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Examining Organizational and Individual Drivers Influencing Big Data Adoption in South Korean Companies: A UTAUT2 Perspective

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Abstract. This study explores organizational and individual drivers influencing big data adoption in 187 South Korean companies using an extended UTAUT2 model. Quantitative survey analysis reveals performance expectancy, effort expectancy, social influence, facilitating conditions and hedonic motivation significantly predict usage intention and performance. Flexible cognition regarding big data is also found to positively impact technological innovation outcomes. The research contributes by unraveling an interconnected framework of factors fostering data-driven advancement. It offers actionable insights for managers to optimize data leveraging. Further validation through longitudinal data across more sectors is recommended.

Keywords: UTAUT2, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Habit

1. Introduction

The business environment is changing fast in tandem with the paradigm shift to-ward the Fourth Industrial Revolution. (Paschek, Mocan & Draghici, 2019) However, companies use big data at a conceptual level and fail to perceive the importance of big data or avoid active introduction owing to various regulations and a lack of professional workforces. (See-To & Ngai, 2018)

Therefore, investigating key factors affecting big data performance from various perspectives and presenting their relationships is a meaningful study. Furthermore, this study could provide an opportunity for a consciousness shift in companies to leverage big data actively. (Verhoeven, Sinn & Herden, 2018)

As such, various studies have examined the impact of big data on organizational performance, but there are some differences in the research trends (Yoon & Joung, 2020; Rialti, Marzi, Ciappei & Busso, 2019). In fact, although researchers have examined the complex relationship between big data development and performance, they are still at the stage of proposing theories (Huang, 2023). Moreover, quantitative research on big data is still in its infancy (Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba & Roubaud, 2019). Thus, despite the growing importance of big data, research on the impact of organizational and individual factors on big data remains limited. Therefore, this study aims to investigate the influence of organizational factors and individual factors on the utilization of big data by employing the UTAUT2 model as the basis for analysis. Unlike the existing UTAUT model, which only considers organizational factors and overlooks individual elements, the UTAUT2 model, addresses this limitation by encompassing both aspects.

The primary objective of this study is to investigate how organizational and individual factors impact the utilization of big data. Given the rapidly evolving management landscape influenced by the Fourth Industrial Revolution, this study aims to comprehensively explore the key factors influencing big data usage within companies. By considering various perspectives and identifying the interdependent causal relationships between variables, we aim to bridge the gap in research that lacks studies examining the relationship between organizational factors, individual factors, and big data performance. In view of this, we will design a research model based on the UTAUT2 model and conduct factor derivation. By illustrating and presenting these relationships of influence, this study delivers meaningful implications and has the potential to change companies' mindset toward actively leveraging big data. Accordingly, we have developed a conceptual research model, as depicted in Figure 1, and aim to address the following two research questions.

Q1: Does the inclusion of UTAUT2 Organizational Factors impact big data performance?
Q2: Does the incorporation of UTAUT2 Individual Factors influence big data performance?

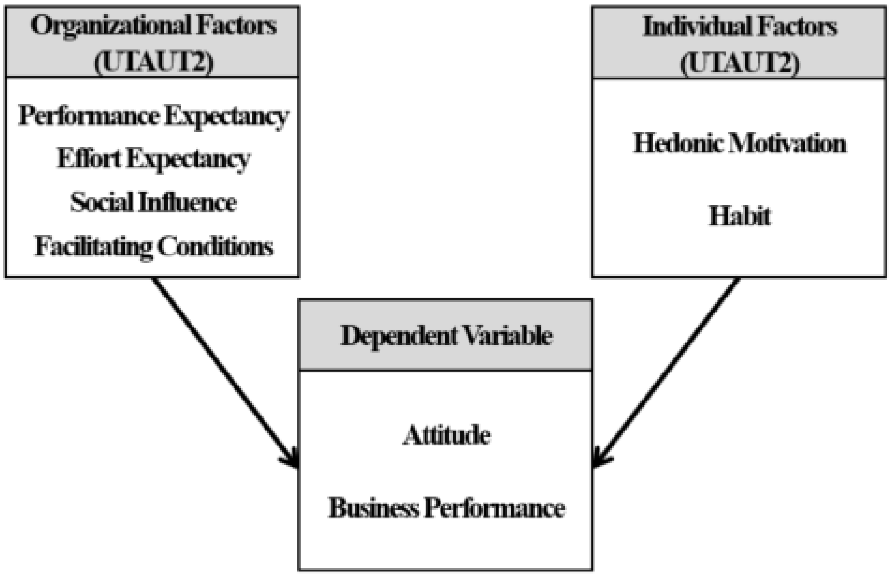

Fig 1: Conceptual research model

To answer these two questions, we configured a survey by operational definitions using SPSS 24.0 and AMOS 24.0 for empirical analysis. We studied companies listed in the Korean securities market Korea Composite Stock Price Index (KOSPI), which are the representative companies of South Korea announced by the South Korean government based on market representation, liquidity, and industry representation.

According to the Economist Intelligence Unit (EIU), South Korea rose to second place in the IT Human Resource Index with 58.9 points after the US with 75.6 points. In the index released by the UK's Economist Intelligence Unit, South Korea ranked third after the US and Japan. (Economist Intelligence Unit, 2007) Therefore, an increasingly globalized market requires research from a global perspective. This study presents strategies for introducing big data by governments and enterprises by analyzing factors influencing their usage intention. We expect to develop acceptance models for big data and present the influence factors on their usage intention. In addition, we provide a framework for the policy formulation for big data introduction and activation to improve the competitiveness and values of the government and enterprises.

2. Literature Review

2.1. Big Data

When using big data, meaningful information could be created from data that could not be processed with conventional methods for use in decision-making (Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017). Big data allows to analyze, process, and visualize vast and data beyond the scope of storage, management, and analysis with existing databases in real-time. (Zamrudi & Wicaksono, 2018) The scope of big data includes integrating internal data (e.g., transaction, log, and sales data) and external data (social media text, audio, photo, video, visual, weather, exchange rate, and other public data) to be processed according to the purpose of use. (Yu, Chen, Yao & Liu, 2021)

Big data use starts with the desire to expand the business and refers to using big data to improve decision-making accuracy and activate information sharing. (Wamba, Akter, Edwards, Chopin & Gnanzou, 2015) Table 1 defines big data, its utilization, and its scope and level of utilization.

Research related to big data technology has been increasing, and several studies have been conducted on big data-related technology development. However, research into the key factors that leverage big data in business performance is in its infancy. Moreover, research on its introduction and utilization is insufficient. (Sun, Cegielski, Jia & Hall, 2018)

Table 1: Definitions of Big Data terms

Classification		Contents
Big Data utilization	Definition	Big data utilization is to store, manage, analyze, and visualize large and diverse standard and non-standard data using existing databases in real-time.
	Scope	Find meaning and use it in decision-making and work in various forms of data that cannot be processed in an existing way.
	Level	The construction of big data platforms, data collection, and storage, and defining the process of data analysis and usage.

The effectiveness of big data utilization in processing large amounts of data of various forms will vary depending on how well we are using big data and at what level. (Venkatesh, Morris, Davis & Davis, 2003) Definitions and discussions about the level of big data utilization are needed to determine the achieved or expected big data utilization effects. (Lian, Yen, Wang, 2014) A maturity model is being studied as a framework or guidance criterion for judging the level of big data utilization. Global leading companies that use data well know the importance of big data and use the big data maturity model to evaluate how well they use. The big data maturity model defines the level of big data utilization as As-Is and decides whether to go to the future To-Be. (Tokkozhina, Martins & Ferreira, 2022) The big data maturity model can efficiently check the level of big data utilization while applying and leveraging big data to the enterprise rather than for theoretical and academic purposes. (Braun, 2015)

2.2. UTAUT

As a theory to understand the intention and behavior of information system users, the UTAUT integrates the theory of reasoned action (TRA), theory of planned behavior (TPB), technology acceptance model (TAM), motivation model (MM), model of PC utilization (MPCU), innovation diffusion theory (IDT), and social cognitive theory (SCT). (Venkatesh, Morris, Davis & Davis, 2003) As shown in Figure 2, the UTAUT model uses performance expectancy, effort expected, social influence, and facilitating conditions as predictive variables that affect the intention to use information systems. Gender, age, experience, and voluntariness of use are used as control variables. (Yu, Chen, Yao & Liu, 2021)

While TAM's explanation power is approximately 40%, UTAUT improved the model's explanatory power by approximately 70% by including various predictive variables. (Zamrudi & Wicaksono, 2018) It is more useful for verifying acceptance intentions for the latest in-formation technology and application programs (work systems such as accounting systems) and is being used to expand UTAUT in various studies. (Dulle & Minishi-Majanja, 2011)

The term "performance expectancy" in the UTAUT constructs is similar to TAM's "perceived usefulness" and refers to the degree to which an individual believes that using the technology will help them improve their expected job performance. Effort expectancy refers to the perceived degree of ease of use when utilizing the technology and is similar to TAM's perceived ease of use. Social influence is a term similar to TAM's subjective norm and can be described as the degree to which people around an individual believe that the individual should use the new technology. Facilitating conditions refers to the degree to which organizational and technical infrastructure is in place to support the use of a new technology. Table 2 presents the relevant theories for the UTAUT variables, that is, performance expectancy, effort expectancy, social influence, and use behavior.

Table 2: UTAUT Construct

Construct	Related Theory
Performance Expectancy	TAM/TAM2 (Technology Acceptance Model / Technology Acceptance Model2) TPB (Theory of Planned Behavior) C- TAM-TPB (Combined Technology Acceptance Model-Theory of Planned Behavior) MM (Motivation Model) MPCU (Model of PC Utilization) IDT (Innovation Diffusion Theory) SCT (Social Cognitive Theory)
Effort Expectancy	TAM/TAM2 (Technology Acceptance Model / Technology Acceptance Model2) C- TAM-TPB (Combined Technology Acceptance Model-Theory of Planned Behavior) MPCU (Model of PC Utilization) IDT (Innovation Diffusion Theory)
Social Influence	C- TAM-TPB (Combined Technology Acceptance Model-Theory of Planned Behavior) TPB (Theory of Planned Behavior) DTPB (Decomposed Theory of Planned Behaviour) TRA (Theory of Reasoned Action) TAM (Technology Acceptance Model) MPCU (Model of PC Utilization) IDT (Innovation Diffusion Theory)
Facilitating Conditions	C- TAM-TPB (Combined Technology Acceptance Model-Theory of Planned Behavior) TPB (Theory of Planned Behavior) DTPB (Decomposed Theory of Planned Behaviour) MPCU (Model of PC Utilization) IDT (Innovation Diffusion Theory)

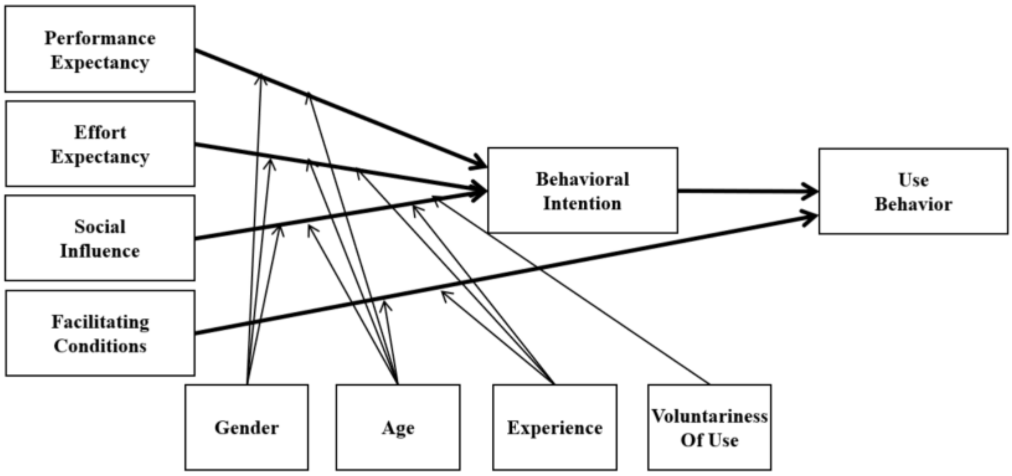

Fig 2: UTAUT model (Venkatesh, Morris, Davis & Davis, 2003)

2.3. UTAUT 2

Venkatesh, Thong & Xu (2012) expanded the UTAUT model to incorporate individual factors, namely Hedonic Motivation, Price Value and Habit, as shown in Figure 3. As the original UTAUT model overlooked individual user characteristics, Venkatesh sought to overcome this limitation in the research. Price Value represents the cognitive evaluation of the benefits derived from using a technology relative to the perceived cost. Hedonic Motivation, a reconceptualization of the perceived pleasure derived from using a service, refers to the enjoyment and satisfaction experienced when using technology. (Alalwan, Dwivedi & Rana, 2017) Habit refers to the unconscious inclination to use a specific technology or service, often influenced by previous usage experiences. Prior research indicates that Price Value exhibits a positive correlation with perceived service quality and a negative correlation with perceived price. (Ain, Kaur & Waheed, 2016)

Hedonic Motivation and Habit are factors considered when individuals utilize certain technologies for leisure, personal enjoyment, or entertainment purposes. How-ever, since our study focuses on businesses, we have excluded Price Value as it is not directly applicable to individual users within organizational contexts.

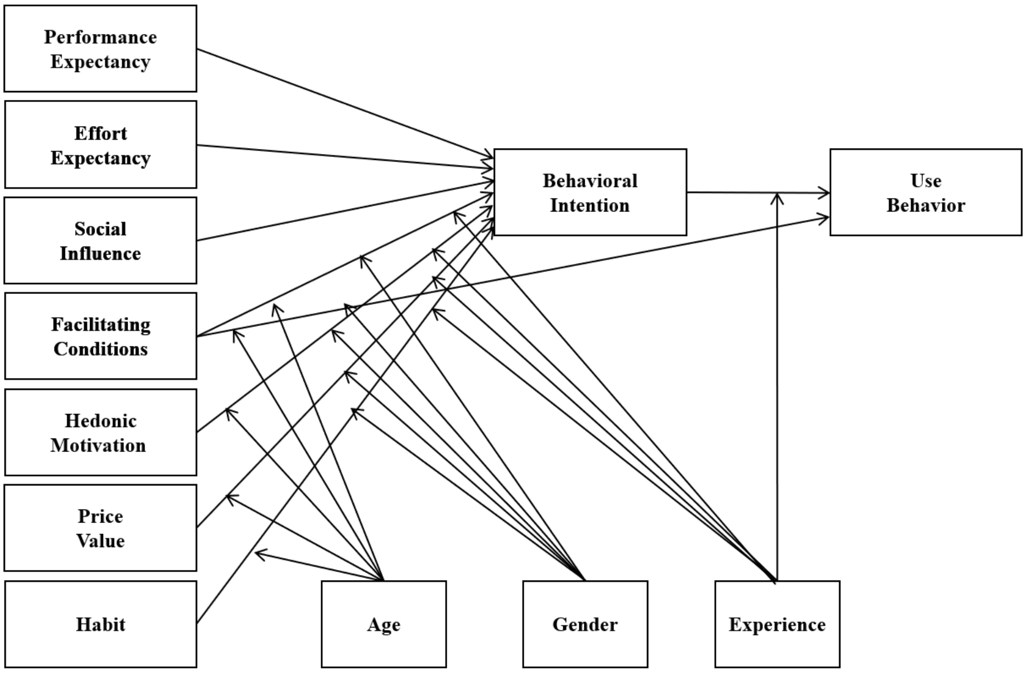

Fig 3: UTAUT 2 model (Venkatesh, Thong & Xu, 2012)

The inclusion of Hedonic Motivation and Habit in the UTAUT2 model reflects the recognition of the crucial role played by an individual's desire or expectation to use technology, in addition to their perception of it, as crucial variables in the technology adoption and usage process. (Raman & Don, 2013) Drawing upon the expected value theory, innovation diffusion theory, self-determination theory, and the task-technology fit model, re-searchers have examined the influence of various variables on new technologies. (Wang, Chen & Xu, 2016) These variables, introduced as extraneous or independent factors, include individual innovativeness, intrinsic and extrinsic motivation to use, job fit, self-efficacy, trust, perceived risk, anxiety, and attitude.

3. Research Methodology

The study identifies big data introduction factors based on the UTAUT2 model and the impact of mutually beneficial causal relationships between these factors on the performance. The proposed research model is shown in Figure 4. In addition, we derive the research hypotheses and empirically analyze them through a structural equation model.

3.1. Hypotheses Development

The positive impact of UTAUT2 organizational factors on the behavioral intention of big data and the performance of big data in information systems (IS) has been demonstrated through many studies. (Zakk & Teguh, 2018) UTAUT2 organizational factors have a high explanatory power that positively affects dependent variables (Queiroz, Fosso Wamba, De Bourmont & Telles, 2021) In studying factors affecting the utilization of new technologies, the UTAUT2 organizational factors have the highest impact on IS performance. Based on the above discussion, we establish the following hypothesis:

Hypothesis 1: UTAUT2 organizational factors will influence attitude towards big data.

Hypothesis 2: UTAUT2 organizational factors will influence business performance of big data.

Studies in the field of Information technology have confirmed the impact of hedonic motivation on behavioral intention and use behavior, driven by the enjoyment experienced during the IT usage process. (Alalwan, Dwivedi & Rana, 2017) Furthermore, it has been observed that habits formed through repeated IT use create a cyclical process that leads to behavioral intention and actual usage behavior. (Raman & Don, 2013) Consequently, it is anticipated that UTAUT2 individual factors, encompassing the pre-, during, and post-IT usage stages, can exert a positive influence on the dependent variable.

Hypothesis 3: UTAUT2 individual factors will influence attitude towards big data.

Hypothesis 4: UTAUT2 individual factors will influence business performance of big data.

Many studies have presented positive attitude as a leading variable in the relationship with performance and as an important factor that can increase positive intentions for introducing products and services such as new technologies. (Queiroz, Fosso Wamba, De Bourmont & Telles, 2021; Venkatesh, Morris, Davis & Davis, 2003) Therefore, we establish the hypothesis that the attitude towards big data will influence business performance of big data.

Hypothesis 5: Attitude towards big data will influence the business performance of big data.

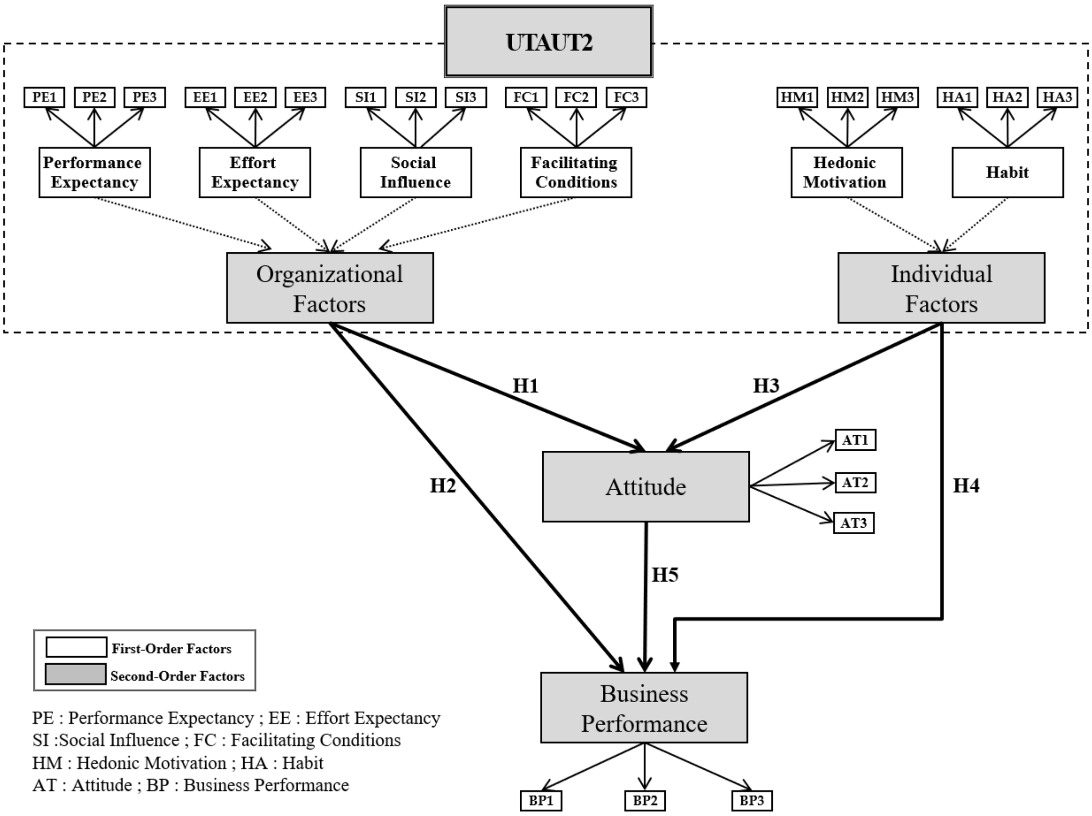

Fig 4 : Research model

4. Analysis

A survey was conducted based on prior studies to verify the research model and study hypothesis (the survey questions are listed in Table 3). To conduct more systematic surveys, we revealed the study's purpose to the persons in charge of the companies and sent a questionnaire to them for a pilot test. The survey respondents were companies listed in the Korean securities market KOSPI, which includes the representative companies of South Korea announced by the Korean government based on market representation, liquidity, and industry representation. The survey collected 250 questionnaires by telephone, email, and direct visits between October 2022 to December 2022. We recovered 191 answered questionnaires with a recovery rate of approximately 76.4%. After excluding missing values, 187 data were used for the final study analysis. Statistical analysis was conducted using SPSS 24.0 and AMOS 24.0.

Table 3. Research constructs and operationalization.

Construct	Items	References
Performance Expectancy	Big data will provide information that is helpful in decision making Big Data will help improve management performance. Big data will make it easy to use a variety of information.	Zamrudi & Wicaksono, 2018 Venkatesh, Morris, Davis & Davis, 2003
Effort Expectancy	Business processing using big data is easy to understand. Business processing using big data is easy to handle. Business processing using big data is easy to learn.	
Social Influence	The use of big data is socially recommended. Big data is becoming increasingly generated in society. Social evaluation of big data is good.	
Facilitating Conditions	We have the resources needed to utilize big data. We have conditions to utilize big data. We have the knowledge needed to utilize big data.	
Hedonic Motivation	Engaging with big data for work is fun. Engaging with big data for work is enjoyable. Engaging with big data for work is interesting.	Venkatesh, Thong & Xu, 2012 Alalwan, Dwivedi & Rana, 2017 Ain, Kaur & Waheed, 2016 Raman & Don, 2013
Habit	Engaging with big data for work has become a habit. Engaging with big data for work feels instinctive. Engaging with big data for work is part of the daily routine.	
Attitude	I support the utilization of big data. I embrace the changes brought about by utilizing big data. I actively contribute to the utilization of big data.	Lian, Yen, Wang, 2014 Zakk & Teguh, 2018
Business Performance	Leveraging big data has significantly enhanced information sharing. Big data utilization has streamlined work processes. The use of big data has expedited decision-making.	Sun, Cegielski, Jia & Hall, 2018 Venkatesh, Morris, Davis & Davis, 2003 Queiroz, Fosso Wamba, De Bourmont & Telles, 2021

The demographics of the participants are listed in Table 4 & Figure 5. Based on this data, we concluded that there is no problem in generalizing the results of this study.

When determining the results of the confirmatory factor analysis, the variables in the survey items are grouped by construct. If the eigenvalue is at least 1.0, and the sample size is more than 100, the significant factor value is 0.50 to 0.55. (Hair, Black & Babin, 2006)

The analysis was conducted using the Varimax method to prevent multicellularity between factor points. The results, as shown in Table 5, revealed that our selected factors have a load greater than 0.50. Hence, they were compatible with the criteria and had no problems with validity.

Table 4. Profiles of companies and respondents

	Frequency	**Percent (%)**
Gender of respondent		
Male	149	79.7
Female	38	20.3
Age of respondent		
30–40	65	34.8
40–50	93	49.7
Over 50	29	15.5
Title of respondent		
Assistant manager	28	15.0
Manager	71	38.0
General manager	75	40.0
Executive director	13	7.0
Type of Industry		
Manufacturing/engineering	56	29.9
Services and utilities	52	27.8
Transportation and logistics	37	19.8
Retailing and wholesale	42	22.5

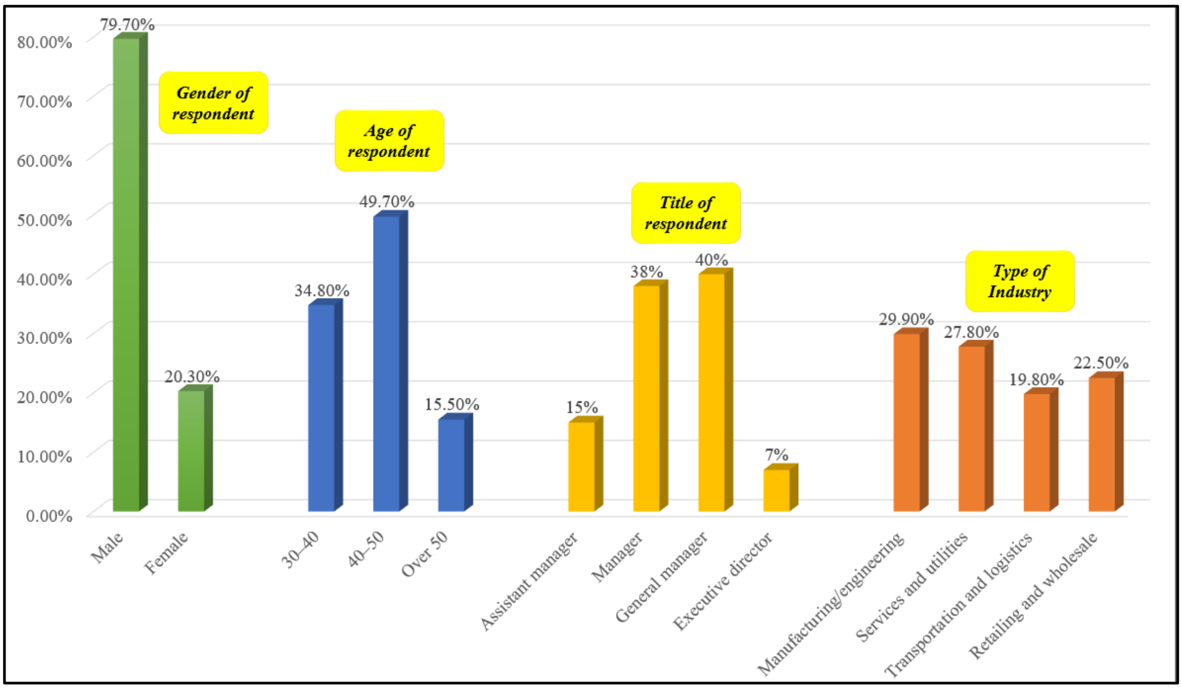

Fig 5: Sample Distribution

Table 5. Confirmatory factor analysis (each item was measured with a 5-point Likert type scale).

Item	SI	BP	AT	EE	HM	PE	HA	FC
PE1	.215	.065	.098	-.146	.188	.737	.123	.021
PE 2	.099	-.128	-.386	.372	.076	.821	.027	-.418
PE 3	.024	.129	-.044	.146	.197	.777	.128	.163
EE1	-.329	.012	-.138	.772	.194	.226	-.291	.170
EE2	-.066	.034	-.082	.823	.098	.045	.074	.259
EE 3	-.013	-.163	-.244	.819	.053	-.024	-.095	-.124
SI1	.721	.052	.056	.118	.043	.210	-.019	-.319
SI 2	.883	-.042	.129	-.193	.018	.089	.052	.073
SI 3	.892	-.018	-.078	-.099	.154	-.057	.076	.086
FC1	-.096	.039	.240	-.024	.439	.213	.165	.724
FC2	-.310	.194	.112	.319	.011	.406	-.242	.688
FC3	-.024	.059	-.072	.149	.066	.084	.149	.786
HM1	.040	-.122	-.092	-.073	.828	.231	.176	-.011
HM 2	.088	.026	.118	.253	.836	.115	.124	.027
HM 3	.156	.172	.270	.098	.714	.064	.075	.255
HA1	.005	.129	.057	.147	.125	.079	.832	.076
HA2	-.063	.141	.232	-.367	.270	.297	.782	.189
HA3	.198	.082	.310	-.224	.113	.018	.771	.057
AT1	.080	.161	.782	-.172	.066	.152	.245	-.114
AT2	-.046	.016	.753	-.084	.288	-.068	.121	-.076
AT3	.095	.097	.821	-.119	-.032	-.044	.087	.227
BP1	.059	.831	-.011	-.177	.094	-.023	.274	.117
BP2	.048	.929	.097	.036	.052	.048	-.029	.049
BP3	-.186	.864	.146	-.037	-.092	.182	.075	-.042

PE: performance expectancy; EE: effort expectancy; SI: social influence; FC: facilitating conditions;
HM : Hedonic Motivation ; HA : Habit ; AT : Attitude ; BP : Business Performance
The shaded numbers>=0.5 (factors loadings)

In addition, this study verified the research model using the second-order con-struct model to measure UTAUT2 organizational factors and individual factors. We used the structural equation path model to verify significance. Consequently, convergent and discriminant validities were implemented for the conformity assessment of the research model.

The construct reliability (CR) for each variable must be greater than 0.7 and the average variance extracted (AVE) must be higher than 0.5 for convergence validity. In Table 6, CR and AVE values are above the reference values of 0.70 and 0.50, respectively. Thus, convergent validity was proven. (Hair, Black & Babin, 2006)

Table 6. Results of convergent validity. CR, construct reliability; AVE, average variance extracted.

Constructs	AVE	CR	Cronbach α
Performance Expectancy	0.738	0.856	0.752
Effort Expectancy	0.728	0.839	0.733
Social Influence	0.741	0.857	0.762
Facilitating Conditions	0.814	0.917	0.814
Hedonic Motivation	0.797	0.904	0.788
Habit	0.751	0.853	0.812
Attitude	0.728	0.818	0.752
Business Performance	0.721	0.826	0.817

Discriminant validity measures if one construct is unrelated to another. We com-pare the correlation between each of the two constructs that is the subject of the discriminant validity assessment. In addition, we determine if the value of AVE is greater than the squared correlation coefficient. As shown in Table 7, the AVE value is greater than the squared correlation coefficient of all constructs. (Hair, Black & Babin, 2006) Therefore, discriminant validity is established. Furthermore, the absolute value of any relative number of all constructs shall not exceed the reference value of 0.85. Therefore, there is no problem of multicollinearity between constructs, and the constructs are discernible.

Table 7. Results of discriminant validity.

Construct	PE	EE	SI	FC	HM	HA	AT	BP
Performance Expectancy	0.859							
Effort Expectancy	0.332 **	0.853						
Social Influence	0.217 **	0.263 **	0.861					
Facilitating Conditions	0.293 **	0.278 **	0.268 **	0.902				

Hedonic Motivation	0.413 **	0.293 **	0.242 **	0.372 **	0.893			
Habit	0.239 **	0.262 **	0.234 **	0.295 **	0.242 **	0.867		
Attitude	0.226 **	0.343 **	0.266 **	0.266 **	0.277 **	0.326 **	0.853	
Business Performance	0.237 **	0.277 **	0.274 **	0.234 **	0.266 **	0.331 **	0.274 **	0.849

The shaded numbers in the diagonal row are square roots of the AVE * Significant at α = 0.05 ** Significant at α = 0.01

Additionally, variance inflation factor (VIF) and tolerance (TOL) methods were used to review the multicollinearity problem in Table 8. The results showed no multi-collinearity problems, as indicated by the VIF value of less than 10 and TOL of more than 0.3.

Table 8. Variance inflation factor (VIF) and tolerance (TOL).

	Tolerance	**VIF**		**Tolerance**	**VIF**
UTAUT2 Organizational Factors	0.723	1.351	Attitude	0.712	1.667
UTAUT2 Individual Factors	0.812	1.287	Dependent Variable: Business Performance		

We performed structural equation analysis using AMOS 24.0. The fit statistics were favorable except for TLIs, as shown in Table 9. As stated in the metrics, continuing the analysis under current conditions was thought to be sufficient. (Gallagher, Ting & Palmer, 2008)

Table 9. Fit statistics used to validate the measurement model.

Recommended Value		**Measurement Model**
Fit statistics	X^2/DF (≤3.000)	2.731
	GFI (≥0.900)	0.914
	RMSR (≤0.050)	0.047
	RMSEA (≤0.080)	0.072
	AGFI (≥0.800)	0.836
	CFI (≥0.900)	0.911
	TLI (≥0.900)	0.881
	PGFI (≥0.600)	0.618

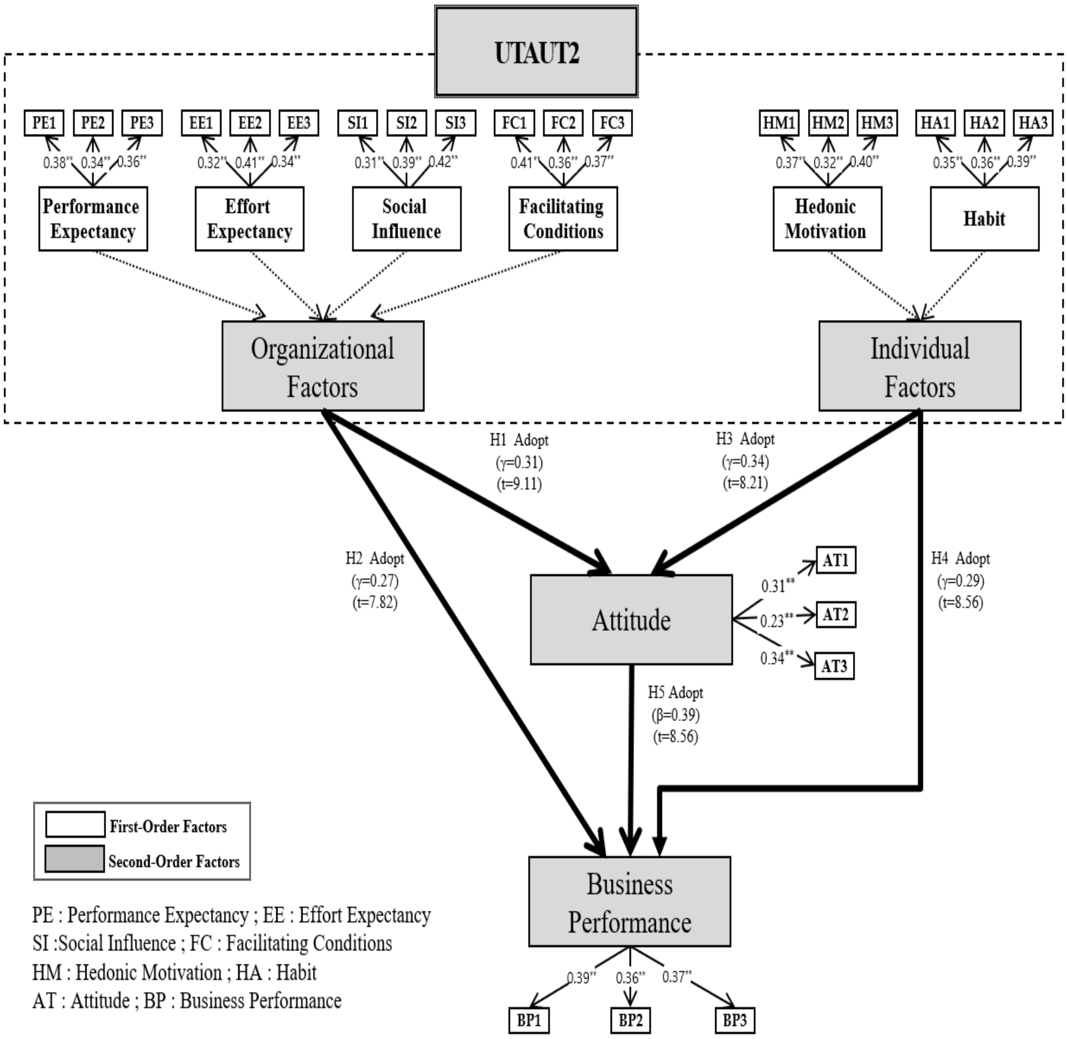

Fig 6: Results of hypothesis testing. Note: ** significant at 0.01

As shown in Figure 6, this study analyzed the UTAUT2 organizational factors from the perspective of performance expectancy, effort expectancy, social influence, and facilitating conditions after subcontracting these variables.

The hypothesis that UTAUT2 organizational factors would significantly influence attitude appeared significant (γ = 0.31, t = 9.11). UTAUT2 organizational factors also significantly impacted attitude in the first-order construct model verification for de-tailed model verification. In addition, the hypothesis 2 pathway that UTAUT2 organizational factors will have a significant effect on the business performance of big data was found to be significant (γ = 0.27, t = 7.82). In the first-order construct model verification, the UTAUT2 organizational factors significantly impacted business performance of big data, a dependent variable. These results are similar to the findings of studies (Queiroz, Fosso Wamba, De Bourmont & Telles, 2021; Zakk & Teguh, 2018) that emphasized the mutually beneficial relationship between factors based on the UTAUT2 organizational factors and IS behavioral intention of big data and the performance of big data. Therefore, UTAUT2 organizational factors have high explanatory power that positively affects dependent variables. We analyzed the UTAUT2 individual factors from the hedonic motivation and habit, using subconstructs, as shown in Figure 6.

The hypothesis that UTAUT2 individual factors will significantly impact attitude was significant (γ = 0.34, t = 8.21). In the first-order construct model verification for detailed authentication, UTAUT2 individual factors significantly impacted attitude. Furthermore, the hypothesis that UTAUT2 individual factors will significantly impact the business performance of big data was again significant (γ = 0.29, t = 8.56). In the first-order construct model verification, the UTAUT2 individual factors significantly impacted the business performance of big data. These findings are similar to studies (Tokkozhina, Martins & Ferreira, 2022; Lian, Yen, Wang, 2014) that claimed the mutually beneficial relationship between factors based on the UTAUT2 individual factors and IS attitude and business performance. Thus, UTAUT2 individual factors have significant effects on the practical performance of big data

Hypothesis 5, that the attitude will influence the business performance, was significant (β = 0.39, t = 8.56). The attitude has significantly impacted the business performance of big data in verifying the first-order construct model for detailed model verification. These findings are similar to many studies (Queiroz, Fosso Wamba, De Bourmont & Telles, 2021; Venkatesh, Morris, Davis & Davis, 2003) that presented a relationship between attitude and business performance. Thus, the attitude towards big data is a positive leading variable that leads to the business performance of big data.

The detailed effects are summarized in table 10 & figure 7.

Table 9. Coefficients of direct, indirect, and total effects

		Attitude	**Business Performance**
Organizational Factors	Direct Effect	0.31 **	0.27 **
	Indirect Effect	-	0.11 **
	Total Effect	0.31 **	0.38 **
Individual Factors	Direct Effect	0.34 **	0.29 **
	Indirect Effect	-	0.12 *
	Total Effect	0.34 **	0.41**
Attitude	Direct Effect		0.39 **
	Indirect Effect		-
	Total Effect		0.39 **

Note: * significant at α = 0.05; ** significant at α = 0.01.

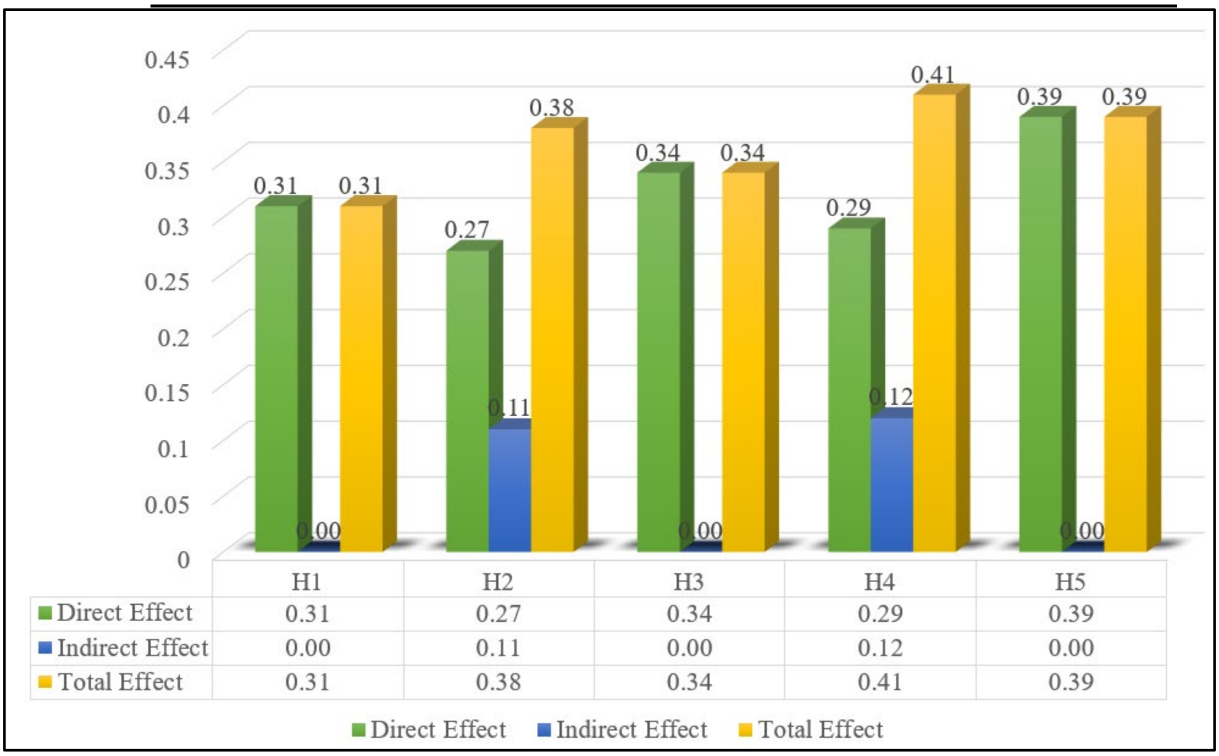

Fig 7: Testing Result

5. Discussion and Conclusion

This study identified big data factors based on the UTAUT2 organizational factors and individual factors and the impact of mutually beneficial causal relationships be-tween these factors on performance. To this end, we reviewed the definition, scope, level, and ad-vantages of big data in prior research. After examining the UTAUT2 organizational factors and individual factors, we designed the research model. The main study findings are as follows:

First, this study analyzed UTAUT2 organizational factors in big data from the perspective of performance expectancy, effort expectancy, social influence, and facilitating conditions. The UTAUT2 organizational factors significantly influenced the attitude and business performance of big data. In the first-order construct model verification, the UTAUT2 organizational factors significantly influenced the attitude and business performance of big data. These findings are similar to those of Queiroz, Fosso Wamba, De Bourmont & Telles (2021) and Zakk & Teguh (2018). Therefore, UTAUT2 organizational factors have a high explanatory power that positively affects dependent variables.

Second, this study analyzed UTAUT2 individual factors influencing big data from the perspective of hedonic motivation and habit. UTAUT2 individual factors significantly influenced the attitude and business performance of big data. In the first-order construct model verification for detailed authentication, the UTAUT2 individual fac-tors significantly impacted the attitude and business performance of big data. These findings are similar to those of Tokkozhina, Martins & Ferreira (2022) and Lian, Yen, Wang (2014). Thus, the attitude towards big data is a positive leading variable that leads to the business performance of big data.

Third, this study analyzed the relationship between the attitude and business performance of big data. In the first-order construct model verification for detailed authentication, the attitude significantly impacted business performance of big data. These findings are similar to those of Queiroz, Fosso Wamba, De Bourmont & Telles (2021) and Venkatesh, Morris, Davis & Davis (2003). Thus, the attitude is considered a positive leading variable influencing the business performance of big data.

5.1. Implications and Limitations

The academic and practical implications of this study are as follows.

First, in this study, the UTAUT2 model was employed to examine both organizational and individual aspects as the original UTAUT model lacked consideration for individual variables. The UTAUT2 model was modified to construct a new model for empirical analysis. This novel model holds promise for future research endeavors.

Second, this study offers useful data for the expansion strategy and theoretical re-search of big data techniques. The impact of rapid environmental change, as reflected by the management trends of the recent Fourth Industrial Revolution, and the pre-dominant use of big data by market competitors is emphasized. In addition, big data technology is socially and economically necessary. Thus, the research could provide valuable data for theoretical research, including government and corporate expansion strategies and developing big data-related technology adoption models.

Third, while many companies have recognized the need to introduce big data, it has not yet been widely adopted. In the rapidly changing managerial environment of the Fourth Industrial Revolution, companies are critically aware of the need to lever-age big data.

Despite its positive contributions from academic and practical perspectives, this study has some limitations regarding research content and methodology.

First, the analysis reveals UTAUT2 organizational and individual factors positively influence big data adoption intentions and performance improvement in Korean companies. However, generalizability remains limited owing to the cross-sectional research design. Future studies conducted longitudinally across more heterogeneous industry samples can better substantiate the findings. Practically, the research provides useful cues for managers to promote data driven decision making by emphasizing usefulness, building collective data oriented culture and capabilities. But real-world challenges persist regarding mitigating data privacy risks and overdependence.

Second, in this study, we conducted a survey, but the sample was insufficient, limiting the generalizability of the study. We surveyed 187 companies, which was sufficient to obtain results but did not obtain adequate industry-specific samples. Future studies need to be conducted using a larger sample.

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