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Big Data Technology Acceptance Model (TAM) in Indonesian state-owned financial services and banking

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ABSTRACT

The aim of this study in general is to examine the influence of perceived ease of use, perceived usefulness, and perceived risk on intention to use. The subject of this study is the account officer of the big data user of a state-owned company in Malang, East Java, Indonesia. Specifically, this research has the purpose of finding out both the simultaneous and partial influence of perceived use, perceived usefulness, and perceived risk on the intention to use the big data of State-Owned Bank customers. This study is a survey employing both quantitative and qualitative data analysis. The samples of the subjects used were 95 account officers of a state-owned bank in East Java who used customer big data. The analysis conducted in this study included multiple linear regression testing and hypothesis testing for both simultaneous and partial The result of the F testing indicates that collectively, the perceived ease of use, perceived usefulness, and perceived risk variables have a simultaneous and positive influence on the intention to use the customer's big data. However, based on the T-test, it was observed that perceived usefulness is the only variable that has a partial influence on the intention to use the big data of the customers. While the other two variables, perceived ease of use and perceived risk, were found to have no significant influence on the intention to use the bank's customers' big data..

Introduction

In the era of technological advancement today, most modern companies have adopted computer-based information systems to handle their business management. It has resulted in a rapid growth in the volume of data, leading to substantial data stacks within databases. With such a massive and continually expanding data volume, both in terms of the number of records and fields, it becomes exceedingly challenging for humans to analyze it manually. Therefore, the implementation of data analytics is necessary to assist in analyzing data obtained from transactions within information systems. It is necessary to be done in order to find patterns that can be turned into new knowledge for predicting customer migrations to competing companies.

The phenomenon of big data has already noticed by both the state-owned and public companies that lead many organizations to make big investments to gather, integrate and analyze the data and later to use it for business activity. The widespread adoption of massive data across various sectors has brought customer relationship management into sharp focus. Therefore, it is essential to incorporate the role of big data into company strategic planning.

Technological advancements have expanded the capacity to record, store, and measure various types of data (Cao et al., 2015). More than 98% of information is now stored in digital formats, and it has been widely embraced by the business community due to its perceived benefits. Big data is a new technology capable of effectively managing and analyzing data, whether it is well-structured or unstructured. It requires vast volumes, diversity, and velocity, making it a strength against competitors (Rahman, 2017).

Some technologies may not be suitable for every situation, and their acceptance or rejection can often be predicted using the Technology Acceptance Model (TAM) proposed by Davis (1989). This model aims to forecast the adoption of new technologies by

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both individual users and organizations. TAM is built upon the foundations of Fishbein and Ajzen's Theory of Reasoned Action (TRA) (1975), which is rooted in social psychology. It seeks to explain why individuals become involved in certain actions on a subconscious level

People's acceptance or rejection of new technology can typically be attributed to two key factors. Firstly, their beliefs about whether the technology can genuinely assist them or potentially complicate their work; this factor is commonly referred to as perceived usefulness (PU). Secondly, even if a technology is considered useful, it must also be perceived as easy to use, which is captured by the variable known as perceived ease of use (PEU). Numerous researchers have conducted studies on information systems, and their findings consistently demonstrate that both perceived usefulness and perceived ease of use significantly influence individuals' intention to adopt information system technology (Rauniar et al., 2014).

There are several challenges associated with the utilization of Big Data, especially when companies aim to optimize its use. Some of these challenges include the complexity of exploring Big Data, lack of clear management practices, time constraints, high costs, limited availability of software for data analysis in the Indonesian context, and a shortage of skilled personnel for Big Data development. However, the advantages of utilizing Big Data for organizations are significant. It enables organizations to understand customer responses to their new products through sentiment analysis within Big Data systems, supports data-driven decision-making for more accurate outcomes, enhances the company's image, aids in strategic planning by understanding customer behavior (particularly in telecommunications and banking), and helps identify market trends and customer preferences.

Literature Review

Theoretical and Conceptual Background

Big Data

According to Cao et al. (2005), Big Data refers to a vast and intricate dataset that becomes challenging to process using simple data management or traditional data processing methods. Buyya et al. (2016), in their book titled 'Big Data: Principles and Paradigms,' outlined three major components of Big Data: 1. Volume: This pertains to the sheer quantity of data generated from transactions and data storage, 2. Velocity: It related to the speed at which data is accessed and processed, 3. Variety: It encompasses various types of data including structured data, unstructured data and semi-constructed data.

Big Data represents a pervasive trend within the realms of business and technology. It encompasses the technologies and initiatives that involve diverse, rapidly changing, and vast datasets, challenging the effectiveness of conventional technology, skills, and infrastructure in handling them. In other words, Big Data is characterized by its massive volume, high velocity, and diverse variety, all of which pose significant challenges to traditional systems.

Theory of Reasoned Action

The Theory of Reasoned Action was developed by Ajzen and Fishbein (1980), constructed upon previous research related to the theory of attitudes, which evolved both attitude and behavior. This theory was primarily developed in response to the unsatisfactory and unsuccessful results obtained from testing, which consistently demonstrated a weak correlation between attitude and expected volitional behavior

The Theory of Reasoned Action model explains that a person's attitude towards taking an action originates from specific reasons and progresses through distinct stages. The first stage centers on a person's behavior depending on their intention, while the second stage involves understanding intentions in terms of attitude towards the behavior and subjective norms. The final stage considers attitudes and subjectivity as beliefs regarding the risks associated with these attitudes and the normative expectations formed by reference points. In conclusion, an individual's attitude can be comprehended by considering their beliefs, as these beliefs reflect the information they have gathered about themselves and their environment. Therefore, one can assert that attitudes are contingent on the information possessed by an individual.

Technology Acceptance Model (TAM)

According to Rauniar et al. (2013), TAM specifically elucidates the factors influencing the general acceptance of computers and the ability to analyse user behaviour across various end-user computing technologies and user demographics. Among various research findings, the Technology Acceptance Model (TAM), which integrates the Theory of Reasoned Action (TRA) developed by Davis (1989), provides a foundational framework for a deeper comprehension of user behavior in accepting and utilizing information systems (Davis et al., 1989). TAM primarily aims to enlight the principal determinants of technology users' behavior concerning their beliefs, attitudes, and technology-related objectives

The Technology Acceptance Model (TAM) predicts and explains how technology users accept and employ technology within their professional roles. The TAM model relies on psychological theory to clarify the behavior of information technology users by examining the relationship between beliefs, attitudes, intentions, and user actions (Lai and Li, 2005). Therefore, it is evident that the reactions and perceptions of technology users will influence their acceptance of technology-related information. One of the key influencing factors is the user's perception of the usefulness and ease of technology utilization, which ultimately enables them to experience the benefits of technology information and fully received it.

Based Davis's (1989) opinion, perceived ease of use, in contrast,refers to the degree to which a person believes that using a particular system would be free of effort. All else being equal, we claim, an application perceived to be easier to use than another is more likely to be accepted by users. Perceived usefulness is defined here as the degree to which a person believes that using a particular system would enhance his or her job performance. A system high in perceived usefulness, in turn,is one for which a user believes in the existence of a positive use-performance relationship (Davis et al., 1989). Perceived risk is a choice that individuals should consider in relation to the significant impact and uniqueness of the risk before the system is applied (Jain and Raman, 2022).

Conceptual Framework

Big data networking presents various opportunities, including communication, collaboration, access to diverse data, and fulfilling necessities. All of these aspects are suggested as the main factors influencing the adoption of big data systems. The next hypothesis questions which perception (perceived ease of use, perceived usefulness, or perceived risk) is considered the most dominant influence on intention to use. Therefore, we propose the following hypothesis:

H1: It is expected that there is simultaneous influence of perceived of use, perceived usefulness, perceived risk toward the intention to use.

Perceived Ease of Use (PEU) is defined as the extent to which a person believes that using a system can reduce their workload (Venkatesh and Davis, 2000). Other definitions provided by Sukma (2018), Destiana and Salman (2015), and Aryoussef and Al-Rahmi (2022) describe PEU as how well users can perform the necessary actions to manage a system, how easily they can adapt to it, the mental effort required for system interaction, and the overall ease of use. Thus, this research employs the PEU factor to gauge employee intentions in utilizing big data accounts for bank customers. Based on the explanations above, the following hypotheses are proposed

H2: It is expected that perceived ease of use influences the intention to use.

Previous studies on the effect of perceived usefulness on big data utilization intention have been conducted by Alagoz and Hekimoglu (2012), Rauniar et al. (2014), and Munoz-Leiva et al. (2017). These studies concluded that perceived usefulness is defined as the extent to which big data users believe that employing a particular application can fulfill the specific needs of users. Each big data application offers specific primary services, so providing a variety of tools and applications can increase the utilitarian value for the audience. Therefore, we propose the following hypothesis:

H3: It is expected that perceived of usefulness influences the intention to use.

Existing strategies should consider risk as an important factor, mainly due to the complexity of implementing big data for studying its impact. Risk is a choice that individuals should consider in relation to the significant impact and uniqueness of the risk before the system is applied. Prior studies have found that considering risk is already an important consideration (Tripathi, 2014; Zhang et al., 2021; Kaur and Arora, 2022). Therefore, this study uses perceived risk as a factor to measure employees' intention to utilize big data from bank customers. We propose the following hypothesis:

H4: It is expected that there is an influence on perceived risk toward intention to use.

Research and Methodology

This research applied the quantitative approach to examine the influence of perceived ease of use, perceived usefulness or perceived risk toward the intention to use the Technology Acceptance Model (TAM). Testing in this study included validity testing, reliability testing multiple regression testing. The independent variables are perceived ease of use (X1), perceived usefulness (X2) and perceived risk (X3) while the dependent one is the intention to use (Y).

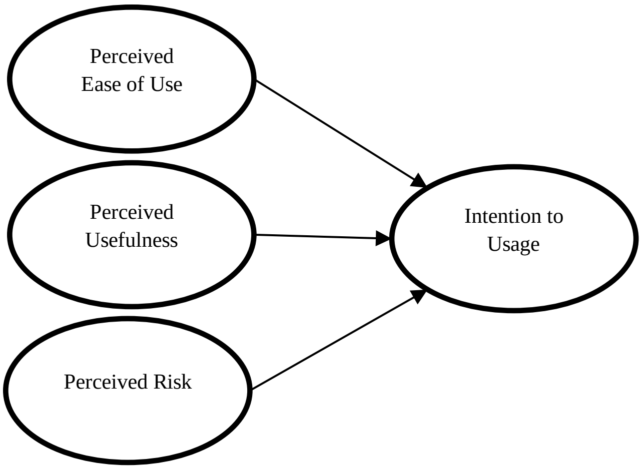

Figure 1: Conceptual Model of The Study; *Source:* Authors

The sample in this study consisted of account officers who work in state-owned Bank in Malang, East Java, especially of BRI, BNI, BTN and Mandiri Bank. The total population from those four banks are 95 respondents, all whom received questionnaire sent via email. Each respondents completed the questionnaire, and their responses were used as the research sample.

Findings and Discussions

Respondents Characteristics

The characteristics of the respondents, including gender, age, and educational background, reveal some key trends. A significant majority of the respondents are male, primarily falling within the age range of 31 to 40 years old. This observation suggests that those working in the sales department, a role often demanding strength and tenacity, are predominantly male. Furthermore, in terms of education, most respondents have graduated with a bachelor's degree. For detailed statistics, please refer to the table below:

Table 1: Respondents Characteristic

Gender	
Male	72%
Female	28%
Age	
21-30	33%
31-40	61%
41-50	6%
Education Background	
Diploma	12%
Bachelor	82%
Magister	6%

Source: Authors

Descriptive Analysis

Based on the frequency distribution presented in table 2, Perceived ease of use showed the average mean was 4,27. This score falls within the high range on the Likert scale with the range of 1-5 that indicates the respondents generally found Perceived ease of use to be highly favorable. The Perceived of Usefulness and Perceived Risk are 3,86 and 3,21 which also considered as high score that make them remains in the positive perception. The last variable is Intention to use received score 3,76 which also categorized as favorable as well.

Table 2: Descriptive Analysis

Variable	Mean
Perceived Ease of Use	4.27
Perceived Usefulness	3.86
Perceived Risk	3,21
Intention to Use	3.76

Source: Authors

Validity Test Results

To assess the significance, we compared the calculated r value with the critical r value from the table for degrees of freedom (df) equal to n-2. In this case, with a sample size of 95 respondents, the degrees of freedom can be calculated as 95 - 2 = 93. Using df = 93, we found the critical r value from the table to be 0.2017. Since the calculated r value is greater than the critical r value (r count > r table), we can conclude that all indicators are valid.

Table 3: Validity Test Results

Items	r count	r table	Results
PEU1	0,797	0,2017	Valid
PEU2	0,823	0,2017	Valid
PEU3	0,744	0,2017	Valid
PEU4	0,800	0,2017	Valid
PEU5	0,349	0,2017	Valid
PU1	0,525	0,2017	Valid
PU2	0,554	0,2017	Valid
PU3	0,735	0,2017	Valid
PU4	0,894	0,2017	Valid
PU5	0,733	0,2017	Valid
PR1	0,816	0,2017	Valid
PR2	0,848	0,2017	Valid
PR3	0,935	0,2017	Valid
PR4	0,887	0,2017	Valid
IU1	0,789	0,2017	Valid
IU2	0,778	0,2017	Valid
IU3	0,783	0,2017	Valid
IU4	0,769	0,2017	Valid
IU5	0,826	0,2017	Valid

Source: Authors

Note: PEU: perceived ease of use; PU:perceived usefulness; PR: perceived risk; IU: intention to usse

Based on table 3, all the measuring variables, perceived ease of use, perceived usefulness, perceived risk and intention to use, are considered as valid. It can be seen from the calculated r value is higher that the r table value.

Reliability Test Results

We use Cronbach's Alpha value to test the reliability with the testing criteria is if Cronbach's Alpha coefficient is >0,7, it means that it considered reliable or consistent in examining the variables.

Table 4: Reliability Test Results

Variable	Cronbach's Alpha value	Results
Perceived Ease of Use	0,719	Reliable
Perceived Usefulness	0,709	Reliable
Perceived Risk	0,895	Reliable
Intention to Use	0,847	Reliable

Source: Authors

The conclusion drawn from the reliability test indicates that all instruments employed in this study have a Cronbach's Alpha score > 0.7. This categorizes them as reliable and consistent tools for measuring the variables, thereby validating their suitability for collecting data in this research.

Multiple Regression Analysis

After the SPSS 26 program for Windows testing was conducted, the result of the multiple regression analysis result is presented in this following table:

Table 5: Multiple regression analysis test results

Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta		
Constant	1,837	8,452		3,217	0,009
Perceived Ease of Use	0,383	0,339	0,192	1,129	0,268
Perceived Usefulness	0,439	0,307	0,360	1,977	0,013
Perceived Risk	- 0,323	0,234	0,285	1,737	0,039

Source: Authors

$Y = a+ b_1X_1 + b_2X_2+b_3X_3$

$Y = 1.837 + 0.383X_1 + 0.239X_2 + (-)0,323X_3$

Information:

Y: Intention to use

a : Konstanta

X_1: Perceived ease of use

X_2: Perceived usefulness

X_3: Perceived risk

b1, b2: Regression coefficient of each variable

The regression equation above can be summarized as follows: (1) The constant term (a) is 1.837, indicating that if the strategies of effectuation and niche marketing remain constant (unchanged), the measurement of competitive advantage is 1.837. (2) The regression coefficient for the perceived ease of use variable is 0.383, with a t-test value of 1.129 and a significance value of 0.268, indicating that perceived ease of use does not have a significant impact on intention to use. (3) The regression coefficient for the perceived usefulness variable is 0.439, with a t-test value of 1.977 and a significance value of 0.013, suggesting that perceived usefulness has a positive and significant influence on intention to use. (4) The regression coefficient for the perceived risk variable is -0.323, with a t-test value of 1.737 and a significance value of 0.039, indicating that perceived risk have a significant impact on intention to use.

According to Sanusi (2011), to determine the F-table, α = 0.05 or 5%, df1 = k - 1 (4-1=3), df2 = n - k (95-4=91), resulting in the values shown in Table 6. After conducting the test using the SPSS 26 program for Windows, the results of the F-test (simultaneous test) can be seen in the table below:

Table 6: F Test Results

Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	88.487	3	29.496	3.245	.004[b]
	Residual	381.028	91	13.139		
	Total	469.515	95			

Source: Authors

Based on the F-test table, an F-value of 3.245 was obtained. Therefore, the calculated F-value (F count) of 3.245 is greater than the tabulated F-value (F table) of 2.70. As a result, the null hypothesis (H0) is rejected in favor of the alternative hypothesis (Ha). This means that the variables perceived ease of use (X1), perceived usefulness (X2), and perceived risk (X3) collectively have a positive and significant influence on intention to use (Y). Thus, the first hypothesis, which states that the variables perceived ease of use (X1), perceived usefulness (X2), and perceived risk (X3) collectively influence intention to use (Y), is supported.

This finding aligns with previous research conducted by Alagoz and Hekimoglu (2012) and Munoz-Leiva et al. (2017). It also supports the view of Rauniar et al. (2014), which suggests that the primary benefits of perceived ease of use, perceived usefulness, and perceived risk of a website or application are crucial determinants in shaping users' intention to use the application, which, in turn, is an indicator of actual application usage behavior.

However, this finding contradicts the second hypothesis, which states that the perceived ease of use (X1) has a partial effect on Intention (Y). This result differs from previous research by Venktatesh & Davis (2000) and Gangwar (2020), which found that perceived ease of use significantly affects Intention to Use. This research also supports the opinion of Aslam et al. (2017), who suggested that users may no longer consider perceived ease of use as important and it may no longer be a significant variable in the intention to adopt this technology. This is also because the application users have received training so that they can easily use the application to make daily work easier. Nevertheless, service providers should strive to make their systems user-friendly and easy to use.

In line with the third hypothesis, which states that the PU variable (X2) has a partial effect on Intention (Y), this research result aligns with previous studies by Sukma et al. (2019) and Shahid et al. (2022). This finding also supports Davis (1989), who emphasized the role of perceived usefulness in influencing the intention to use technology applications. It pertains to the extent to which users believe that using the system will enhance their job performance without being overly cumbersome. If so, individuals are more likely to commit to using the system.

However, this result contradicts the fourth hypothesis with previous research conducted by Alyoussef and Al-Rahmi (2022) and Osakwe et al. (2022). This research finding supports the earlier study by Jain and Raman (2022), concluding that respondents believed that the big data system does not guarantee the security of customer profiles and their status as users of the big data system, which consequently affects their intention to use the customer data. The account officers still feel the high level of uncertainty and undesirable consequences that can arise.

Conclusions

Based on simultaneous testing, all four hypotheses proposed in this study have been substantiated and accepted. Consequently, the independent variables simultaneously exert a positive and significant influence on the dependent variable. Perceived ease of use, perceived usefulness, and perceived risk all collectively, positively, and significantly impact the intention to use. However, upon conducting partial testing, it was found that only the perceived usefulness variable has a partial influence on the intention to use the bank's customer data through big data analytics. In contrast, the other two variables, perceived ease of use and perceived risk, do not significantly influence the intention to use the bank's customer data through big data analytics.

The theoretical implications drawn from this study underscore the importance of utilizing big data while highlighting the significant need for enhanced data security and privacy measures concerning bank customer data. This arises from the perception of respondents in this research, who believe that the bank's customer data system does not guarantee the safety and privacy of customers' information during its use within the big data application. This perception directly influences their intention to utilize the bank's customer data application system.

Future research in this field on the use of big data adoption in state-owner financial service and banking must also be considered by manager and other state-owner bank leaders. Although this study indicates that account officer may find it quite positive, limitations and facilitators should be examined. Exploring and evaluating perspectives from and with other countries would also enrich the findings achieved in the current study and build a larger perspective on how state-owner bank adoption of Big Data is perceived.

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