The discussion that can be generated from the quantitative and qualitative results is that firm employee who is aware that the analytics technology has some advantages over the traditional way of performing a function may be a way to improve their willingness to use the analytics system. There is a statistically significant relationship between performance expectancy and intentions because the qualitative results indicate that firm employees are optimistic about the performance implications of marketing analytics. Cabrera-Sánchez and Villarejo-Ramos (2020), discussing this result, indicated that the employees having knowledge about the uses and relevant information about analytics systems improve their perception of performance expectancy and are likely to accept to use the system. This study supports the argument and results by existing studies that the perception of firm employees that they can perform better and increase marketing performance using marketing analytics is an important issue in the use of the technology.

The relationship between effort expectancy and intentions to use marketing analytics

There is a need to provide some discussions on the result that effort expectancy does not have a significant relationship with intentions to use marketing analytics. Empirical studies in the consumer context have shown that effort expectancy is a predictor of intention to use networking apps (Chua et al., 2018) and mobile learning (Thomas et al., 2013). The result of this study confirms that of Slade et al. (2015) that effort expectancy is not a predictor of intentions to use technologies. The quantitative study result does not support the proposition that the low level of effort to learn and understand a new technology will affect the intention to use the technology. On the other hand, the qualitative result points to the importance of the availability of training and skills development to use analytics systems. The qualitative result indicated that firm managers perceive marketing analytics systems as easy to use.

A possible explanation of these results could be based on the argument made by Im et al. (2011) that technology users in collectivist societies in most developing countries may possess lower effort expectancy than those in individualistic economies where the effect of effort expectancy on intentions to use technologies may be higher. Another explanation for this result is that an effort-oriented construct may be more salient at the early stages of a technology acceptance behaviour (Schaupp, Carter, & McBride, 2010; Venkatesh et al., 2003). The effort hurdles overcome at the initial stages may not be recalled by technology users, making the usefulness of the technology more important to users (Schaupp et al., 2010). The later reason will be appropriate to explain the quantitative result since the qualitative study showed that firm employees have gone past the initial stages of accepting the technology. It is expected that the training and support that exist make the issue of ease of use less important in predicting intentions to use the system.

The finding of this study that effort performance is not a predictor of intentions supports that of business analytics empirical studies of Demoulin and Coussement (2020), Jaklič et al. (2018), and Cabrera-Sánchez and Villarejo-Ramos (2020). Yoon et al. (2017) explain that effort expectancy may not significantly affect intentions to use analytics technology because the perception that these technologies may enhance performance may motivate employees to use the system despite the system's complexity. On the other hand, some empirical studies in analytics have found that effort expectancy is a predictor of use intentions (Okcu et al., 2019; Shin, 2016; Shorfuzzaman et al., 2018).

This study result supports findings that the perception of how easily employees can learn to use and understand the marketing analytics system will not significantly influence the intentions to use the system. The result of this study may be due to the importance ascribed to other acceptance factors such as the performance expectations than the perception of ease of use of marketing analytics technology among study participants. From this study's qualitative and quantitative results, the study respondents indicated that marketing analytics systems are easy to learn and use. The role of organisational training and support may play a crucial role in enhancing the ease of use of the systems. It is expected that studies with a high level of perception that the technology under investigation is difficult to use may negatively affect the intention to use the system and may have a significant effect on intentions to use.

The relationship between social influence and intentions to use marketing analytics

The study result showed that social influence is not a predictor of intentions to use marketing analytics technology. From the qualitative results, the study participants indicated that the influence from other people in their social circle, such as friends, is not important in the use of marketing analytics. It was revealed that colleagues in the organisation and other analytics users in the industry play a minor role in influencing them to use marketing analytics systems. The respondents were of the view that the organisation systems rather play a major role in their use of the system and that the use of the system is involuntary.

The quantitative study result is not in line with the study of Sun et al. (2019) and Jaklič et al. (2018) that the influence of peers will predict intentions to use analytics technologies. A possible reason for this result deduced from the qualitative study is that study respondents did not perceive friends to be very interested in marketing analytics in the study context. The qualitative data also showed that analytics technologies are not usually available to the general public, and it is expected that many people may not know to use the system; therefore, these individuals may not serve as advocates for the use of the system.

The systems are organisation-based technologies, and the social relationship among employees and management members may account for the social influence. Vanketesh et al. (2003) also posit that in mandatory settings, and in early stages where the individuals' opinions are ill-informed, social influence will significantly affect intentions to use technology. It is expected that the normative pressure will reduce over time as the use of the system will lead to functional rather than a social influence on intentions (Venkatesh et al., 2003). In the view of Schaupp et al. (2010), the social influence in mandatory settings is basically a result of compliance by others. Therefore, a possible reason why social influence is not a predictor of marketing analytics use intentions in developing country context may be the low compliance by others. The result supports Yoon et al. (2017) that social influence is not a predictor of intentions to use business intelligence technology.

The relationship between facilitating conditions and intentions to use marketing analytics

This study results indicate that facilitating conditions is a predictor of intentions to use marketing analytics. In the consumer context, studies such as that in the area of healthcare wearables (Wang et al., 2020), virtual reality (Huang, 2020), and telemedicine (Kamal et al., 2020) found that facilitating conditions influence intentions to use these technologies. In a developing country context, El-Masri and Tarhini (2017) concede that facilitating conditions in a technology context does not have a greater influence on using technology than in the developed country context. The disparities in facilitating conditions in the developing and developed world in influencing technology acceptance were not confirmed in this study. In the context of marketing analytics, this study found that facilitating conditions are an important predictor of intentions to use.

From the quantitative result, facilitating conditions influence intentions to use marketing analytics. This is in line with studies in a developed context that found that facilitating conditions is an important factor affecting the intentions to use analytics technologies (Cao et al., 2019; Behl et al., 2019; Sun et al., 2019). The qualitative result also provides a link between facilitating conditions and intentions to use marketing analytics. The study participants indicated that organisational support, investments in analytics, availability of data and information technology, analytics culture and skills as important factors in predicting intentions to use marketing analytics was supported. This implies that existing perceptions about facilitating conditions by study respondents are a significant predictor of intentions to use marketing analytics.

The relationship between perceived trust and intentions to use marketing analytics

The perception of trust in analytics technologies is relevant to many stakeholders, including customers, firm employees, governments, and firm management. These perceptions relating to security, privacy, and perceptions of the reliability and accuracy of analytics technologies affect intentions to use the systems. Empirically, many studies have found that the perception of trust for analytics technologies influences the intentions to use them (Madhlangobe & Wang, 2018; Shahbaz et al., 2019).

Studies have found that perceived trust influences use intentions in other technologies such as cloud-based computing (Chen & Nakayama, 2016) and mobile commerce (Yadav et al., 2016). These studies and that of this study support the security and reliability of analytics systems will improve the rate of their use. The qualitative study results indicated that firm employees trust the marketing analytics systems in place in their organisations. The qualitative results showed that firms have legal agreements with analytics software providers, making the issue of data protection and dissemination secure. The study results from the qualitative study also showed that the analytics systems used for marketing are generally reliable, accurate, and timely, so far as the users are able to use the system for the intended purpose. The statistical relationship between perceived trust and intentions to use marketing analytics supports the qualitative result that the systems are safe, reliable, and are trusted by firm employees to produce accurate data.

The relationship between personal innovativeness and intention to use marketing analytics

It is worth noting that most studies on the effect of personal innovativeness on intentions to use technologies were based on individual-level technologies (Lu, 2014; Lu et al., 2005; Xu & Gupta, 2009; Wijesundara & Xixiang, 2018). Therefore, the empirical evidence is replete with results indicating innovative technologies can be accepted and used due to the innovativeness of technology users. In the organisational context, this study contributes to the relatively limited empirical evidence. In the organisation technology acceptance domain, the studies of Yi et al. (2006) and Hwang (2014) are among the limited studies acknowledging the importance of personal innovativeness of firm employees in acceptance and use of technologies.

Based on the quantitative result, this study found that personal innovativeness has a positive relationship with intentions to use marketing analytics but does not predict intentions to use the system. From the qualitative perspective, this study found that there is also a high level of personal innovativeness, but this may have a greater impact in the case of aiding the introduction of new technologies. The effect of personal innovativeness on the use of mandatory technology like marketing analytics may not have a strong effect on intentions to use the systems. From the result, a study participant indicated lower personal innovativeness but expressed a strong will to try and use marketing analytics systems. Therefore, the implication is that since the systems are to be used for marketing activities, which is mandatory, the personal innovativeness may not have a stronger influence on the use of the system. Firm employees may have a passion for trying new technologies but, this may not translate to the use of analytics if the systems and facilities are not in place.

In the context of novel technologies such as marketing analytics, it is expected that personal innovativeness will predict intentions to use the system. The result of this study, however, does not support that of Larsen and Sorebo (2005) and Kim, Choe, and Hwang (2021), who found that personal innovativeness is crucial in determining the use of novel technologies. The difference in empirical results may be due to the type of information technology under investigation (Wang, Li, & Hsieh, 2013). It can be argued that studies that consider technologies that are regarded as operation-oriented complex information technology such as Enterprise Resource Planning tools and business intelligence tools (Wang et al., 2013), the personal innovativeness of employees is expected to produce a greater effect on the use of the system.

A possible explanation for this result is that personal innovativeness may be an important factor in voluntary settings than in involuntary technology settings. This study may be considered more of an involuntary setting technology; therefore, the influence of personal innovativeness may not be strong in predicting intentions to use marketing analytics. It is worth noting that for organisational technologies that are voluntary, personal innovativeness may play a greater role in predicting intentions to use the technology. Lu et al. (2005) also propose that personal innovativeness may predict use in circumstances where the technology is new and may be voluntary. This study result may be explained that most organisations included in this study have marketing analytics as an involuntary technology, and personal innovativeness may not have a greater effect on the use of the system. Therefore, organisations must consider personal innovativeness in situations where the use of analytics technology is voluntary.

The relationship between attitudes towards marketing analytics and use intentions

The attitude towards innovative technologies has in the extant literature been regarded as influencing the willingness to use technology. This effect is expected because the attitude towards a technology explains whether an individual has a favourable or unfavourable likeness for the technology leading to the intention to use. Dwivedi et al. (2019) strongly argue that an individual's attitude toward technology is shaped by the perception of ease of use and the extent to which the technology may be useful.

The quantitative result of this study indicates that there is a positive attitude towards marketing analytics as study participants perceive the technology as a good idea and could help the marketing profession. In the context of business analytics, Verma et al. (2018) explain that a favourable attitude towards the technology means that the user will perceive the system as useful. Another study by Wang et al. (2017) supports that a positive attitude towards analytics technology influences the perception of usefulness. The effect of a positive attitude towards technologies on the perception of usefulness means that end-users will be prepared to use the systems.

The qualitative results indicate that firm managers perceive marketing analytics systems are exciting, fun, and a new form of marketing that is changing the marketing discipline. The general consensus is that analytics application marketing must be embraced by all firm managers. The effect of this on the intentions to use marketing analytics can be proposed since all the managers had a favourable attitude towards analytics and were also willing to try and use the systems.

The moderating effect of firm employee characteristics on use intentions

With research objective one, the effect of age, gender, and experience of employees were found not to be moderators of the relationship between performance expectancy, social influence, facilitating conditions and intentions to use marketing analytics technology. These results do not support that of the UTAUT by Venbkatesh et al. (2003) that employee characteristics moderates the relationship between antecedents of technology acceptance and intentions to use technology. A possible explanation could be that analysing the effect of age and gender in a predictive model with all the four constructs of the UTAUT will lead to results not to be significant (see Pan & Jordan-Marsh, 2010). Pan and Jordan-Marsh (2020) also explain that the effect of gender of technology users on technology use over the years is lessening.

The study, however, found that age moderates the relationship between effort expectancy and intentions to use marketing analytics. This is the only moderation relating to age that was supported. This is in line with the result of Venkatesh et al. (2003) and AbuShanab and Pearson (2007). This study found that the moderating effect of age on the relationship between effort expectancy and intentions is stronger for older workers. This moderation result confirms the

UTAUT by Venkatesh et al. (2003). Therefore, the older workers may need more effort to understand to use marketing analytics, leading to the intentions to use the systems.

A study to determine whether age and gender are moderators of intentions to use technologies in developing countries by Baker et al. (2007) found that these factors do not have a significant effect on intentions to use technologies. A reason provided for this is that most workforce in developing countries is very homogenous. In this study, a possible reason for not recording a significant effect of demographic factors on the intentions to use marketing analytics could be that not much differences exist in terms of interest in using analytics technology across age and gender groups.

The majority of employees may not have experienced analytics technology, and therefore differences might not exist among employees as a result of the experience with the use of such technologies. The study finding that the experience of employees in using technology is not a moderator on the relationship between performance expectancy and facilitating conditions supports the result of the UTAUT by Venkatesh et al. (2003). The study of AbuShanab and Pearson (2007) also found that apart from social influence, experience is not a moderator in the relationship between UTAUT constructs and intentions to use internet services. This result does not support that of Venkatesh et al. (2003) that the experience in using technology moderates the link between effort expectancy, social influence and intentions.

On the moderating role of type of innovator, the study found that there is a significant effect of type of innovator (early adopter or late adopter) on the relationship between effort expectancy and intentions to use marketing analytics. On the other hand, the relationship between intentions to use marketing analytics and the other UTAUT constructs (i.e., performance expectancy, facilitating conditions, and social influence) were not moderated by the type of innovator.

These results do not support that of Tzou and Lu (2009) that different groups of innovators will vary in intentions to use technologies. A possible explanation is that the technology under investigation is voluntary and usually promoted by organisations. This system makes the type of innovator an employee is may not be significant in predicting the use of marketing analytics. Therefore, firm technologies such as marketing analytics may be mandatory and will demand that early adopters and late adopters will all try and make efforts to use the systems. It is worth noting that there is a difference in the effect of effort expectancy on the intentions to use marketing analytics due to the type of innovator group. The late adopter's intentions to use marketing analytics technology will be influenced by effort expectancy than early adopters. The intention to use marketing analytics will be much easier for early adopters than employees who are late adopters. Late adopters may not have the skills to immediately use marketing analytics systems as compared to early adopters who are regarded as technologically savvy.

Research Objective Two - The Effect of intentions to Use Marketing Analytics and Actual Use

The proposition that intentions to use marketing analytics is a predictor of actual use of the technology emanates from the TPB theoretical view of Ajzen (1991) and the empirical support from the UTAUT by Venkatesh et al. (2003).

This study result supports these theoretical positions that intentions to use technology is a predictor of the actual behaviour. Current extant literature also points to the influence that intentions have on technology acceptance and have used it as a predictor of actual use (Dwivedi et al., 2019; Venkatesh et al., 2003).

This study in the context of marketing analytics adds to the abundance of studies that technology users will be influenced to use technology after they have gone through planning processes leading to their intentions to use the system. Intentions explain the willingness to use a technology influenced by some factors. The study thus provides strong empirical support for the UTAUT that technology use intentions are a good predictor of actual technology use behaviour.

The qualitative study provides some insights into the planning efforts firms and individuals go through in order to use marketing analytics. The results indicate that the use of use analytics is a planned endeavour involving employee training and support. The results generally point to the willingness of firm employees to try using the analytics systems for their marketing activities. There is an indication that for all firm managers that try hard to use the systems, these managers also indicated they actually use the systems for various marketing functions. Therefore, a relationship between intentions and actual use is established through the qualitative result.

The moderating effect of type of industry

The moderating effect of type of industry (service or manufacturing) on the relationship between intentions to use marketing analytics technology and actual use of the technology was assessed. The result indicates that there is no statistical difference in the use of marketing analytics by employees of service and manufacturing firms. The result does not support that of Hernández-Ortega et al. (2006) that type of industry has a significant effect on technology use. The multigroup analysis results of this study do not imply a significant difference in the intentions to use marketing analytics and actual use of the technology due to the industry.

Research Objective Three - The Relationship between Actual Use of Technology and User Satisfaction

This study supports relatively few empirical studies on the effect of actual use of technology and technology user satisfaction. This testing of the actual use and user satisfaction hypothesis enables technology acceptance research to progress from actual use as a final predictor to other technology use outcomes such as user satisfaction and continuance usage. This relationship has been supported by findings in the context of electronic patient records (Maillet et al., 2014) and internet systems (Isaac et al., 2017).

The qualitative data revealed that the actual use of marketing analytics is extensive among firms studied. The actual use ranges from the tracking of sales and forecasting, automation of pricing, segmenting and profiling customers, managing marketing communications, and monitoring customer behaviour. All the firm managers who indicated they use marketing for their marketing responsibilities also indicated they are satisfied with the system.

This study may be among the first to examine this relationship between actual use and user satisfaction in the context of marketing analytics. The user experience of technologies can only be evaluated when there is the actual use of the technology. Therefore, user satisfaction can be a result of actually using the technology for intended purposes. Organisational users of marketing analytics actually using the marketing analytics technology can lead to their satisfaction, thus, generating a positive experience with the technology.

Research Objective Four - The Relationship between User satisfaction and Continuance Usage

The relationship between user satisfaction and continuance usage of technology is explained by the popular information success model by DeLone and McLean (2003). This study supports this empirical result that user satisfaction with technologies is a predictor of continuance usage. The studies that are supported by this result include that of Hadji and Degoulet (2016), Garg and Sharma (2020) that continuance usage of technology is an outcome of user satisfaction. Based on the qualitative results, the satisfaction with the marketing analytics systems directly influenced the continuance usage perceptions. All firm managers indicated they are satisfied with the analytics systems since they provide accurate and reliable data for decision making.

This finding makes a valuable contribution that the marketing of innovative technologies to employees can be achieved through ensuring user satisfaction. The satisfaction of technology users, who are regarded as customers from the marketing perspective, is very important because the marketing literature supports that continuance usage of services highly depends on how satisfied the customer is. In the context of marketing analytics technology, this study contributes to the empirical literature on the statistical relationship between user satisfaction and continuance usage.

CHAPTER NINE

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

Introduction

This final chapter presents a summary of this study, conclusions, and recommendations for practice, policy, and future research. The chapter first provides highlights of the study findings by summarising the findings. The summary discusses the research problem, research objectives, and the major results from the research objectives. The chapter also provides some contributions of the research for theory and research, as well as recommendations for practice and policy. The final part of this chapter discusses future research by suggesting some relevant research areas other studies can focus on.

Summary of the Study

The research started with the aim of understanding the factors that determine the acceptance and use of innovative technologies using the context of marketing analytics. The study sought to understand the factors that predict the intentions to use marketing analytics technology and also the factors that will predict the continuance usage of marketing analytics technology by firm employees. The study examined the role played by antecedents of technology acceptance in influencing firm employees' intentions to use, actual use, user satisfaction, and continuance usage of marketing analytics.

The first objective was, therefore, to use the constructs of the UTAUT to understand the factors that may influence the intentions to use marketing analytics technology. The study also attempts to take note of perceived trust, user attitudes and personal innovativeness, which are considered as very important technology acceptance factors. This objective relied on quantitative and qualitative data from firm employees who use marketing analytics technology.

Based on the assumption that intentions are the strongest predictor of actual behaviour, the study also sought to examine the role behavioural intentions play in influencing the actual performance of behaviour. Therefore, the role of behavioural intentions to use marketing analytics technology in predicting the actual use of the technology was examined.

In addition to this objective, the role employee characteristics such as age, gender, experience, and type of innovator play in moderating the relationship between antecedents of technology acceptance and intentions to use marketing analytics were examined. The characteristics of firm employees are important variables in technology studies, thus, requiring close attention.

The study also acknowledges that the actual use of technology may be due to the industry a firm operates in. An analysis is, therefore, performed to assess whether service firms or manufacturing firms are more prone to use marketing analytics. The study also took a strong position on the need to understand the post-adoption issues relating to technology acceptance. In this regard, the study examines the role of user satisfaction in using innovative technologies and how firm employees will continue to use these technologies.

Drawing from the information success model, marketing concepts of user satisfaction in using marketing analytics technology is examined as a means of promoting technology continuance usage. The focus on pre-adoption antecedents using the UTAUT and post-adoption outcomes of technology using the information success model seeks to develop a comprehensive model on innovative technology continuance usage. This led to the development of a conceptual model guiding this current research.

The framework of this study proposes that the technology acceptance factors can be well understood by combining different technology acceptance factors from theories and models. Organisations that are seeking to enhance the use of innovative technologies must consider factors that are very important to influence users to develop the intention to use them. These theories and models seek to indicate what factors organaisations can manipulate to develop the intention to use technologies that have been adopted through organisations investments. The study model proposes that the post-adoption of technologies is very crucial as the pre-adoption of technologies since huge investments in innovative technologies must yield benefits through sustained use.

The current study, therefore, reviewed extant literature to identify the factors that might predict intentions to use innovative technologies, the actual use of the technology, user satisfaction and continuance usage. The literature review was followed by an empirical study using a survey from firm employees who use marketing analytics technology and interview of firm managers. The analysis of the data provided some results. Subsequently, the results were discussed in line with extant literature. The summary of the results is presented in Table 33.

Table 28: Summary of Major Findings

Research Objective	Major Results/Findings
Research Objective One (1) - Factors affecting Intention to use marketing analytics technology	The study provided evidence that the intentions to use marketing analytics technology can be predicted by constructs of UTAUT, namely performance expectancy, facilitating conditions. Performance expectancy is needed to motivate firm employees to decide to use marketing analytics technology. Performance expectations are perceptions among firm employees that marketing analytics technologies will enhance the performance of their job and increase marketing productivity. The study also acknowledges the importance of facilitating conditions, which measures the availability of resources, analytics skills, and support to enable the use of innovative technologies. The study, however, found that social influence and effort expectancy did not predict intentions to use marketing analytics. Apart from the UTAUT constructs, the study found that attitude and perceived trust are predictors of intentions to use marketing analytics. The personal innovativeness construct introduced into the model was found not to be an important predictor of intentions to use marketing analytics technology.
To examine the moderating role of firm employee characteristics on the relationship between antecedents of technology acceptance and intentions to use marketing analytics	The study findings did not generally support the empirical literature that the age, gender, and experience of firm employee moderates the relationship between antecedents of technology acceptance and intentions to use innovative technologies. Specifically, the findings lead to a conclusion that demographic characteristics of firm employee do not lead to differences in the effect of performance expectancy, effort expectancy, social influence, and facilitating conditions on intentions in the context of marketing analytics. Therefore, the study provides evidence that age and type of innovator moderates the effect of effort expectancy on intentions to use marketing analytics.

Source: Author’s construct, Twum (2021)

Table 33, continued: Summary of Major Findings

Research Objective	Major Results/Findings
Research Objective Two (2) - To determine the effect of intentions on actual use of marketing analytics technology	The study provides evidence that behavioural intention is a predictor of actual use of technology in the context of marketing analytics. The firm employees' intention to use marketing analytics technology is a good predictor of actual use of the technology. Evidentially, the study supports empirical support that actual use of innovative technologies is planned behaviour that is achieved when there is an intention. The study also found that type of industry does not have a significant effect on the relationship between intention to use and actual use. In the study context, evidence is provided that there is no difference among firm employees regarding the effect the type of industry they operate has on the link between intentions and actual use of the marketing analytics technology.
The moderating effect of type of industry on the relationship between intentions and actual use of marketing analytics	The results reveal that the type of industry does not influence the link between intentions and actual use of marketing analytics. This implies that there is no difference between how intentions affect service firm and manufacturing firm employees to use marketing analytics.

Source: Author's construct, Twum (2021)

Table 33, continued: Summary of Major Findings

Research Objective	Major Results/Findings
Research Objective Three (3) - To examine the effect of actual use of marketing analytics on user satisfaction	From the technology post-adoption conceptualisation, this study provides evidence that the use of marketing analytics technology for intended purpose predicts user satisfaction. The satisfaction derived from using innovative technologies is a result of the actual use of these technologies.
Research Objective Four (4) - To examine the effect of user satisfaction of marketing analytics and continuance usage	The study provides evidence that user satisfaction with marketing analytics technology is of importance to ensuring there is continuance usage of the technology. User satisfaction of marketing analytics leads to a confirmation that the technology has met expectations, and therefore, the user is motivated to continue to use the system.

Source: Author's construct, Twum (2021)

Contribution to Knowledge

This section of the chapter reflects on the entire study by discussing the two main contributions of this study. The study's contribution to knowledge is derived from the new insights generated from the empirical study conducted. These contributions will guide future research and practice.

First, the study has been able to successfully extend the UTAUT by including perceived trust, personal innovativeness and user attitude. The study provides a theoretical contribution that the UTAUT can be combined with constructs from other theories to predict intentions to use technology. The contribution to the literature is that studies using the UTAUT can include user attitudes, perceived trust, and personal innovativeness as constructs. These constructs have proved to contribute to predicting user intentions to use marketing analytics technology.

Second, the intention to use marketing analytics is not primarily affected by the characteristics of firm employees. The contribution to knowledge is that the age, gender, experience, and type of innovator may not influence how performance expectancy, social influence, and facilitating conditions affect intentions to use marketing analytics. The study contributes to knowledge that among older firm employees and late adopters of technology, the perception of ease of use of marketing analytics will have a greater on use intentions. The contribution to knowledge is that firm manager characteristics must be used as moderators by researchers.

Third, the study also tested a post-adoption theory, namely expectancy confirmation theory, in the study of marketing analytics. The research model developed aided in assessing the post-adoption outcomes (user satisfaction, continuance usage). This study result contributes to the literature that user satisfaction in the context of marketing is a prerequisite for attaining continuance usage of the technology. Researchers must, therefore, be interested in going beyond user intentions to examine the adoption and post-adoption outcomes of innovative technologies. This study contributes to the marketing literature that user satisfaction of innovative technologies must be ensured to achieve continuance usage of the systems.

Conclusions of the Study

This research concludes that the intentions to use marketing analytics as an innovative technology depends on the attitudes, performance expectancy, facilitating conditions, and perceived trust. The ability of firms to promote the intentions to use marketing analytics technology can be achieved through a positive attitude towards the technology, enhanced perception of performance expectancy, the existence of facilitating conditions, and trust in the technology system. This research also concludes that there is a high level of perception among firm employees that marketing analytics technologies are easy to use, which indicates that firm employees in Ghana have the skills and knowledge to use the system. Apart from effort expectancy, the personal innovativeness of firm employees is high among firm employees. It is contended that the perception of ease of use the technology innovativeness of firm employees is not enough to influence usage intentions of marketing analytics technology unless firms can provide resources, promote a favourable attitude towards the technology, enhances the understanding that the systems will increase the performance of the marketing function, and increase the trust in the systems.

Supported by theory, firm employees' intentions to use innovative technologies is an important determinant of actual acceptance and use of these technologies. Before firm employees accept and use technology, the intention to use the system must already be formed. The theoretical perspective that actual behaviours are planned, and intentions about performing these behaviours is an integral part of these processes. It is, therefore, concluded that firms that have employees who possess the intention to use marketing analytics technology are in the best position actually to make their employees use the system. The actual use of marketing analytics is a manifestation of the existence of intentions among firm employees.

The study concludes that the continuance usage of marketing analytics technology can be achieved through an important marketing concept called user satisfaction. From the confirmation expectation perspective, firms encouraging employees to use marketing analytics technologies must place a greater focus on satisfaction with using the system. There is a likelihood that most firm employees may discontinue using marketing analytics technologies due to dissatisfaction. The negative outcome of user satisfaction with marketing analytics is that firm investments in the technologies may not lead to competitiveness and value.

Ultimately, a significant conclusion from this study is that information technology systems can be marketed to firm employees by putting in place mechanisms to promote satisfaction with using the systems. The ability to ensure user satisfaction with innovative technologies in an organisation is an effective way to achieve the continuous usage of these technologies.

Recommendations for Practice

The findings of this study present several important implications for the management of organisations. The study proposes some implications for management in handling marketing analytics technology acceptance and use among firm employees. These implications are mainly based on the empirical results generated on the perception of firm employees about the marketing analytics system, their intentions to use, the level of satisfaction, and continuance usage perceptions. The study also presented implications based on the firm employee characteristics and market conditions.

The study results on the performance expectancy of using marketing analytics reveal that users do not possess a very high agreement that marketing analytics will increase marketing performance. Even though study participants accepted that marketing analytics is crucial in improving marketing performance, a moderate perception about the performance-related questions is an indication that firm management needs to do more to create awareness about the performance implications of the technology. The interviews with firm managers reveal that marketers perceive marketing analytics to have enormous performance implications. The results indicate that performance expectancy is an important factor influencing intentions to use marketing analytics. Firm managers included in the in-depth interviews were very optimistic about the performance implications of marketing analytics technology.

To enhance performance expectancy, firm employees must be educated about the ability of marketing analytics to enhance marketing task performance and can lead to a rise in marketing performance. This objective can be achieved through employee engagements. Analytics experts can be used to demonstrate to employees how the technology can enhance their work output. Firm employees who are knowledgeable about using these technologies can serve as individuals to assimilate the use of the technology.

Despite indicating that effort expectancy is not a predictor of intentions to use marketing analytics, the study acknowledges that firm employees perceive marketing analytics technology as easy to use, which shows that firm employees possess the skills and understanding to use analytics technology. In the Ghanaian context, especially in the formal sector private sector, the study participants have high technology skills and knowledge, which means that they can be able to use marketing analytics.

From a practical perspective, firms must acknowledge that firm employees have the technological skills to use innovative technologies. In the formal sector in developing economies, such as the context of this study, there exist adequate technical skills to enable the use of analytics technologies. Therefore, the ease of the technologies must be enhanced through organisational support. Firm management must also consider training and educating employees about the use of analytics. Firm managers must be concerned about the skills and understanding of marketing analytics of their employees.

The study results indicated that social influence in the context of marketing analytics relates more to influence from colleagues, senior managers, and experts. Even in the organisational setting, social influence may not play a major role in mandatory technologies where managers do not use compliance to indicate to others the need to use technology. Firm employees usually take an independent position when it comes to their job roles, thus making it difficult to be influenced by others. Compliance by other employees is key in creating the social pressure needed to enhance the acceptance of technologies.

The social influence in the organisational context may not emanate from family and friends since the marketing analytics technologies are not widely available to the general public, and most are not open source. It, therefore, means that the assimilation of marketing analytics technology is not likely to come from people outside the organisation. Firms in developing economies must begin to use compliance policies to drive the acceptance of marketing analytics.

Firm managers and supervisors must use their personal relationships to encourage the use of analytics among employees. Finally, firm management must encourage their employees to seek motivation and assistance from other analytics users in the industry. It is expected that the network of analytics users in an industry will help firm employees to learn new trends and systems used for analytics in marketing.

The study findings also have implications on whether firms in the developing country context like Ghana possess the right resources, skills, culture, information technology infrastructure, to enable users to use the technology. The study results indicated that firms in Ghana have the resources, the knowledge, and qualified people to use these analytics tools. Firms in Ghana can be said to have the ability to use these marketing analytics systems. The most important thing needed is how to initiate the use of these technologies by top management. Top managers initiative serves as the catalyst for the acceptance of marketing analytics. There must be a conscious effort by top managers to make analytics the main decision-making tool in marketing.

Despite the study revealing there are resources to ensure the use of marketing analytics, the study also found some challenges relating to budgets and investments in the technology. It is obvious firms in Ghana and in developing economies will be faced with the challenge of committing resources to marketing analytics. It is crucial to dedicate part of the marketing budget to analytics technologies to enable the firm employees to have the resources to use the systems.

The findings indicate that the perception of trust for marketing analytics technologies is encouraging among firm employees. The study revealed that firm employees have confidence in marketing analytics systems there is a contractual agreement with system providers. The rules relating to the security and privacy of data generated through an analytics system must be clear, easy to be followed, and enforceable. Firm managers must ensure to have their analytics systems very secured and provide evidence of how secured and competent the systems are to provide information for the marketing function. To ensure trust in the systems, firms can develop standard data input and output procedures so that accurate and reliable data can be generated.

The study has implications on the effect of the level of personal innovativeness of firm employees on the use of marketing analytics. The study reveals that most of the study participants indicated they possess high personal innovativeness in information technology. The implication of this result for firm managers is that employees are willing to try new technologies. Firm managers must see the personal innovativeness of employees as an important aspect of technology use and can alter this through programmes to ensure employees try new technologies.

A major practice implication identified in this study is that the personal innovativeness of firm employees in mandatory technologies like analytics may not be a major concern. Despite the novelty of analytics technologies in emerging economies, the innovativeness of firm employees must not be a major positive factor to be relied on by firm managers. Every employee must be assisted to use the systems through investments, training, and support. It is expected that in involuntary technology contexts, the personal innovativeness of firm employees may play a major role in the use of technologies since they may take their own initiative to use new technologies.

The current level of attitude of employees towards marketing analytics is high, representing a favourable situation for the use of marketing analytics. The favourable attitude towards marketing analytics by firm employees means that they perceive the technology as a positive way of enhancing the performance of marketing function. The perception of ease of use may also enhance favourable attitude towards marketing analytics. It means that firms can alter the attitude of employees towards analytics by educating them about the performance implications of the technology and training them to perceive the system as easy to use. The attainment of favourable attitude towards marketing analytics is an opportunity for firm management to capitalise on the favourable reaction to the technology. Attempts can also be made to develop a positive attitude toward analytics technology among Ghanaian firm employees.

The study has implications on the determination of the extend of intention to use marketing analytics technology in the Ghanaian context. The intention to use marketing analytics represents how hard firm employees try to use the systems in performing their marketing jobs. The study findings that there is a willingness to use marketing analytics technology among firm employees implies that organisations must provide the necessary opportunity for marketers to do so. The actual use of marketing analytics is predicted by strong intentions, which represent how hard employees try to use the systems. Intentions to use innovative technologies like this needs to be supported with the right attitude, skills, resources, organisational culture, and investments, leading to actual use.

The findings on the factors predicting intention to use marketing analytics found that attitude is the strongest predictor of intentions. The development of a positive attitude towards analytics technology among marketers in organisations in Ghana must be the most important issue management must work on. The strength of the attitude of users towards marketing analytics can be manipulated by management through enhancing their understanding of the ease of use and usefulness of the system. It is also expected that firm management must identify and resolve negative perceptions about analytics technology among employees.

The second most important issue firm managers must take seriously to enhance the willingness to use marketing analytics technologies among employees is the perception of performance expectancy. There should be evidence to prove that using marketing analytics by firm employees will lead to the perception that the systems produce superior results. The actual performance expected out of using marketing analytics must be understood by firm employees. In developing countries, little evidence exists regarding the performance implications of analytics, and this is a task firm management must perform to enhance the belief that analytics can improve marketing function.

Another crucial factor firm management must focus on increasing intention perception about the use of marketing analytics is providing enabling facilitating conditions. Facilitating conditions in the context of marketing analytics include adequate information communication technology, analytics culture, analytics skills among employees, support systems, resources, and training. Top management support is seen as a very important factor in the acceptance and use of analytics technology among firms. Firms in Ghana can promote the use of analytics technologies when top management provides the necessary resources and support. Demonstration of the use of marketing analytics tools can arouse the emotions and expectations of users regarding the ability of the system to help them perform better at their job.

The perception of trust for marketing analytics technology among firm employees must be of great concern for firm managers. The perception of trust for marketing analytics systems is not only about the security and privacy concerns of data but also about the perception of reliability and competency of systems to provide accurate data for decision making. Firm employees will be willing to use the systems when they are aware of security and privacy agreement with providers and users of the system. This approach will instil confidence in the analytics technologies. The development of the analytics systems must be in line with the marketing processes and data which is usually used by employees. The systems must not be alien to firm employees regular marketing activities.

The study findings of the differences in how age influences the relationship between effort expectancy and intentions to use marketing analytics make it paramount for firm managers to consider training employees across different age groups in technological and analytics skills. Especially for older employees in developing countries, this study findings suggest that management must attempt to equip these individuals with modern information technology skills. Most firm employees may be willing to use marketing analytics technology but might not possess the skills to use the system. It is also very important to ensure firm employees across gender groups are also encouraged to use marketing analytics. This study did not find any disparity between male and female employees in terms of their intentions to use marketing analytics. The management of organisations must target all employees irrespective of their gender, age, and experience. This is crucial in building analytics culture in organisations in developing countries.

The study findings on the effect of late adoption characteristics of technology behaviour on intentions to use marketing analytics, the implication to the management of organisations is that individuals who are classified as late adopters of innovative technologies must be identified and assisted. The assistance may come in the form of training and trial of new technologies. The attitudes towards technologies by late adopters can be altered through education about the usefulness and ease of use of the marketing analytics systems.

Reflecting on this study result on type of industry as a moderator, the study has implications on the use of marketing analytics among service and manufacturing firm employees. The study findings suggest there is no difference in the effect of technology adoption factors on intentions and actual adoption based on the industry. In the Ghanaian context, the effect of performance expectancy, effort expectancy, facilitating conditions, social influence, and attitude on intentions to use marketing analytics is not affected by the fact that the employee is in the service or manufacturing industry. In the service sector, even though the effect of intentions on actual use of marketing analytics is higher among service firm employees than that of manufacturing firms, this does not significantly influence actual use of marketing analytics. The development of intentions to use marketing analytics by employees will lead to actual adoption irrespective of the industry of the employee. This implies that firm managers across industries can influence their employees to use marketing analytics technology so far as there exist intentions to use the system.

A major implication of this study is related to the need to ensure that analytics employed in the marketing arena is actually deployed to performing very crucial marketing activities and decision making. A strategy by firms to ensure their employees are satisfied with marketing analytics systems is to ensure the actual use of the systems.

In the marketing literature, user satisfaction is an important determinant of the continuance usage of technologies. Firm management must ensure their employees are very satisfied with the analytics systems. A conscious effort must be exerted to enhance the satisfaction towards marketing analytics in order to get employees to be loyal in using the systems. This approach is the only way to gain competitiveness from investments in marketing analytics.

Recommendations for Policymakers

This research proffers a number of issues policymakers must address to promote the use of marketing analytics technologies. First, the growing global competitiveness and the use of technology to gain competitive advantage, therefore, calls for a need by governments to promote the use of marketing analytics and, for that matter, many forms of business analytics technology in developing countries The first point of call in promoting the use of analytics technology among firm employees. The perspective of enhancing perceptions relating to performance expectations, in the form of the belief that marketing analytics technologies will enhance marketing performance, can be promoted through awareness creation.

It is also expected that the continued education and awareness creation will create a positive attitude towards marketing analytics technology. Apart from media engagements, seminars, and training, the educational curriculum can be used to teach and learn analytics in higher education institutions. Considerable research has focused on promoting analytics through education in developed economies. The Ministry of Education, through tertiary education agencies, must encourage the implementation of courses on analytics across many fields. The labour force in developing countries like Ghana needs skills and an understanding of marketing analytics. The existence of courses on analytics will enhance the performance expectancy, ease of use perceptions, trust, attitudes, and social pressure regarding the use of the system.

There is a very high expectation of higher education institutions in developing countries to contribute to the assimilation of analytics in various fields of study. As part of the objective of higher education institutions to train the human resource for organisations, the use of analytics technologies must become a major aspect of the curriculum since these technologies are driving innovation and competitiveness. There is a need to quickly introduce analytics courses since the developing world is behind in the use of big data and artificial intelligence.

Another important policy issue is the support that governments can offer for firms to invest in analytics technologies. The main approach to consider is a partnership with software and systems providers to offer services in the country. There must be close collaborations with local and international analytics systems service providers. The use of analytics technologies can be a common feature of marketing when there are service providers delivering support to these firms.

The trust of marketing analytics can be enhanced with government regulation of security and privacy of data generated from customers. In the era of consumer data by organisations, there is a need for the government to be concerned about how data generated from artificial intelligence and big data is used. Policies relating to the lawful use of consumer data must be introduced to guide the use of consumer data. In developing economies, governments must be seen responding quickly to fast-growing use of consumer data generated from analytics technologies.

From the perspective of developing personal innovativeness in information technology, this study calls for a nationwide action plan on training and education in information technologies for employees in both the public and private sectors. Information technology skills development must not only be the priority of firms but also other stakeholders. In the context of analytics technologies, government and other agencies such as the Ministry of Communications and Digitalisation must lead in promoting employees and business managers to be willing to try these innovative systems of gathering, analysing, and using data. This can be done through partnerships with the various industries using analytics technology seminars, conferences, training, amongst others.

As part of the United Nations Secretary-General's data strategy, data analytics must be pursued among nations to maximise the value of data and to make better decisions. The adoption of analytics among member countries is to enable the analysis, identification, and communication of meaningful patterns to derive meaningful decisions. Developing countries must incorporate analytics culture in data management for government services. The private sector can also be encouraged to adopt analytics drive across various industries.

Suggestions for Future Research

The study considering the methodology, the findings, and limitations, propose a number of future research directions. These research directions cover areas to build on the methodology for studying the phenomenon and using different approaches to produce empirical results to understand the phenomenon.

First, it is worth noting that the research regarding understanding the adoption of marketing analytics and, for that matter, business analytics technologies is scant as compared to other innovative technologies. There are few studies on the acceptance and use of marketing analytics in both developed and developing economies from the available literature. It is expected that abundant studies on factors affecting marketing analytics acceptance will inform firms on what areas they can work on to promote the use of the technology. Research in developing economies on the phenomenon is more needed considering the low use of these technologies in marketing. The ultimate aim of further research on marketing analytics in developing economies will start the debate and popularity of the technology use.

Furthermore, based on the strength of this model as a result of the inclusion of theories in the development of the research model, this study calls for researchers to explore the importance of other factors in studying technology use intentions and continuance usage. Future research can integrate more theories and models to understand marketing analytics acceptance and use by firm employees. As a norm, theories and models proposed as affecting technology acceptance must be extensively explored to offer different approaches to study the phenomenon under consideration. This study proposes that some of the theories to consider are the social cognitive theory, uses and gratification theory, and the motivational model.

One important research area this study could not pursue is that of the performance implications of using marketing analytics by firms in developing economies. The existing literature in developed economies is replete with studies indicating the use of marketing analytics technologies to enhance competitiveness and firm performance. Future studies can provide evidence of the use of marketing analytics technology to enhance decision making and performance in developing country contexts. It is also important to conduct more research even in developed economies on the performance implications of marketing analytics.

From a methodological viewpoint, more qualitative studies can be pursued as evidence suggest that there is a lack of qualitative studies on the acceptance of marketing analytics by firm employees. More specifically, a case study approach could provide very insightful details about how marketing analytics technology is diffused in an organisation. This research direction is necessary since context-based related catalysts and obstacles may determine the use of marketing analytics by firm employees, thus making case studies very important. This is even more crucial for developing countries as a case study approach will provide evidence of how firms promote the acceptance, use, satisfaction, and continuance usage of marketing analytics technologies. The case study approach will provide evidence of the actual process organisations go through to encourage the use of analytics technologies in developing countries.

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APPENDIX A: SURVEY QUESTIONNAIRES

Dear Respondent,

This survey questionnaire is to examine firm employees' acceptance and use of Marketing Analytics technology in Ghana. This survey is for an academic purpose, which will have an implication on understanding the acceptance of innovative technologies by firms in Ghana. This survey will take about 15 minutes of your time. You will be contributing immensely towards the success of this research and knowledge by answering the questions as frankly as possible. Your responses are strictly anonymous, and in the case of publication of the results. Be assured that the information provided by you will not be identifiable since the final data will be aggregated.

Please, I would be grateful if can you complete the questionnaire within a week. Please forward this survey to other individuals who use marketing analytics technology in your organisation to also provide their responses. Thank you for your valuable time and input.

SECTION A: DEMOGRAPHIC INFORMATION

1. Age …………………………….
2. Gender Male ( ) Female ( )
3. Type of Industry

Services ( )

Manufacturing ( )

Trade ( )

Finance and Insurance ( )

Construction and Mining ( )

Other …………………………

4. Position in Organisation ……………………………

5. I have experience in using marketing analytics Yes ( ) No ()

6. Which marketing analytics technology do you use?. State as many as possible.……………………………………………………

7. How often do you use marketing analytics technology?

Seldom ( ) Once a month ( ) several times a week ( ) daily ( )

Category of Innovator (Early Adopter and Late Majority)

8. Which of the following categories best describes your perception about technologies?

(Please check one)

( ) I made my decision to use marketing analytics technology because I always wanted to use the newest form of technology on the market. I am always willing to try new technologies.

( ) I will make my decision to use marketing analytics when everybody in my organisation has started using it. I will take time to understand the systems even though it has become popular.

SECTION B

For each of the questions, please indicate your response by ticking (√) on the scale of 1 (Least Agreement) to 5 (Strong Agreement).

Performance Expectancy	1	2	3	4	5
I would find the marketing analytics system useful in my job					
Using the marketing analytics system enables me to accomplish tasks more quickly					
Using the marketing analytics system increases my productivity					
If I use the marketing analytics system, I will raise my marketing task					
Effort Expectancy	1	2	3	4	5

My interaction with the marketing analytics system would be clear and understandable					
It would be easy for me to become skillful at using marketing analytics					
I would find the marketing analytics system easy to use					
Learning to operate the marketing analytics system is easy for me					
Social Influence					
People who influence my behavior think that I should use the marketing analytics system					
People who are important to me think that I should use the marketing analytics system					
The senior management of this business has been helpful in the use of the marketing analytics system					
In general, the organisation has supported the use of the marketing analytics system					
Facilitating Conditions					
I have the resources necessary to use the marketing analytics system					
I have the knowledge necessary to use the marketing analytics system					
The system is not compatible with other systems I use					
A specific person (or group) is available for assistance with marketing analytics system					
Attitudes					
Using the marketing analytics system is a good idea					
The marketing analytics system makes work more interesting					
Working with the marketing analytics system is fun					
I like working with the marketing analytics system					
Personal Innovativeness in Information Technology					
If I heard about a new information, I would look to ways to experiment it					
Among my peers, I am usually the first to try out new information technologies					
In general, I am not hesitant to try out new information technologies					
I like to experiment with new information technologies					

Perceived Trust	1	2	3	4	5
The marketing analytics technology would be competent in delivering in a timely manner					
I trust the marketing analytics system to be reliable					
I trust the marketing analytics system to be secure					

Overall, I trust the marketing analytics system					
In general, I trust I trust the information provided by the marketing analytics system					
Intention to use Marketing Analytics					
I intent to use the marketing analytics system in the next months					
I predict I would use the system in the next months					
I plan to use the marketing analytics system in the next months					
Actual Use of Marketing Analytics					
I use marketing analytics-based insights to support decisions					
In my marketing duties, I back my arguments with analytics-based facts					
I use marketing analytics to support pricing decisions					
I use marketing analytics to support promotions decisions					
I use marketing analytics for sales forecasting					
I use marketing analytics for segmentation and targeting					
User Satisfaction					
The output information from the marketing analytics system is reliable					
There is relevant output information (to intended function) from the marketing analytics system					
The output information from the marketing analytics system is accurate					
There is precision of output information from the marketing analytics system					
There is completeness of the output information from the marketing analytics system					
Overall, I am satisfied is the experience with the marketing analytics system					
Continuance Usage					
I intent to continue using the marketing analytics system for my job					
I intent to continue using the marketing analytics technology for more decision making					
I intend to continue using the marketing analytics system for more of my job responsibilities					

APPENDIX B: INTERVIEW PROTOCOL FOR QUALITATIVE STUDY

Basic Information About Respondent and Organisation

1. What is your age, gender, and the name of your company and the industry?
2. What is your role in the organisation?
3. How long have you worked in this organisation?
4. Describe the use of marketing analytics technology in your organisation. What analytics tool or software(s) are being used?

Details about Perception about Marketing Analytics

5. What are your expectations in terms of the marketing analytics technology to enhance performance of marketing activities? Provide details of the ways marketing analytics enhances your marketing duties and responsibilities. How do you use the system in product strategy, pricing, promotions, and distributions?
6. What is your perception of the ease of use of marketing analytics technology? Are you able to easily use marketing analytics technology? How difficult is it to receive training to learn using the system?
7. Which individuals influences you to accept using marketing analytics technology. What is the influence of your superiors and friends?
8. What are the necessary conditions management of your organisation have put in place to support the use of marketing analytics? Are the necessary facilities and technology infrastructure provided to support the use of marketing analytics?

9. Do you trust marketing analytics technology(es) used by your organisation? Do you believe the data provided by the system is accurate? Do you perceive the data provided is protected?
10. Are you very innovative in terms of using new technologies? How good are you in using new technologies? Among your friends and colleagues at work, are you the first to usually use a new technology?
11. What is your general attitude towards the use of marketing analytics by marketers? Do you think marketing analytics should be preferred over traditional marketing for decision making?
12. Are you satisfied with the marketing analytics tool your firm is using now? Is the marketing analytics systems having high quality and performing to your expectation?
13. Are you sure you will continue using the marketing analytics technology for marketing?

APPENDIX C: DETAILS OF LITERATURE ON MARKETING ANALYTICS

Details of Literature on Marketing Analytics

Author(s)	Aim of Research	Research Approach and Design	Research Findings
Wedel and Kannan (2016)	Tracing the development of analytics in marketing and how it supports marketing decisions	A review of literature	Big data marketing analytics moves from an unstructured external data to a structured internal data and helps in marketing mix.
Germann et al. (2013)	Improving firm performance through the use of marketing analytics	Quantitative. Survey of 212 firm managers in US.	Top management support etc affect implementation of MA. MA affects firm performance.
Xu et al. (2016)	Examining the effect of analytics systems in enhancing new product success	Conceptual paper	Proposes a fusion of big data analytics and traditional marketing to ensure product success
Hauser (2007)	Discusses the current state of marketing analytics	Review Paper	A review was conducted on marketing analytics process, data mining and interpretation, customer segmentation. The role of marketing analytics education is proposed.
Miles (2014)	Using marketing analytics to understand customer behaviour	Quantitative data of 198 businesses	Marketing analytics can moderately predict consumer behaviour
Liu and Burns (2018)	Design a marketing analytics course	Literature Review. Using data set from four sources to extract topics	Proposed a course design for marketing analytics.

Cao et al. (2019)	Examining the effect of marketing analytics on competitive advantage	Quantitative. Using survey of 221 UK firms	There is a link between marketing analytics on decision making and product development.
Erevelles et al. (2016)	Linking marketing analytics to marketing function	A review of literature	Marketing analysis has the potential of affecting marketing function
Fan et al. (2015)	Investigating how big data is used in the marketing function	Literature review	Identification of data source, methods, and applications relevant to marketing.
Hallikainen et al. (2019)	The effect of big data on customer relationship management	Survey of 417 2B firms	The use of big data enhances customer relationship management.
France and Ghose (2019)	Examining the use of analytics for segmentation, visualising, and grouping	Review of literature	Identification of packages used in segmentation, grouping, and visualising
Jobs et al. (2015)	Explaining the use of big data on marketing	Qualitative using interviews	Development of framework to explain agencies, data management platforms, etc.
Wilson et al. (2018)	Providing insight to develop marketing analytics curriculum	A review of course content	Proposed an integrated marketing analytics curriculum
Järvinen and Karjaluoto (2015)	Explains the use of Web Analytics to enhance digital marketing	Qualitative study using surveys	Recommends the design of web analytics to measure performance
Kakatkar and Spann (2019)	The use of marketing analytics to track consumer in retail setting	Review Paper	The study finds that using anonymised and fragmented tracking data can be applied in many retail settings
Chaffey and Patron (2012)	Using web analytics to improve marketing	Review Paper	The paper provides some techniques to improve digital marketing performance

Branda et al. (2018)	Factors leading to Marketing Analytics Orientation	Qualitative - Expert knowledge	Marketing orientation factors include top management support, funding, etc
Kumar and Sharma (2017)	How can marketing analytics be used to improve marketing performance	Review paper	The paper concludes that for firm to gain competitive advantage and profitability it must use marketing analytics
Hair Jr (2007)	Examine the use of predictive analytics in knowledge creation	Review Paper	Predictive analytics is useful in marketing for product development, advertising, distribution and retailing
Atwong (2015)	Developing a course on social media marketing analytics	Review Paper	The structure, process and tools help student to support a practical course in analytics.
Mintu-Wimsatt and Lozada (2018)	Discussion of how analytics has been integrated in marketing curriculum	Review Paper	Curriculums must include four pillars: content, pedagogy, structure, and purpose
Jussila et al. (2017)	Examine the use analytics to capture customer emotions on social media	Data collected from Tweets from software companies	The development of five affective experience terms to identifying experience.
Plaza (2011)	Explains how Google analytics is used to improve web performance	Time series analysis	Direct visits and search engine visits are effective to improve web performance
Corrigan, Cracium and Powell (2014)	Describes the use of Customer analytics by Target	The case study of Target customer analytics	The study identifies type of data, privacy, and how analytics affects marketing decisions

Haywood and Mishra (2018)	A description of marketing analytics course	Text mining and sentiment analysis exercise with students	Students are able to use data and make decisions
Moe and Schweidel (2017)	Explaining the use of social media analytics to understand consumers	Review Paper	The study highlights on characteristics, challenges, and use of social media analytics
Germann et al. (2014)	Examining the role of analytics related to customers to improve performance	Quantitative study using a survey of 418 firms	Firms in the retail show better performance using customer analytics than other industries.
LeClair (2018)	To provide some recommendations for business analytics study in marketing course	Review Paper	The study proposes eight recommendations of business analytics in marketing course
Liu and Levin (2018)	Proposal on using innovative ways of teaching analytics in various marketing courses	Review Paper	The study proposes the teaching of analytics and marketing together but not separately
Leventhal (2015)	Discusses the use of analytics technologies in direct marketing	Review paper	Proposes a need to continue monitoring analytics models.
Bradlow et al. (2017)	Examines the use of analytics in retailing	Review Paper	Examines the use of analytics data on customers, products, time, location and channels.
Côrte-Real et al. (2017)	To examine the business value of big data analytics	Quantitative study of 500 Europeans firms	The study finds big data as affecting business value
Bijmolt et al. (2010)	Examines the models and challenges of customer analytics	Review paper	The paper explains the use of customer analytics for customer acquisition, customer development etc.

Acker et al. (2011)	Examine the use of analytics to handle CRM	Technical research	The study describes CRM analytics framework, drivers and steps of CRM analytics
LaValle et al. (2011)	Explain how firms use analytics to gain insights	Practitioner research	Top performing firms are likely to use analytics
Kiron et al. (2012)	To examine the use of analytics to innovate	Survey data of firms	Analytics aids in innovation in marketing
Shuradze et al. (2018)	To determine the effect of marketing-oriented analytics on firm innovation	Survey data of firms	Deployment of marketing-oriented analytics improves firm innovation success
Kauffmann et al. (2019)	The use of sentimental and fake review detection for marketing decision	Content analysis of online reviews	Development of useful analytics tool for decision making
Cao and Tian (2020)	Examines the use of marketing analytics to improve customer relationship management	Survey of managers of Chinese firms	Marketing analytics significantly affects CRM
Ashrafi and Ravasan (2018)	The moderating role of Business analytics on intelligence dissemination and responsiveness	Survey of 114 firms	Business analytics moderates the link between intelligence dissemination and responsiveness
Kitchens et al. (2018)	Explains how to create agility in customer analytics	Review Paper	The challenges include identification, collection, and integration of customer data. The study develops a framework to enhance the agility of analytics
Wright et al. (2019)	Examines the use of big data in innovation in B2B marketing	Case studies of firms	Big data abilities help in firm innovation

Source: Author's construct, Twum (2021)

APPENDIX D: MAPPING OF MARKETING ANALYTICS STUDIES

Mapping of Marketing Analytics Studies

Author(s)	Performance Implications	Marketing analytics Education	Marketing analytics Techniques	Adoption of Marketing analytics
Wedel and Kannan (2016)			√	
Germann et al. (2013)	√			√
Xu et al. (2016)			√	
Hauser (2007)			√	
Miles (2014)	√			
Liu and Burns (2018)		√		
Cao et al. (2019)	√			√
Erevelles et al. (2016)			√	
Fan et al. (2015)			√	
Hallikainen et al. (2019)	√			
France and Ghose (2019)			√	
Jobs et al. (2015)			√	
Wilson et al. (2018)			√	
Järvinen and Karjaluoto (2015)	√		√	
Kakatkar and Spann (2019)			√	
Chaffey and Patron (2012)			√	
Branda et al. (2018)				√
Kumar and Sharma (2017)	√		√	
Hair Jr (2007)			√	
Atwong (2015)		√		
Mintu-Wimsatt and Lozada (2018)		√		

Jussila et al. (2017)			√	
Plaza (2011)	√			
Corrigan et al., (2014)			√	
Haywood and Mishra (2018)		√		
Moe and Schweidel (2017)			√	
Germann et al. (2014)	√			
LeClair (2018)		√		
Liu and Leven (2018)		√		
Levanthal (2015)			√	
Bradlow et al. (2017)			√	
Côrte-Real et al. (2017)	√			
Bijmolt et al. (2010)			√	
Acker et al. (2011)			√	
LaValle et al. (2011)			√	
Kiron et al. (2012)	√			
Shuradze et al. (2018)	√			
Kauffmann et al. (2019)			√	
Cao and Tian (2020)	√			
Ashrafi and Ravasan (2018)	√			
Kitchens et al. (2018)				√
Côrte-Real et al. (2017)	√			
Bijmolt et al. (2010)			√	
Acker et al. (2011)			√	
LaValle et al. (2011)			√	
Kiron et al. (2012)	√			
Shuradze et al. (2018)	√			
Kauffmann et al. (2019)			√	

Cao and Tian (2020)	√			
Ashrafi and Ravasan (2018)	√			
Kitchens et al. (2018)				√
Wright et al. (2019)	√			

Source: Author's construct, Twum (2021)

APPENDIX E: LIST OF STUDIES USING THE UTAUT

List of Studies Using the UTAUT

Author(s) and Year	**Technology Context**	**Research Design**
Im et al. (2011)	Internet banking among users in Korea and US	Survey of 550 users
Kijsanayotin et al. (2009)	Health IT system in Thailand	Firm-based Cross-sectional Survey of 1607 officers
Magsamen-Conrad, Upadhyaya, Joa, and Dowd (2015)	Use of Tablet	Survey of users
Oliveira et al. (2014)	Mobile banking in Portugal	Survey of 194 students
Venkatesh, and Zhang (2010)	A new technology	Survey of 300 employees from a firm each in US and China
Uzoka (2008)	E-commerce adoption by firms in Botswana	Survey of employees from firms
Venkatesh, Sykes and Zhang (2011)	Electronic Medical Records	Survey of 144 Doctors out of 400 full time doctors of a private hospital
Bawack, and Kamdjoug (2018)	Adoption of Health Information system in Cameroon	Survey of 228 employees of 4 out of 7 major public hospitals
Liu et al. (2015)	New technologies used by therapist in Canada	Survey of therapist in Canada
Im, Kim, and Han (2008)	Wireless PDA, Webboard, MSN messenger	A survey of 161 participants in US
El Ouirdi, El Ouirdi, Segers and Pais (2016)	Social media adoption for recruitment	Survey of 224 recruiters in Europe

Wong, Russo, and McDowall (2013)	Acceptance and use of interactive whiteboard	Survey of 112 student teachers on a university programme
Mukred, Yusof, Alotaibi, Mokhtar and Fauzi (2019)	Adoption of electronic management system in Yemen	364 survey of educational practitioners in institutions
Silva et al. (2019)	Using UTAUT to predict big data acceptance and use	Survey of 564 managers of SMEs
Oye, Iahad, and Rahim (2014)	Acceptance of ICT by lecturers in Adamawa State University in Nigeria	A survey of 100 lecturers in a university
Kabra et al. (2017)	Technology adoption by humanitarian workers in India	Survey of 192 humanitarian practitioners employed in humanitarian organisations
Shin (2016)	Acceptance of big data of users in South Korea	Survey of marketing directors, business analytics, chief information officers
Cabrera-Sánchez and Villarejo-Ramos (2020)	Acceptance and use of big data in Spain	Survey of 199 company managers
Seethamraju, Diatha, and Garg (2018)	Assessing the usage intentions of mobile technologies in India	Survey of 98 health care professionals from tuberculosis clinics
Curtis et al. (2010)	Adoption of social media by PR practitioners	Survey of 409 non-profit PR practitioners from Non-profit firms
Rempel and Mellinger (2015)	Use of bibliographic management tool	Interview of librarians in public university in US
Carter, et al. (2011)	Use of online tax filing in US	Survey of 304 US tax payers

Source: Author's construct, Twum (2021)

APPENDIX F: LIST OF STUDIES USING TAM

List of Studies Using TAM

Authors (Year)	Title of Paper	Research Design
Brock and Khan (2017a)	The effect of organisational factors on the acceptance of big data.	A survey of 359 participants
Verma et al. (2018)	The application of the TAM in big data analytics studies	Survey of 150 big data users
Shahbaz et al. (2019)	The acceptance of big data by health care professionals	A survey of 224 analytics users in Pakistan
Brock and Khan (2017b)	The readiness of enterprises to use big data analytics	A survey of 359 information technology practitioners in 83 countries
Madhlangobe and Wang (2018)	The factors influencing the acceptance of big data in firms	A pilot study using 40 respondents
Demoulin and Coussement (2020)	The acceptance to use text-ming analytics	Survey of 177 marketing decision analyst in US and Europe
Yoon et al. (2017)	The acceptance to use business intelligence technology	Survey of 47 functional managers
Grublješič and Jaklič (2015)	The effect of compatibility in acceptance of business intelligence technology	Case study of two companies using interviews of 4 firm managers
Castro Jr. and Hernandez (2019)	The acceptance to use predictive analytics technology by humanitarian workers	Survey of 50 professionals working social welfare department in Philippines

Source: Author's construct, Twum (2021)

APPENDIX G: LIST OF STUDIES USING THE TOE FRAMEWORK

List of Studies Using the TOE Framework

Environmental Variables	Author(s)
Competitive pressure, industry type, customer orientation pressure	Kumar and Krishnamoorthy (2020)
External pressure, industry type	Verma and Bhattacharyya (2017)
External market factors, higher regulation compliance	Lautenbach Johnson and Adeniran-Ogundipe (2017)
Analytics engagement by other parties	Ijab, Wahab, Sallah and Baker (2019)
Competitive pressure	Chen, Preston and Swink (2015)
External Support from Vendor, competitive pressure, high degree of regulation	Maroufkhani et al. (2020)

Source: Author's construct, Twum (2020)

APPENDIX H: INFORMATION CONSENT FORM

INFORMATION SHEET

Title: Marketing analytics acceptance and continuance usage: firm management perspective

Principal Investigator: Kojo Kakra Twum

Address:

C/O Department of Marketing and Supply Chan Management

School of Business

University of Cape Coast

+233 246462686

General Information about the Research

This research is aimed at investigating the factors that influence the beheviorual intentions to use marketing analytics in Ghana. The marketing analytics technology includes technologies used for the collection of consumer and market data such as SAP and Hadoop. The study proposes that the behavioural intentions to use technology is the most important predictor of actual use of a technology. The study also seeks to address the issue of little use of innovative technology by trying to understand how service quality affects user satisfaction of a technology. The study seeks to examine how satisfaction towards technology will lead users to continue to use it. This study addresses how firms can promote the use of innovative technologies.

By filling this questionnaire and answering questions, you will be contributing to this study to examine the factors that influence you to use marketing analytics technology that your organisation has adopted.

The information recorded will only be accessed and used by the principal investigator, Mr. Kojo Kakra Twum. You are assured on confidentiality and anonymity. You can also contact the principal supervisor on twumkojo2@gmail.com or the Institutional Review Board of the University of Cape Coast using the following email address: irb@ucc.edu.gh.

APPENDIX I: ETHICAL CLEARANCE

UNIVERSITY OF CAPE COAST

INSTITUTIONAL REVIEW BOARD SECRETARIAT

TEL: 0558093143 / 0508878309
E-MAIL: irb@ucc.edu.gh
OUR REF: UCC/IRB/A/2016/944
YOUR REF:
OMB NO: 0990-0279
IORG #: IORG0009096

5TH APRIL, 2021

Mr. Kojo Kakra Twum
Department of Marketing and supply Chain Management
University of Cape Coast

Dear Mr. Twum,

ETHICAL CLEARANCE – ID (UCCIRB/CHLS/2021/02)

The University of Cape Coast Institutional Review Board (UCCIRB) has granted **Provisional Approval** for the implementation of your research titled **Marketing Analytics Diffusion and Acceptance: A Management Perspective.** This approval is valid from 5TH April, 2021 to 4TH April, 2022. You may apply for a renewal subject to submission of all the required documents that will be prescribed by the UCCIRB.

Please note that any modification to the project must be submitted to the UCCIRB for review and approval before its implementation. You are required to submit periodic review of the protocol to the Board and a final full review to the UCCIRB on completion of the research. The UCCIRB may observe or cause to be observed procedures and records of the research during and after implementation.

You are also required to report all serious adverse events related to this study to the UCCIRB within seven days verbally and fourteen days in writing.

Always quote the protocol identification number in all future correspondence with us in relation to this protocol.

Yours faithfully,

Samuel Asiedu Owusu, PhD
UCCIRB Administrator

ADMINISTRATOR
INSTITUTIONAL REVIEW BOARD
UNIVERSITY OF CAPE COAST