Antecedents of big data adoption in financial institutions

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ABSTRACT

Big data (BD) adoption is still relatively slow despite the numerous business opportunities that it embodies. Within the context of financial institutions in South Africa, the specific drivers of big data adoption remain largely indeterminate. Consequently, this study explores the possible relationships between perceived usefulness and perceived ease of use and actual big data adoption, while being cognizant of the role that behavioural intention to adopt big data could play. The study employed a survey research approach and relied on data collected from a purposive sample of 195 management level employees of financial institutions. Regression analysis to test the hypothesised relationships in the study revealed that perceived usefulness and perceived ease of use were statistically significant predictors of big data adoption. Instructively, this relationship was subject to the extent of behavioural intention to adopt big data. For respondents with a low behavioural intention to adopt big data, perceived usefulness and perceived ease of use displayed a statistically insignificant relationship with big data adoption. Conversely, the regression model for the group of respondents with a high behavioural intention to adopt big data is statistically significant. These findings enrich literature related to big data from a developing country context while concurrently identifying veritable antecedents of big data adoption in financial institutions.

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Introduction

The financial industry seems to be developing at a rapid pace in consonance with the constantly evolving expectations of consumers. Some of this is evident in the adoption of emerging technologies as well as the development of a plethora of products and services by financial institutions. This trend has been observed by Shirazi and Mohammadi (2019) who contend that the financial industry has become very dynamic and competitive, largely because of threats posed by competitors as well as technology-induced disruptions.

Due to this intensely competitive environment, Sivarajah, Kamal, Irani, and Weerakkody (2017) argue that organisations have been compelled to adopt innovative technologies, such as big data (BD) in a bid to improve business operations and performance. This is unsurprising as the use of BD has been recognised as a leading-edge technology-based (Wamba, Akter, Edwards, Chopin & Gnanou, 2015) business practice. As a testimonial to the unrelenting uptake of BD, the global cloud computing market, for instance, is expected to grow from US$371.4 billion in 2020 to US$832.1 billion by 2025 (Chauhan & Sood, 2021). The growth partly stems from the ability of BD to create new knowledge through its reliance on intelligent data sets. Additionally, BD can also transform information into patterns that generate valuable insights (Fredriksson, 2018).

Convinced by this, Janssen, van der Voort and Wahyudi (2017) affirmed that big data adoption (BDA) can enhance an organisation’s strategic capability for effective decision-making and performance. Consequently, BD is described as a potential game-changer in driving organisational decisions (Maroufkhani, Iranmanesh, Ismail & Khalid, 2020) due to its potential to offer critical competitive advantage to adopting organisations (Haddad, Ameen, Isaac, Alrajawy, Al-Shbami & Chakkaravarthy, 2020).

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Against this background, the need for a profound understanding of factors that could affect BDA (Alharthi, Krotov & Bowman, 2017) cannot be over-emphasised. Propelled by this assertion, this study investigates the antecedents of adoption of BD in South Africa’s financial industry by relying on the theoretical lens of the technology acceptance model (TAM). Importantly, the study recognises that behavioural intentions (BI) to adopt BD are likely to be at different levels. Cognisant of this, the study specifically explores whether the independent variables of perceived usefulness (PU) and perceived ease of use (PEU) display any relationships with BDA. Additionally, the anticipated relationships are tested in two groups of respondents - those with a high behavioural intention (HBI) and those with a low behavioural intention (LBI) to adopt BD.

This study is expedient partly because of the concern expressed by Sun, Cegielski, Jia and Hall (2018) that there is a dearth of literature focussed on drivers of big data adoption. This may even be more so, within the specific context of a developing economy, such as South Africa. So, the relevance of this study is three-fold. Firstly, this study contributes to the literature on BDA since Wiener et al. (2020) note that research on the BD is quite limited as it is a relatively new field of study. Consequently, Côrte-Real et al. (2019) assert that BDA is deserving of the attention of academic and professional communities. Secondly, it adds to the limited academic literature on BDA from the context of a developing economy. This is of essence given that Wamba et al. (2015) confirmed that literature related to the adoption of such sophisticated technologies is predominated by perspectives emanating from developed countries. This indicates a lack of research in emerging markets which skews the body of knowledge in this specific regard in favour of the developed world. Lastly, this study was conducted within the context of financial institutions and so it makes a practical contribution by illuminating industry-specific antecedents of BDA in the context of South Africa’s financial sector.

This paper is organized as follows: the introduction section is succeeded by a literature review of theoretical and empirical studies in other to establish the state of academic discourse related to BD and technology adoption. This literature review is leveraged to deductively formulate the hypotheses for the study. Subsequently, the third section elucidates the methodological pathway that was followed for the conduct of the study. This is succeeded by a presentation of the results and a discussion of the study’s findings. Finally, this paper concludes with a discussion of recommendations, study limitations and future research directions.

**Literature Review**

The literature review has been undertaken in two parts that consist of a theoretical and conceptual background as well as an empirical review and hypothesis development. The theoretical and conceptual background is preoccupied with engendering a deeper appreciation of BD based on academic discourse. Stemming from this, it became pertinent to examine previous scholarly positions in literature pertaining to relationships pivoting around BD. The purpose of this was to create the veritable foundation for the formulation of the study’s hypotheses in consonance with a deductive reasoning approach.

**Theoretical and Conceptual Background**

Jee, Kwon, Ha and Sohn (2019) likened the development of technology to the process of biological evolution. Rapid and disruptive advances in IT surfaced in the mid-1950s when computers became available in the private sector (Niederman, Ferratt & Trauth, 2016). The advancements resulted in benefits to organisations as evidenced in improvements to internal production processes and resource throughput (Acemoglu, Akcigit & Kerr, 2016). Similarly, Sestino, Prete, Piper and Guido (2020) note that the Internet of Things (IoT) and BD are being employed to re-engineer business processes in modern-day organisations.

Undoubtedly, the generation and use of data has developed drastically in the past 20 years with over 3.1 billion individuals globally connected to the Internet (Gupta, Baabdullah & Al-Khowaiter, 2018). The records sprouting from this huge population of Internet users can be categorised as BD. Interestingly, the term BD has, to a substantial extent, been varyingly used. Though, Yaseen and Obaid (2020) defined BD as large data sets with varied and complex structures which are difficult to store and process, Favaretto, De Clercq, Schneble and Elger (2020) contend that there is no univocal definition of BD.

Characteristically, BD embodies a constantly increasing flow of information from diverse sources, requiring advanced processing methods (Sun et al., 2018) as well as sophisticated storage, administration, visualisation and arithmetical analysis (Bumblauskas, Nold, Bumblauskas & Igou, 2017). BD has been described as a high-volume, high-variety and high-velocity information asset (Raguseo, 2018; De Mauro, Greco & Grimaldi, 2016). Consequently, as shown in Figure 1, Shah, Soriano and Coutroubis (2017) proposed a three-dimensional model of volume, velocity and variety to synthesise different perceptions of BD.
According to Moktadir, Ali, Paul and Shukla (2019), this model helps foster a better understanding of BD. The volume dimension in the model is concerned with the generation and collection of large data. The velocity dimension of BD describes the unrelenting speed at which data are created, analysed and acted upon (Gandomi & Haider, 2015; Esomonu, Esomonu & Eleje, 2020). The BD dimension of variety relates to the availability of data in diverse forms and could range from machine data to relationship data, that are unlimited to internet pages, videos, audios and text (Oussous et al., 2018). Shah et al. (2017) forecast a rapid increase in the volume of BD because of the advent of the internet of things (IoT), cloud computing, wearable smart devices, amongst other things. The forecast of this rapid increase is rational given that the study of 325 commercial enterprises undertaken by Ahmed, Tezel and Aziz (2017) revealed that BD enabled better market-targeting, increased sales and improved business insights.

**Empirical Review and Hypothesis Development**

In the context of the financial industry, Hasan, Popp and Oláh (2020) accentuate the value of BDA by asserting that BD is particularly useful for credit management as it enhances the assessment of borrowers. BD also contributes to organisational performance by aiding improvements in traditional value-chain activities, such as product development, distribution and customer service (Verma & Chaurasia, 2019). Worryingly, the expected value creation associated with the concept of BD may not necessarily crystallise due to poor application (Benoit, Lessmann & Verbeke, 2020) possibly stemming from a weak understanding of the essential antecedents of BDA.

Sun et al. (2018) observe that monetary costs and organisational alignment with an innovative technology could impact on an organisation’s decision to adopt BD. Concurring, Maroufkhani et al., (2020) posited that the adoption of BD can be hindered by lack of financial resources, IT infrastructure and human resource skills. This is understandable given that Nguyen et al. (2020) describe BDA as a capital-intensive exercise, which requires synchronisation with already existing systems in an organisation. Clearly, a variety of factors can influence an organisation’s proclivity to adopt a technology (Behl, Dutta, Lessmann, Dwivedi & Kar, 2019). Notably, these factors that act as antecedents of BDA are not homogenous across various sectors. For instance, Alalawneh and Alkhatib (2021) found that with respect to BDA, technological and data-related factors were influential in the financial sector while organizational/people factors played prominent roles in the public sector.

As participants in the literary discourse of BD, Lei et al. (2021) opine that the TAM provides a veritable framework that can underpin studies on the adoption of BD. Therefore, given that the current research pivots around technology and BD in particular, the TAM is considered as relevant and this study will be anchored on it. Arguably, the TAM is one of the most well-known models utilised by scholars to investigate the adoption and integration of technologies in various sectors. For good measure, the TAM has been employed in previous studies (see Folkinshteyn & Lennon, 2016; Rahimi, Nadri, Afshar & Timpka, 2018; Scherer et al., 2019) to effectively predict adoption and use of innovative technologies.

The TAM centres on user motivation and so the constructs of PU and PEU are two of its critical components (Riantini & Wandrial, 2018; Balkaya, 2019). Brock and Khan (2017) suggest that PU is the degree to which individuals believe that employing a particular system would enhance their job performance. In essence PU reflects how people use (or would not use) a specific technology based on their belief that it will aid (or impede) their work. This is the backdrop against which PU is considered as the most widely used variable for studying the user’s intention to adopt a particular technology for work purposes (Shahbaz et al., 2019).
The variable of PEU is the degree to which an individual believes that the use of a particular technology will not require enormous effort. Tahar et al., (2020) opine that PEU relates to how easy it is to access and utilise a technology system. In the context of Financial Technology (FinTech), Barbu et al. (2021) argue that PEU is concerned with the simplicity with which one can operate FinTech applications. In effect, ease in using a particular technology would likely improve its acceptability amongst users.

The value of PU stems from the view that a technological advancement is only relevant to the extent that it is useful. Affirming the importance of PU, Hubert et al. (2019) found that PU was a significant determinant of the adoption of smart home technologies. This is supported by the results of a study conducted by Shahbaz et al. (2020) that showed that PU is an important predictor of the recourse to the employment of big data analytics in organisations. Similarly, while investigating critical factors influencing the application of big data analytics in Sri Lanka’s clothing sector, Bolonne and Wijewardene (2020) found that PU had a positive influence on the user’s attitude towards the employment of big data analytics. Chen and Aklikokou’s (2020) study of public sector organisations revealed that PU significantly influenced technology adoption. While this may not necessarily be the case with financial institutions in the private sector, given the contextual nuances that may apply, this study is swayed by extant literature that hints at the existence of a relationship between PU and technology adoption and so, it is hypothesised that:

**H1:** There is a relationship between PU and BDA among employees of financial institutions

As one of the main constructs of TAM, PEU has been found to significantly influence adoption of information systems (IS) across various disciplines – a characteristic hailed as a strength of TAM (Venkatesh, 2000). In consonance with this observation, Kashada and Allaeddinghaydi (2020) observed, in their study, that PEU directly and indirectly influenced the adoption of information systems in organisations. Also, Moslehpour et al. (2018) detected that PEU had a significant impact on e-purchase intention. In a study focused on predicting the intention to use mobile banking in India, Singh and Srivastava (2018) revealed that among other factors, PEU had a significant influence on the behavioural intention to adopt mobile banking technology. Further, Kalayou et al., (2020) established that PEU had a significant relationship with the intention to adopt technology among healthcare professionals in Ethiopia. PEU was also found to be a significant factor in the prediction of BI in a study investigating adoption of cloud-based learning in developing countries (Kayali & Alaaraj, 2020).

After examining the adoption of Industry 4.0 by small and medium enterprises in Vietnam, Nguyen and Luu (2020) concluded that PEU significantly influenced adoption of industry 4.0. Similarly, while exploring determinants of semantic web adoption, Kim et al. (2018) observed that PEU was a significant determinant of innovation adoption. The consistency of the results on the relationship between PEU and intention to adopt different technologies encourages this study to hypothesise that with respect to actual adoption:

**H2:** There is a relationship between PEU and BDA among employees of financial institutions

Figure 2 depicts the proposed conceptual model for the study. It illustrates the hypothesised relationships between the study’s independent variables (PU and PEU) and the dependent variable of BDA in financial institutions.

![Conceptual model for big data adoption in financial institutions](image)

**Research and Methodology**

A quantitative research design was utilised for the study and data was collected from a pool of employees working in South Africa’s financial sector. Hassani et al. (2018) observe that in the banking sector, BD is typically used for security, fraud detection and customer relationship management. Behl et al. (2019) also contend that management-level employees are more attuned to issues like...
BDA. For these reasons, the study’s target population comprised management level employees working in units responsible for technology, risk and security, sales and marketing, customer services and product development. Realising that no accessible and comprehensive sampling frame exists for the cohort of targeted respondents, the non-probability sampling techniques of purposive sampling and convenience sampling were employed.

The data collection instrument for the study was a self-administered questionnaire that was created using Qualtrics™ software. It was sent to 1,200 potential respondents and 220 of these were returned. However, only 195 of the returned questionnaires were deemed usable which equate to an effective response rate of 18%. The low response rate is not unexpected as Daikeler et al. (2020) suggest that low response rates are characteristic of online surveys.

PU was measured with the use of a scale adapted from the study of Amoroso and Hunsinger (2009) that investigated the acceptance of internet technology by consumers. Scales developed by Dulcic et al. (2012) were employed for the measurements of PEU, BI and BDA. All the scales comprised statements accompanied by 5-point Likert answer options ranging from ‘strongly disagree’ to ‘strongly agree’. Composite scores for the study’s constructs of PU, PEU, BI and BD adoption, were calculated by averaging the score amongst all the items in each construct.

Since the study’s constructs were measured with existing scales that had been employed in other studies, confirmatory factor analysis was undertaken to ascertain scale reliabilities. The results of the analysis are presented in Table 1. As shown in the table, the Cronbach's Alphas obtained for PU, PEU, BI and BDA were 0.888, 0.834, 0.835 and 0.674, respectively. This provides evidence that the Cronbach Alphas obtained for the study constructs of PU, PEU and BI are above the generally recommended threshold of 0.7 and therefore signal high scale reliability.

## Table 1: Confirmatory factor analysis and scale reliabilities

<table>
<thead>
<tr>
<th>Scale / Items</th>
<th>Item loadings</th>
<th>Alpha if item deleted</th>
<th>Cronbach alpha for scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Usefulness (PU)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.1</td>
<td>0.817</td>
<td>0.865</td>
<td>0.888</td>
</tr>
<tr>
<td>2.2</td>
<td>0.798</td>
<td>0.869</td>
<td></td>
</tr>
<tr>
<td>2.3</td>
<td>0.813</td>
<td>0.866</td>
<td></td>
</tr>
<tr>
<td>2.4</td>
<td>0.810</td>
<td>0.867</td>
<td></td>
</tr>
<tr>
<td>2.5</td>
<td>0.815</td>
<td>0.866</td>
<td></td>
</tr>
<tr>
<td>2.6</td>
<td>0.751</td>
<td>0.878</td>
<td></td>
</tr>
<tr>
<td>Perceived Ease of Use (PEU)</td>
<td></td>
<td></td>
<td>0.834</td>
</tr>
<tr>
<td>3.1</td>
<td>0.829</td>
<td>0.785</td>
<td></td>
</tr>
<tr>
<td>3.2</td>
<td>0.784</td>
<td>0.797</td>
<td></td>
</tr>
<tr>
<td>3.3</td>
<td>0.717</td>
<td>0.814</td>
<td></td>
</tr>
<tr>
<td>3.4</td>
<td>0.586</td>
<td>0.836</td>
<td></td>
</tr>
<tr>
<td>3.5</td>
<td>0.674</td>
<td>0.824</td>
<td></td>
</tr>
<tr>
<td>3.6</td>
<td>0.842</td>
<td>0.783</td>
<td></td>
</tr>
<tr>
<td>Behavioural Intention to Adopt Big Data (BI)</td>
<td>0.835</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.1</td>
<td>0.825</td>
<td>0.809</td>
<td></td>
</tr>
<tr>
<td>4.2</td>
<td>0.805</td>
<td>0.813</td>
<td></td>
</tr>
<tr>
<td>4.3</td>
<td>0.215</td>
<td>0.815</td>
<td></td>
</tr>
<tr>
<td>4.4</td>
<td>0.213</td>
<td>0.810</td>
<td></td>
</tr>
<tr>
<td>4.5</td>
<td>0.226</td>
<td>0.816</td>
<td></td>
</tr>
<tr>
<td>4.6</td>
<td>0.736</td>
<td>0.806</td>
<td></td>
</tr>
<tr>
<td>4.7</td>
<td>0.738</td>
<td>0.823</td>
<td></td>
</tr>
<tr>
<td>Big Data Adoption (BDA)</td>
<td></td>
<td></td>
<td>0.674</td>
</tr>
<tr>
<td>5.2</td>
<td>0.868</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>5.3</td>
<td>0.868</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

Source: Authors

The Cronbach Alpha associated with the construct of BDA, however, falls below this threshold. This could have resulted from the fact that the original 3-item scale had an item which, according to the results of the correlation analysis seemed to be an outlier as it did not fit in with any of the other scale items. This item was subsequently removed leaving only two items for the measurement of the construct. Nonetheless, the resultant Cronbach alpha value of 0.674 for the BDA scale, according to Perry Hinton et al. (2004:364) is indicative of a moderate scale reliability and so the scale can still be utilised.

## Findings and Discussions

### Findings

Some descriptive statistics associated with the constructs of the study were determined. In particular, the measurements of the means, standard deviations, variances, and skewness for the study’s constructs are shown in Table 2.
Table 2: Descriptive statistics for the constructs in the study

<table>
<thead>
<tr>
<th>Constructs</th>
<th>N</th>
<th>Mean (M)</th>
<th>Std. Deviation</th>
<th>Variance</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>PU</td>
<td>191</td>
<td>4.15</td>
<td>1.03</td>
<td>1.06</td>
<td>-1.51</td>
</tr>
<tr>
<td>PEU</td>
<td>183</td>
<td>3.54</td>
<td>1.04</td>
<td>1.10</td>
<td>-0.50</td>
</tr>
<tr>
<td>BI</td>
<td>190</td>
<td>4.22</td>
<td>0.89</td>
<td>0.80</td>
<td>1.69</td>
</tr>
<tr>
<td>BDA</td>
<td>189</td>
<td>3.22</td>
<td>1.19</td>
<td>1.41</td>
<td>-1.10</td>
</tr>
</tbody>
</table>

Source: Authors

The resultant means for all the scales signal that at an aggregate level, the respondents’ perspective of the constructs of PU, PEU, BI and BDA was largely positive. More specifically, the measures of central tendency for the PU construct were M=3.54 and SD=1.04 while those for PEU were M=4.15 and SD=1.03. Evidently, respondents’ favourable inclination towards PEU exceeded that of PU. The same measures for the construct of BI were M=4.22 and SD=0.89 while those for BDA were M=3.22 and SD=1.19. The mean score of 4.22 associated with BI was the highest across the four study constructs and arguably signals the existence of a BI to adopt BD in the pool of respondents.

Since the study was interested in investigating the nature of the hypothesised relationships not only for its universe of respondents but also among respondents in two mutually exclusive groups of high and low BI to adopt BD, these groups had to be created. The score range for the entire BI scale was 5 - 35 since it was made up of 7 items with five Likert scale options of strongly disagree to strongly agree accompanied by ratings of 1-5. Aggregate scores below the scale’s score midpoint of 17.5 were associated with a low BI to adopt BD category while scores above the 17.5 mark were indicative of a high BI to adopt BD.

A regression analysis was employed to interrogate the possible existence of relationships between the independent variables (PU and PEU) and the dependent variable (BDA). This was done for the entire sample of respondents and subsequently for the two groups of respondents (low BI to adopt BD and high BI to adopt BD). The results of the analysis are presented in Table 3.

Table 3: Regression Analysis Results

<table>
<thead>
<tr>
<th>Dependent variable BD adoption</th>
<th>Std. coefficient</th>
<th>Std. Error</th>
<th>t-stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entire sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PU</td>
<td>0.165</td>
<td>0.065</td>
<td>2.546</td>
<td>0.012</td>
</tr>
<tr>
<td>PEU</td>
<td>0.445</td>
<td>0.065</td>
<td>6.885</td>
<td>0.000</td>
</tr>
<tr>
<td>R²</td>
<td>0.269</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F statistic</td>
<td>35.335***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group with low BI to adopt BD</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PU</td>
<td>0.063</td>
<td>0.382</td>
<td>0.098</td>
<td>0.925</td>
</tr>
<tr>
<td>PEU</td>
<td>0.233</td>
<td>1.265</td>
<td>0.362</td>
<td>0.730</td>
</tr>
<tr>
<td>R²</td>
<td>0.082</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F statistic</td>
<td>0.266</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group with high BI to adopt BD</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PU</td>
<td>0.175</td>
<td>0.070</td>
<td>2.655</td>
<td>0.009</td>
</tr>
<tr>
<td>PEU</td>
<td>0.412</td>
<td>0.073</td>
<td>6.263</td>
<td>0.000</td>
</tr>
<tr>
<td>R²</td>
<td>0.219</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F statistic</td>
<td>25.663***</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

***Significant at 1%

Source: Authors

Discussion

For the entire group of respondents, PU and PEU demonstrated that they were statistically significant predictors of BDA. The p-value associated with the relationship espoused in H₁ is 0.012 and that for the relationship expressed in H₂ is 0.000. On this account,
H₁ and H₂ are statistically supported. Overall, the regression model shows that the two predictors (PU and PEU) can explain approximately 35% of the variation in the outcome variable - BDA, when the entire population of employees from financial institutions that participated in the study, is considered.

The study sample was then divided into two groups and the regression analysis was repeated for each of the groups. As shown in Table 3, the predictive ability of PU and PEU differs between the two groups of respondents based on whether they have low or high BI to adopt BD. For respondents with a low BI to adopt BD, PU and PEU have a statistically insignificant relationship with BDA. The p-values of 0.925 and 0.730 associated with the relationships expressed in H₁ and H₂, respectively, imply that in the specific case of the low BI to BD group, the hypotheses are not supported. Expectedly, the model in this case is also statistically insignificant.

Conversely, the regression model for the group of respondents with a high BI to adopt BD is statistically significant. The F-statistic of 25.663 indicates that for this group, the PU and PEU can explain approximately 25% of the variation in BDA. For this cohort, the p-value associated with the hypothesised relationship between PU and BDA is 0.009. For the hypothesised relationship between PEU and BDA, the p-value is 0.000. These results bear testimony to the existence of statistically significant relationships between each of the predictor variables (PU and PEU) and the outcome variable of BDA. Consequently, for respondents in the cohort of a high BI to adopt BD, the study’s hypotheses are supported.

These findings are understandable as respondents in the low BI to adopt BD tended to disagree with the items contained in the PU and PEU scales. This meant that they did not really perceive BD to be useful or easy to use with respect to their work. Consequently, they were not favourably disposed towards BDA. The converse was, however, the case for respondents in the high BI to adopt BD category.

The statistically significant result linked to the relationship expressed in H₁ resonates with the findings of Riantini and Wandrial (2018), who based on a review of multiple studies, concluded that PU can predict BD adoption. Similarly, the study’s results reveal that as expressed in H₂, PEU is statistically associated with BDA. This is aligned with the findings of studies conducted by Dulcic et al. (2012) as well as Riantini and Wandrial (2018). Previous studies (Folkinshteyn and Lennon, 2016; Rahimi et al. 2018; Scherer, Siddiq & Tondeur, 2019) also produced findings that are in harmony with those of the current study.

Conclusions

The results of this study confirm that the TAM predicts user behaviour related to BDA even in the context of the respondents drawn from financial institutions in South Africa that participated in this study. This finding could be of interest to future users of innovative technology such as BD. The results of this study potentially provide policymakers and management with a framework regarding elements that need to be focused on when driving the adoption of innovative technologies such as BD within the organisation.

While the study emphasises the relationships that antecedents such as PU and PEU have with BDA, the role of BI cannot be ignored. This is especially the case because the absence of a high BI to adopt BD among employees obfuscates the predictive role of PU and PEU as it pertains to BDA. This perhaps lends credence to the postulation of the theories of planned behaviour and reasoned action that suggest that intentions are critical precursors of behaviour.

From a managerial perspective, while touting the usefulness and ease of use of BD among employees to pave the way for BDA, managers in financial institutions should exercise collateral effort to shape the psyche of employees in a way that nurtures the right BI for BD. The utilisation of a participatory approach that emphasises astute employee-engagement for the purpose of BDA as well as the introduction of incentives for BDA may prove essential. Proactive interventions such as providing training and highlighting the benefits of BDA, could also engender the right BI for BDA in the work undertaken by employees in financial institutions.

Due to the non-existence of a sampling frame with all members of the targeted population, a non-probability sampling method had to be utilised for the study. A strategic limitation linked to the use of data drawn from a group of respondents created through a non-probability sampling technique is that the findings cannot be generalised to a larger population (Clow and James, 2014). Consequently, the results of this study should not be generalised across the entire South African financial industry.

Though, predominantly, the constructs of this study were adapted from the TAM which has been used extensively in prior research, the Cronbach alpha associated with BDA indicated a relatively low reliability value. This low reliability could be because of the low number of items utilised to measure BDA. It could also be due to the applicability of the instrument without modifications to suit an emerging economy context, such as South Africa. Therefore, Wang and Hajli (2017) have emphasised the importance of re-evaluating research instruments before utilising them in a different context.

Another shortcoming of this study is that additional factors, such as employee years of professional experience, the department where they are employed, and past or current exposure to working with BD, were disregarded. Anecdotally for instance, employees exposed to BD may have responded differently to scale items relative to their counterparts without BD exposure. This type of demarcation may have resulted in a richer analysis of the data and the unveiling of deeper insights. Future studies may therefore consider profiling the respondents based on years of work experience, business unit or department where they work, including experience using BD in their work. Further, to enrich BD-related literature, it is imperative to conduct studies based on different industrial and economic
contexts. This will create research opportunities for the comparison of findings of studies of BD adoption using TAM, between advanced and emerging economies as well as across industries.

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References


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