



Factors Affecting Accountants Adopting Business Analytics and Business Intelligence

Irvan Bravely^(✉), Harmiati Hatta, Husna Khairunnisa and Queen Tesselonika Panggalo

Accounting Department, Politeknik Negeri Ujung Pandang, Makassar, 90245, Indonesia
irvanbravely@poliupg.ac.id

Abstract. Accountants as producers of financial reporting data for organizations have an important role in creating and analyzing economic data in organizations. Adapting to technological developments and business competition requires accountants to adopt business intelligence and business analytics. Business intelligence is a set of methodologies, processes, architectures, and technologies that transform raw data into valuable information to create effective, tactical, and operational strategies that are more effective in decision-making. Business analytics is the set of skills, applications, technology, architecture, process, and methodology used to collect, store, and retrieve data for data analysis purposes in order to support decision making, inform business strategies, and ultimately drive performance. The study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) to measure the adoption factor of business intelligence and business analytics (BI&A) by accountants. Four factors influence user acceptance, namely: performance expectancy, effort expectation, social influence, facilitating conditions. The population of this study is accountants in Indonesia and the sample of this research is the accountants who have adopted business analytics and business intelligence. The entire test of the accepted hypotheses is H1, H2, H3, H4, and H5 so that organizations that want to increase competitive advantage through BI&A can use the variables in this research to increase the adoption of the use of BI&A.

Keywords: Business Analytics, Business Intelligence, Accountant, UTAUT.

1 Background

Since the 1970s, the use of technology to support decision-making using data or known as decision support systems has increased [1]. Until now, organizations that adopt technology have captured and stored a huge amount of data-based information [2]. Stored data can be analyzed for historical trends and patterns as well as forecasting future outcomes and events [3]. This data analysis is then able to bring competitive advantage to organizations [4] because it helps make business decisions faster and better by providing the best identification results when several variable changes are made [5] and then becomes a new science called business intelligence (BI) and business analytics (BA). BI is a set of applications, technologies, and processes used to collect, store, take, and

analyze data to help business users make the right decisions. BA is a decision-making process based on historical data analysis. The BA consists of three levels: descriptive, predictive, and prescriptive analytics [6]. Descriptive analysis provides an understanding of what is happening, predictional analytics determines what will happen in the future, and prescription analytics provides recommendations on how to address business problems [7].

BI ranks first as a matter of consideration to be noticed by the company's directors in the field of technology worldwide [8]. Besides, BI analysts are ranked third in the growing profession [9]. Accountants as producers of financial reporting data for organizations have an important role in creating and analyzing economic data in organizations. However, there has been a decline in job demand especially in the data entry segment as this job has been replaced by computer automation [9] [10].

Accountants are then required to adapt or perish in the face of the phenomenon of technological development. One of the latest technologies that has an impact on the skills and roles of accountants that is most researched is business intelligence and analytics (BI&A) [11]. Adaptation to technological developments and business competition requires accountants to adopt BI&A. BI&A capabilities, accompanied by π -shaped skills, are able to provide innovative performance for organizations, resulting in competitive advantage. [12]. Accountants have an advantage in understanding business, and are accustomed to working with structured data sets as well as performing data analysis so that they are able to be a key player in conducting problem analysis using structural data or not to support value creation in their organization [10]. BI&A utilizes a lot of data to be processed, so data literacy skills will be very useful for accountants and can potentially change the competency profile of management accountants [13]. Currently, accountants' activities still focus on descriptive analysis of financial data rather than more complex analysis activities that use external data, operational data, and data modeling [5], so in-depth knowledge is needed regarding the things that cause accountants to adopt BI&A as a whole.

Previous research related to BI&A adoption has mostly focused on user organizations. Such as BI&A adoption in small and medium businesses [14], the banking industry [15], and universities [16]. At the individual user level, related research has been conducted by Wang [17], but it focuses on managers. Apart from that, Hou[18] has also conducted research related to the acceptance and use of BI&A adoption by individuals in the electronics industry, but not specifically accountants. Individual adoption research by Yoon et al. [19] and Tanja [20] also focuses on individual functional responsibilities such as sales, marketing, information technology, logistics, accounting, finance, service, production, and human resources at operational, managerial, strategic, and executive levels. Based on these facts, the factors related to BI&A adoption at the individual level, especially in the accounting profession, have not received much attention.

One theoretical model used to explain user acceptance and use of information technology is the Unified Theory of Acceptance and Use of Technology (UTAUT) that proposes four factors of influence on users' acceptance: (1) performance expectancy, i.e. user expectation about system performance, (2) effort expectancy, i.e. user perception of effort about what is needed to use a new system, (3) social influence, i.e. users

perception about system urges that derive from individual influences that are important to users, and (4) facilitating conditions, i.: user expectations about the availability of technical infrastructure and in organizations to support the use of the system [21].

1.1 Problem Formula

Based on the background explained by the researcher, the problem in this research is the factors that influence accountants' adoption of business analytics and business intelligence.

1.2 Research Hypothesis

Performance expectancy, namely the extent to which a person believes that using the system will help him improve performance in his work [21]. BI&A is expected to be able to increase effectiveness so that it can increase the speed of work and increase the work productivity of accountants [20] [22]. This research assumes that performance expectations are a significant factor in accountants' behavioral intentions to adopt BI&A. Therefore, we put forward the following hypothesis:

H1. Performance expectancy has a significant influence on behavioral intention.

Effort expectancy, namely the user's perception of the effort required to use the new system. Model construction related to effort expectancy is: perceived ease of use, complexity, and ease of use [21]. Previous research found that the effort expectancy construct was the strongest predictor of users' behavioral intentions to use BI&A [23] [24][25].

H2. Effort expectancy has a significant influence on behavioral intention.

Social influence, namely the user's perception regarding the encouragement to use the system, which comes from the influence of important individuals, according to the user [21]. In the context of BI&A, IS is a driving factor that influences adoption, and this has been proven by previous research [25][20][19]. If colleagues and/or superiors find the implementation of BI&A useful, then a person will be more willing to adopt the system [19].

H3. Social influence has a significant influence on behavioral intention.

Facilitating conditions, namely user expectations regarding the availability of infrastructure and techniques in the organization to support system use [21]. Facilitating conditions refer to the availability of resources that support BI&A adoption, such as necessary knowledge, assistance, and technological resources. The more resources available, the more likely someone is to use BI&A [22]. The easier use of BI&A will then lead to continued use [25].

H4. Social influence has a significant influence on use behavior to adopt BI&A.

Behavioral intention has a big role in the use and adoption of new technology [21]. A person's commitment to engaging in a certain behavior can be mediated by behavioral intention [15], and behavioral intention will lead to the actual use of BI&A [24].

H5. Behavioral intention has a significant influence on use behavior to adopt BI&A.

2 Literature Review

2.1 Accountant Profession

Accountant is someone who has a deep understanding of accounting concepts and principles and uses such knowledge and skills to provide relevant and reliable information to stakeholders for business decision-making [26] [27]. Accountants are professionals who have knowledge and skills in managing financial information, designing and implementing accounting systems, and preparing financial reports for organizations [28]. Accountants should have the knowledge, skills, and wisdom to collect, classify, analyze, and report financial and non-financial information accurately and reliably [29]. According to Accountants not only collect, categorize, and analyze financial data but also non-currency data, then communicate the results of such analysis to stakeholders [30].

2.2 Business Intelligence

Business intelligence (BI) is a set of methodologies, processes, architectures, and technologies that transform raw data into valuable information to create effective, tactical, and operational strategies that are more effective in decision-making [31]. BI is a broad application, technology, and process categorization for collecting, storing, accessing, and analyzing data to help business users [32]. BI is thus a general term used to describe technologies, processes, and applications to support decision-making [1] [33]. BI is a set of integrated strategies, applications, technologies, architectures, processes, and methodologies used to collect, store, take, and analyze data to support decision-making [6]. BI can quickly see factual problems and their interaction in business operations and encourage companies to respond with action that can be implemented to the company's goals [34], so the adoption of BI by accountants as an information provider can provide a competitive advantage for individuals and organizations.

2.3 Business Analytics

Business Analytics (BA) is a set of skills, applications, technologies, architectures, processes, and methodologies used to collect, store, and retrieve data for data analysis purposes to support decision-making, inform business strategies, and ultimately drive performance [6]. BA is a general term for the use of data to make decisions by conducting systematic thinking processes as well as applying tools and methods of qualitative, quantitative, and statistical computing to analyze data, gain insight, inform, and support

decision making [35] and is classified as: descriptive analytics, predictive analysis, and prescription analytics [7].

3 Research Methods

The population of this research is accountants in Indonesia and the sample of this research is accountants who have adopted BI&A. The variables measured in this research are independent variables, namely: performance expectancy, effort expectancy, social influence, and facilitating conditions. The dependent variables are behavioral intention and adoption of BI and BA [21].

The research model uses UTAUT theory in the adoption of BI & BA among accountants, which will then be analyzed using the Structured Equation Model (SEM) analysis tool.

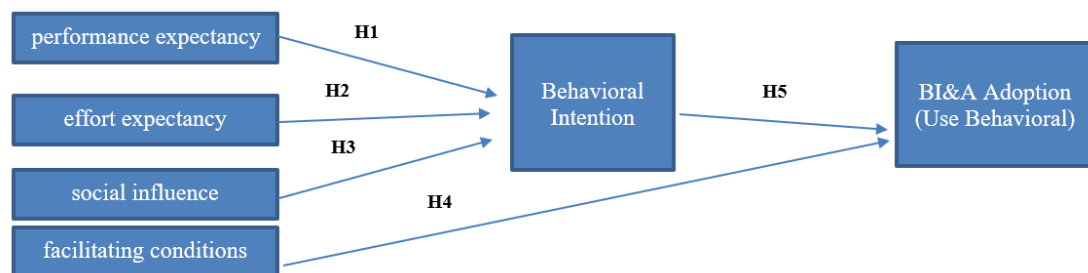


Fig. 1. Research Model.

The data collection technique used in this research is a questionnaire. Questionnaires were distributed to accountants via digital channels and in person. Measuring questionnaire answers uses a Likert scale with a score of 1–5. Strongly Disagree (STS) was given a score of 1, Disagree (TS) was given a score of 2, Undecided (RR) was given a score of 3, Agree (S) was given a score of 4, and Strongly Agree (SS) was given a score of 5.

The completed questionnaires will be tabulated, and then descriptive and reliability analyses will be carried out using Smart PLS 3.2. Next, the SEM model assumptions were tested by testing the normality of distribution and linearity as well as validity and reliability tests. The validity test uses Pearson correlation and the reliability test uses Cronbach's alpha. The identification test is then carried out by calculating the degree of freedom and the criteria. The evaluation test is continued by testing the measurement model and then testing the structural model. The final step is hypothesis testing to analyze the data and draw conclusions.

4 Result

The data collected in this study consisted of 138 accountant respondents who met the minimum sampling criteria set [36], namely that the minimum number of samples that should be used is 10 times the number of all latent variable arrows in the path model.

Table 1 describes the characteristics of respondents, and the research results show that 35.5% of respondents who answered the survey were men, while 64.5% were women. Furthermore, the age categories of respondents are as follows: 75.4% are between 21 and 30 years old, 16.7% are between 31 and 40 years old, 7.2% are between 41 and 50 years old, and 0.7 percent are over 50 years old. The educational level of respondents was Diploma 3 at 16.7%, Diploma 4/Strata 1 at 55.1%, and Strata 2 at 28.3%. The professional classification of accountant respondents was in the private sector as much as 28.3%, public as much as 26.1%, educators as much as 9.4%, and government as much as 36.2%. Respondents' length of work is as follows: 67.4% have worked as accountants between 1 and 5 years, 16.7% between 5 and 10 years, 6.5% more than 10 years, and 9.4% less than 1 year. Respondents using the largest data processing applications were Microsoft Excel as much as 97.8%, Google Sheet as much as 55.1%, Enterprise Resource Planning as much as 19.6%, Microsoft Power BI as much as 4.3%, R as much as 2.2%, artificial intelligence as much as 11.6%, and the rest were other processing applications. Respondents use the application for descriptive analysis activities (interpretation of historical business data to identify trends and patterns). Diagnostic analysis (interpretation of historical business data to find out why something happened). Predictive analysis (use of statistical methods to predict future business performance). Prescriptive analysis (testing variables to determine the best outcome in a business decision scenario).

Table 1. Respondent Characteristics

Respondent Characteristics		Frequency	Percentage (%)
Gender	Man	49	35,5
	Woman	89	64,5
Age	21-30 Years	104	75,4
	31-40 Years	23	16,7
	41-50 Years	10	7,2
	>50 Years	1	0,7
Educational level	Diploga	23	16,7
	Undergraduate	76	55,1
	Graduate	39	28,3
Accountant Category	Educator	13	9,4
	Privat	39	28,3
	Public	36	26,1
	Government	50	36,2
Length of work	0-1 Years	9	9,4
	1-5 Years	93	67,4
	5-10 Years	23	16,7
	>10 Years	9	6,5

Table 2. Reliability and Validity Test Results

Construct	Items	Loadings	rho_A	Composite Reability	Average Variance Extracted
Performance Expectancy (PE)			0,803	0,871	0,628
	PE 1	0,802			
	PE 2	0,789			
	PE 3	0,786			
	PE 4	0,793			
Effort Expectancy (EE)			0,763	0,848	0,582
	EE1	0,776			
	EE2	0,719			
	EE3	0,772			
	EE4	0,783			
Social Influence (SI)			0,814	0,876	0,639
	SI1	0,816			
	SI2	0,787			
	SI3	0,777			
	SI4	0,816			
Facilitating Condition (FC)			0,831	0,886	0,660
	FC1	0,846			
	FC2	0,793			
	FC3	0,819			
	FC4	0,791			
Behavioral Intention (BI)			0,860	0,904	0,703
	BI1	0,838			
	BI2	0,830			
	BI3	0,842			

	BI4	0,844			
Use Behavior (UB)			0,777	0,864	0,680
	UB1	0,873			
	UB2	0,821			
	UB3	0,777			

Table 3. Heterotrait-Monotrait Ratio (HTMT)

	BI	EE	FC	PE	SI	UB
Behavioral Intention (BI)						
Effort Expectancy (EE)	0,641					
Facilitating Condition (FC)	0,709	0,836				
Performance Expectancy (PE)	0,638	0,898	0,704			
Social Influence (SI)	0,659	0,562	0,545	0,634		
User Behavior (UB)	0,774	0,524	0,477	0,543	0,529	

Based on Table 2 above, convergent validity testing meets the rule of thumb. The AVE value is ≥ 0.582 , which means that 58 percent and above of the indicators describe the variable. An outer loading value of ≥ 0.719 means that the variable construct reflects 50 percent of the indicator variance. The discriminant validity test also met the measurement parameters. This can be seen from the cross-loading value of ≥ 0.719 in Table 2 and the HTMT of ≤ 0.898 in Table 3.

In carrying out reliability testing, the parameters used are $\rho_A \geq 0.7$ and composite reliability between 0.6 and 0.95 [36]. The test results in Table 2 show that the ρ_A value is ≥ 0.763 and composite reliability is ≥ 0.848 , which means that the reliability test has been fulfilled. If the composite reliability value is between 0.6-0.95, it means that there is a high correlation between the indicators. However, if the value is above 0.848, it means that one indicator is the same as another indicator.

Table 4. Direct Effect

Path (Hypothesis)	Direct Effect		
	β	t-value	p value
Performance Expectancy => Behavioral Intention	0,438	9,884	0,000
Effort Expectancy => Behavioral Intention	0,185	2,230	0,026
Social Influence => Behavioral Intention	0,377	4,013	0,000
Facilitating Condition => Use Behavior	0,280	5,985	0,000
Behavioral Intention => Use Behavior	0,694	4,427	0,000

The direct relationship between variables can be seen in Table 4. If the t-value is greater than 1.64 and the p value is smaller than 0.05, it indicates that both variables

have a positive influence. The first problem formulation confirms that performance expectancy, effort expectancy, and social influence influence behavioral intention.

Table 5. Total Effect

<i>Path (Hypothesis)</i>	<i>Indirect Effect</i>			<i>Total Effect</i>		
	β	t-value	p-value	β	t-value	p-value
Performance Expectancy => Behavioral Intention				0,438	5,985	0,000
Performance Expectancy => Use Behavior	0,304	5,954	0,000	0,304	5,954	0,000
Effort Expectancy => Behavioral Intention				0,185	2,230	0,026
Effort Expectancy => Use Behavior	0,128	2,134	0,033	0,128	2,134	0,033
Social Influence => Behavioral Intention				0,377	4,427	0,000
Social Influence => Use Behavior	0,261	3,847	0,000	0,261	3,847	0,000
Facilitating Condition => Use Behavior				0,280	4,013	0,000
Behavioral Intention => Use Behavior				0,694	9,884	0,000

Table 5 shows the indirect and total direct and indirect effects between the independent variables on the dependent variable. The highest value is found in the direct relationship between the behavioral intention variable and use behavioral. Meanwhile, the lowest value is found in the indirect relationship between social influence and use behavior.

All tests of variable relationships show a significant effect. Based on the t-value, beta coefficient (original sample), and p-value, the results of testing the H1 hypothesis show that there is a positive influence on behavioral intention. The t-value is $5.985 > 1.65$, and the p-value is $0.000 < 0.05$. So, from the results of testing, hypothesis H1 is accepted. To test the H2 hypothesis, it shows that the t-value is $2.230 > 1.65$ and the p-value is $0.000 < 0.01$, so that there is a positive influence between effort expectancy and behavioral intention. The direct relationship between these two variables explains that ease of use of the application can influence a person's intention to continue using the application. If the user carries out descriptive analysis using Microsoft Excel more quickly and easily, then for the next analysis, the user will use it again.

Testing the H3 hypothesis shows a t-value of $4.427 > 1.65$ and a p-value of $0.000 < 0.05$. This means that hypothesis H3 is accepted. The social influence variable shows that people around an individual can influence their perceptions and actions when using business analytics and intelligence applications. For example, an educational accountant will use Google Sheets if invited by another teaching accountant friend. This proves that social influence greatly influences the actions and perceptions of other people.

The results of testing the H4 hypothesis show that the t-value is $4.013 > 1.65$ and the p-value is $0.000 < 0.05$. This means that hypothesis H4 is accepted. Facilitating conditions are related to the availability of resources that can directly influence a person's behavior when adopting business analytics and intelligence. If someone does not have the technological tools to carry out the analysis process, there is very little chance of adopting BI&A so that the availability of facilities can influence a person's behavior in adopting BI&A. The final hypothesis test is H5. The t-value is $9.884 > 1.68$ and the p-value is $0.000 < 0.05$, meaning that the H5 hypothesis is accepted.

The test results show that behavioral intention in BI&A has a positive effect on use behavior. Someone who already intends to carry out descriptive analysis, predictive diagnostics, and prescriptive analysis is likely to adopt BI&A. From the results of hypothesis testing using BI&A, the supported hypotheses are H1, H2, H3, H4, and H5. In Table 6, R square is used to measure the dependent construct in the structural model. The R square value functions to measure the level of variation in changes in the independent variable towards the dependent variable.

Table 6. R Square Value

Construct	R Square	R Square Adjusted
Behavioral Intention	0,942	0,941
Use Behavior	0,851	0,849

Based on table 6, the R square value for behavior intention is 0.942. This means that the variation in changes in the behavior intention variable that can be explained by performance expectancy, effort expectancy, and social influence is 94.2%, while the rest is explained by variables outside this research model. The use behavior variable obtained an R square value of 0.851. This means that variations in changes in the use behavior variable can be explained by behavioral intention and facilitating conditions of 85.1%, the rest is explained by variables outside this research model. So, the R square value shows that the variation in changes in the independent variable is higher compared to the dependent variable.

5 Conclusion

All hypothesis testing is accepted, namely H1, H2, H3, H4, and H5. The results of this research are expected to provide an overview for organizations regarding the influence of performance expectations, effort expectations, social influence, and facilitating conditions in the adoption of BI&A. So organizations or accountant that want to increase their competitive advantage through BI&A can use the variables above to increase adoption.

Suggestions for future research are to use samples of other professions in the organization. Apart from that, the position levels in the organization can also be researched

further separately. Age and gender are also things that must be considered in adoption so further analysis is needed regarding BI&A adoption.

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