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IMPROVING KNOWLEDGE MANAGEMENT PROCESS USING BIM IN INDONESIAN STATE-OWNED CONSTRUCTION ENTERPRISES

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ABSTRACT

In today's digital era 4.0, the synergy between the construction industry and information technology is inevitable. Knowledge management plays a critical role in the success of construction companies, enabling them to effectively capture, store, share, and utilize valuable information and expertise. In recent years, Building Information Modeling (BIM) has emerged as a powerful tool that improves knowledge management in the construction industry. This article focuses on implementing BIM in Indonesian state-owned construction companies and how it can improve knowledge management, leading to better project outcomes, efficiency, and competitiveness. BIM-based Knowledge Management (KM) systems can capture, store, and disseminate knowledge to manage facilities through their life cycle. To describe in this study first identified from a literature review how BIM can facilitate improved knowledge management in construction projects. Second, a questionnaire survey of respondents of State Owned Construction Enterprises with ISO 1960 BIM in Indonesia will be further analyzed using a quantitative SEM-PLS analysis to determine the KM types that can be leveled using BIM. The variables used in this study are BIM implementation on KM, processes, effectiveness, and barriers to knowledge management. The results of this study show that BIM performance positively affects KM process improvement, KM effectiveness, and KM obstacle alleviation.

Keywords: BIM; Knowledge management; PLS-SEM

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1. INTRODUCTION

Some governments have encouraged the use of Building Information Modeling (BIM) in their countries with commitments embodied in regulations and BIM application regulatory agencies. Researchers at BIM are also encouraged to design new practices and tools to develop industry stakeholders' capabilities to understand and take full advantage of these new technologies. Thus, impact and research on these technologies can contribute to further knowledge in relevant countries, industries, and organizations for continuous improvement. BIM can be seen as an innovation that enables organizations to remain competitive. The ability of BIM to reuse information at subsequent stages of a project is emphasized by (Park et al., 2013). According to Kresnanto et al. (2023), the obstacles must be reduced if you want to expand BIM implementation, mainly financial, policy, and technological barriers. A BIM-based Knowledge Management (KM) system may thus collect, store, and share knowledge to manage a facility throughout its life cycle.

In earlier research, BIM-based KM explored the potential capabilities of BIM to facilitate KM in construction projects, including proactive KM, KM throughout the project life cycle, and BIM-based KM processes and looked at various KM aspects that could be improved through the use of BIM with quantitative survey methods Therefore, academics want to talk about how KM-based BIM is implemented, how effective KM is, and what obstacles there are to KM in Indonesian construction.

This paper aims to have four sections. The first section talks about the literature on BIM-based knowledge management. The second section covers research techniques before moving on to the PLS model and hypotheses. The third section contains the findings from the analysis and discussion, and the fourth section contains the conclusions and recommendations. The research aims to improve knowledge management processes using BIM in Indonesian state-owned construction companies by Exploring the Benefits of BIM for Knowledge Management: Examining the potential benefits of utilizing BIM for knowledge management processes in the construction industry.

Several earlier studies on BIM-based knowledge management (KM) have concentrated on using BIM to simplify knowledge capture, storage, sharing, and reuse; most of them have created the BIM-based KM system based on a web-based tool. For the construction phase, Park et al. (2013) combined BIM, augmented reality, and ontology techniques to help collect and retrieve defect information and knowledge and an AR-based inspection system to enable proactive field defect management. They served to speed up the knowledge exchange process while construction was taking place. A knowledge-based BIM system was created specifically for the maintenance phase that aids in blem-solving by drawing on prior experiences. Table 1 provides a summary of previous research.

Table 1. Literature review journal BIM base Knowledge Management

Phases of project	References	Focus on the KM aspect	Influenced variables
Design dan Construction	(Fruchter et al., 2009)	Knowledge capture, storage	Lifecycle KM
Design dan Construction	(Ho et al., 2013)	Knowledge capture, storage, reuse	KM Proaktif, KM proses, Barriers KM
Design dan Construction	(L. Wang & Leite, 2015)	Knowledge capture	
Design	Meadati dan Irizarry (2010) ; Froese, 2010	Knowledge capture, storage, representation, reuse	Lifecycle KM, Barriers KM
Facility management	(Zhang et al., 2021); (Chen et al., 2018)	Knowledge, capture, representation, sharing	Lifecycle KM, KM Effectiveness
Construction	(Deshpande et al., 2014)	Knowledge storage	KM Effectiveness
Construction	(Ganiyu et al., 2018); (Ferrara & Marques, 2019)	Knowledge storage, sharing	KM Effectiveness
Design	(Jung et al., 2018)	Knowledge sharing	Lifecycle KM
Design	(Aksamija et al., 2010)	Knowledge sharing	
Design dan Construction	Park et al. (2013a).	Knowledge sharing, storage, reuse	KM Proaktif, Barriers KM
Design	(Hossain et al., 2018)	Knowledge sharing	
Construction	(Al Sehrawy & Amoudi, 2020)	Knowledge capture	KM Effectiveness
Construction	(Zhong et al., 2017)	Knowledge sharing	

Phases of project	References	Focus on the KM aspect	Influenced variables
Construction	(Wang & Meng, 2018)	Knowledge sharing	
Design	(Luck, 2007); (Meng, 2013)	Knowledge capture	Proaktif KM
Construction	(Eadie et al., 2013)	Knowledge capture	Lifecycle KM
Construction	Vanlande et al., 2008	Knowledge sharing	Lifecycle KM
Throughout the project life cycle	(Vladim\'\ir N\`yvlt, 2018); (Pruskova, 2018)	Knowledge sharing	Lifecycle KM
Throughout the project life cycle	(Wu, 2013); (Wang & Meng, 2019)	Knowledge storage, Knowledge sharing	Lifecycle KM
Construction	(Wang et al., 2022)	Knowledge reuse, capture	KM proses
Design	(Barlish & Sullivan, 2012);	Knowledge reuse	KM proses
Throughout the project life cycle	(Ozturk & Yitmen, 2019); (Wang & Meng, 2021); (Ganiyu & Egbu, 2018)	Knowledge reuse, sharing, capture, storage	KM Effectiveness
Construction	(Grover & Froese, 2016); (N\`yvlt, 2018)	Knowledge sharing	KM Effectiveness
Construction	(Oti et al., 2018)	Knowledge storage	KM Effectiveness
Design	Hossain, Md Aslam, et al 2018	Knowledge storage	KM Effectiveness
Throughout the project life cycle	(Hu et al., 2021)	Knowledge Extraction, capture	KM Effectiveness
Throughout the project life cycle	(Neff et al., 2010); (Hamid et al., 2018); (Mandičák et al., 2020)	Knowledge sharing, representation	Barriers KM, KM Effectiveness

Source: Data compiled from Artikel journal BIM base Knowledge Management, 2001-2019

2. METHODS

2.1 Research methods

A literature review and questionnaire survey were the research methodology used. First, it provides an up-to-date overview of knowledge management (KM) studies in construction and BIM-supported KM in a building by reviewing many pertinent articles. Additionally, the literature assessment highlights the necessity for empirical BIM-based KM research, particularly in Indonesia's construction sector. The core methodology is a quantitative questionnaire survey, which follows. Partial Least Square (PLS), with the aid of SmartPLS 3.0 software, is the data processing technique used. Partial Least Squares (PLS) is a powerful analytical method because it can be applied to all data scales, does not require many assumptions, and confirms relationships that do not have a robust theoretical basis. PLS has 2 (two) model specifications, namely the inner and outer models. The inner model is a model that describes the relationship between the latent variables to be evaluated. In contrast, the outer model, known as the measurement model, is a model that describes the relationship between indicators and latent variables. The outer model is also one of the essential parts of PLS processing because the hypothesized relationship that occurs in the inner model depends on the validity and reliability of the router model. This study's analysis of the evaluation model uses the Partial Least Squares (PLS) program. There are stages in conducting this analysis, namely:

- Evaluation of the measurement model (outer model) consists of:
  - The indicator Validity Test has two parts: convergent validity to see the value of the loading factor for each construct, where the recommended loading factor value must be greater than

0.7 for confirmatory research; values above 0.5 are still acceptable. In contrast, the value above is still acceptable. Therefore, below 0.5 must be excluded from the model, and the average variance extracted (AVE) value must be greater than 0.5. Then proceed with discriminant validity to see that the cross-loading value for each variable must be > 0.7.

  - The indicator Reliability Test was conducted to prove the instrument's accuracy and consistency in measuring the construct. The reliability test of a construct with reflexive indicators can be done in two ways, namely composite reliability, and Cronbach's Alpha.
- Evaluation of the structural model (inner model) consists of:
  - Testing the Effect Size (f2) value, used to measure the contribution between each variable to the formation of R^2 by looking at the f^2 values, namely 0.02, 0.15, and 0.35, which indicates that the model is weak, moderate, and strong.
  - Testing Prediction Relevance (Q2), measuring how well the model generates the observed values and also the estimated parameters. A value of Q2> 0 indicates that the model has predictive relevance, but the value of Q2 < 0 indicates that the model lacks predictive relevance.
- Hypothesis Testing Model, using statistical values, then for alpha 5%, the t-statistic value used is 1.96 through bootstrapping. The criteria for acceptance/rejection of the hypothesis are:
  - If Sig > 0,05 and t count < t table, then H0 is accepted, or H1 is rejected.
  - If Sig < 0,05 and t count > t table, then H0 is rejected or H1 is accepted.

The sample size for the PLS statistical method is as much as ten times the number of the most significant structural pathways directed at a particular construction in a structural model. Due to the PLS model for the effect of BIM on KM in this study, the number of respondents is expected to be 114 samples. Then there is one independent variable of BIM implementation and three dependent variables in knowledge management.

2.2 Analysis Of Questionnaire Responses

Determining the number of potential respondents for this research survey is still tricky because BIM in Indonesia still needs to be adapted after writing letters to eight BUMN contractors with ISO 19650 and searching the business-oriented social network website LinkedIn. Finally, the questionnaire was completed by 114 respondents. Among the respondents were 42 BIM Engineers/BIM officers, 6 BIM Modelers, 8 BIM Coordinators, 3 BIM Junior Experts, 4 BIM Managers, and 51 Site Engineers/Engineer projects. The number f responses met the sample size requirements. The overall response rate is 100%. BIM Engineer/BIM officer, BIM Modeler, BIM Coordinator, BIM Junior Expert, BIM Manager, and Site Engineer/Engineer project are 37%, 5%, 7%, 3%, 4%, and 45%. According to the responses collected, there was a significant trend in the three public sectors, transportation, and others, namely 34 (30%) respondents, 25 (25%) respondents, and 27 (22%) respondents. This is possible because one company can have more than one type of construction service sector. Furthermore, this suggests that BIM is more widely used for public projects, especially government projects. This is following the PUPR ministry's directives which encourage the use of BIM.

3. RESULTS AND DISCUSSION

3.1 Instrument Validity Test

Testing the validity of the respondents as many as 114 respondents. In this test, the correlation coefficient was obtained from the distribution table r using a significance of 5% with a value of N=114, then df=N-2 (114-2)=112 with a two-way test significance distribution then r-table 0.184. The significance test is done by comparing the r-count with the r-table, which can be seen in Table 2

Table 2. Questionnaire Instrument Validity Test Results

Variable	Indicator	R -count	R - table 5%	Information
BIM Implementation	X.1-1	0.905	0.184	Good
	X.1-2	0.881	0.184	Good
	X.1-3	0.931	0.184	Good
	X.1-4	0.921	0.184	Good
	X.2-1	0.782	0.184	Good
	X.2-2	0.896	0.184	Good
	X.2-3	0.898	0.184	Good
	X.2-4	0.908	0.184	Good
	X.2-5	0.881	0.184	Good
	X.3-1	0.872	0.184	Good
	X.3-2	0.822	0.184	Good
	X.3-3	0.91	0.184	Good
	X.3-4	0.913	0.184	Good
	X.3-5	0.895	0.184	Good
	X.3-6	0.832	0.184	Good
	X.3-7	0.913	0.184	Good
	X.3-8	0.924	0.184	Good
	X.3-9	0.919	0.184	Good
Knowledge Management Process	Y.1-1-1	0.911	0.184	Good
	Y.1-1-2	0.926	0.184	Good
	Y.1-1-3	0.932	0.184	Good
	Y.1-1-4	0.935	0.184	Good
	Y.1-1-5	0.951	0.184	Good
	Y.1-2-1	0.894	0.184	Good
	Y.1-2-2	0.911	0.184	Good
	Y.1-2-3	0.846	0.184	Good
	Y.1-2-4	0.908	0.184	Good
	Y.1-2-5	0.911	0.184	Good
	Y.1-2-6	0.88	0.184	Good
	Y.1-2-7	0.877	0.184	Good
	Y.1-3-1	0.913	0.184	Good
	Y.1-3-2	0.933	0.184	Good
	Y.1-3-3	0.853	0.184	Good
Effectiveness of Knowledge Management	Y.2-1	0.886	0.184	Good
	Y.2-2	0.935	0.184	Good
	Y.2-3	0.884	0.184	Good
	Y.2-4	0.916	0.184	Good
	Y.2-5	0.928	0.184	Good
	Y.2-6	0.94	0.184	Good
	Y.2-7	0.926	0.184	Good

Variable	Indicator	R -count	R - table 5%	Information
	Y.2-8	0.856	0.184	Good
	Y.2-9	0.94	0.184	Good
	Y.2-10	0.913	0.184	Good
	Y.2-11	0.92	0.184	Good
	Y.2-12	0.948	0.184	Good
	Y.2-13	0.912	0.184	Good
	Y.2-14	0.952	0.184	Good
	Y.2-15	0.894	0.184	Good
	Y.2-16	0.906	0.184	Good
	Y.2-17	0.928	0.184	Good
Knowledge Management Barriers	Y.3-1	0.924	0.184	Good
	Y.3-2	0.947	0.184	Good
	Y.3-3	0.914	0.184	Good
	Y.3-4	0.922	0.184	Good
	Y.3-5	0.942	0.184	Good
	Y.3-6	0.837	0.184	Good
	Y.3-7	0.915	0.184	Good
	Y.3-8	0.939	0.184	Good
	Y.3-9	0.944	0.184	Good
	Y.3-10	0.941	0.184	Good
	Y.3-11	0.937	0.184	Good
	Y.3-12	0.936	0.184	Good
	Y.3-13	0.929	0.184	Good
	Y.3-14	0.947	0.184	Good
	Y.3-15	0.945	0.184	Good

Source: results of the author's analysis, 2022

Table 2 shows that the r-count value is more significant than r-table = 0.184, then the instrument question items are declared valid and can be used for further analysis.

3.2 Validity test with convergent validity

Convergent validity aims to assess the reliability of each association between indicators and latent variables or constructs. Based on the findings of the concurrent validity test with outer loadings in Table 3 and values for Average Variance Extracted (AVE) in Table 4, this study used a limited loading factor of 0.7.

Table 3. Test results Convergent Validity with Outer Loadings

Indikator	Loading		Evaluation
X.1-1	0.904	> 0.70	Good
X.1-2	0.88	> 0.70	Good
X.1-3	0.932	> 0.70	Good
X.1-4	0.922	> 0.70	Good
X.2-1	0.778	> 0.70	Good

Indikator	**Loading**		**Evaluation**
X.2-2	0.895	> 0.70	Good
X.2-3	0.899	> 0.70	Good
X.2-4	0.91	> 0.70	Good
X.2-5	0.88	> 0.70	Good
X.3-1	0.872	> 0.70	Good
X.3-2	0.82	> 0.70	Good
X.3-3	0.911	> 0.70	Good
X.3-4	0.913	> 0.70	Good
X.3-5	0.893	> 0.70	Good
X.3-6	0.831	> 0.70	Good
X.3-7	0.914	> 0.70	Good
X.3-8	0.926	> 0.70	Good
X.3-9	0.921	> 0.70	Good
Y.1-1-1	0.911	> 0.70	Good
Y.1-1-2	0.925	> 0.70	Good
Y.1-1-3	0.931	> 0.70	Good
Y.1-1-4	0.934	> 0.70	Good
Y.1-1-5	0.951	> 0.70	Good
Y.1-2-1	0.893	> 0.70	Good
Y.1-2-2	0.91	> 0.70	Good
Y.1-2-3	0.847	> 0.70	Good
Y.1-2-4	0.908	> 0.70	Good
Y.1-2-5	0.91	> 0.70	Good
Y.1-2-6	0.881	> 0.70	Good
Y.1-2-7	0.876	> 0.70	Good
Y.1-3-1	0.914	> 0.70	Good
Y.1-3-2	0.934	> 0.70	Good
Y.1-3-3	0.855	> 0.70	Good
Y.2-1	0.887	> 0.70	Good
Y.2-10	0.913	> 0.70	Good
Y.2-11	0.919	> 0.70	Good
Y.2-12	0.948	> 0.70	Good
Y.2-13	0.911	> 0.70	Good
Y.2-14	0.952	> 0.70	Good
Y.2-15	0.895	> 0.70	Good
Y.2-16	0.905	> 0.70	Good
Y.2-17	0.929	> 0.70	Good
Y.2-2	0.935	> 0.70	Good
Y.2-3	0.884	> 0.70	Good
Y.2-4	0.917	> 0.70	Good
Y.2-5	0.928	> 0.70	Good

Indikator	Loading		Evaluation
Y.2-6	0.939	> 0.70	Good
Y.2-7	0.926	> 0.70	Good
Y.2-8	0.855	> 0.70	Good
Y.2-9	0.94	> 0.70	Good
Y.3-1	0.924	> 0.70	Good
Y.3-2	0.948	> 0.70	Good
Y.3-3	0.914	> 0.70	Good
Y.3-4	0.923	> 0.70	Good
Y.3-5	0.942	> 0.70	Good
Y.3-6	0.838	> 0.70	Good
Y.3-7	0.914	> 0.70	Good
Y.3-8	0.939	> 0.70	Good
Y.3-9	0.944	> 0.70	Good
Y.3-10	0.942	> 0.70	Good
Y.3-11	0.937	> 0.70	Good
Y.3-12	0.936	> 0.70	Good
Y.3-13	0.929	> 0.70	Good
Y.3-14	0.947	> 0.70	Good
Y.3-15	0.945	> 0.70	Good

Source: results of the author's analysis, 2022.

Based on the table above, it can be known that the loading factor value that has more than 0.7 can be concluded to be valid or meet convergent validity

Table 4. Test results from Convergent Validity with Average Variance Extracted (AVE)

Variable	(AVE)		Information
X	0.902	>0.05	Good
Y1	0.920	>0.05	Good
Y2	0.911	>0.05	Good
Y3	0.925	>0.05	Good

Source: results of the author's analysis, 2022

Based on the table above, it is found that all variables meet the convergent validity criteria by having an AVE value above 0.5

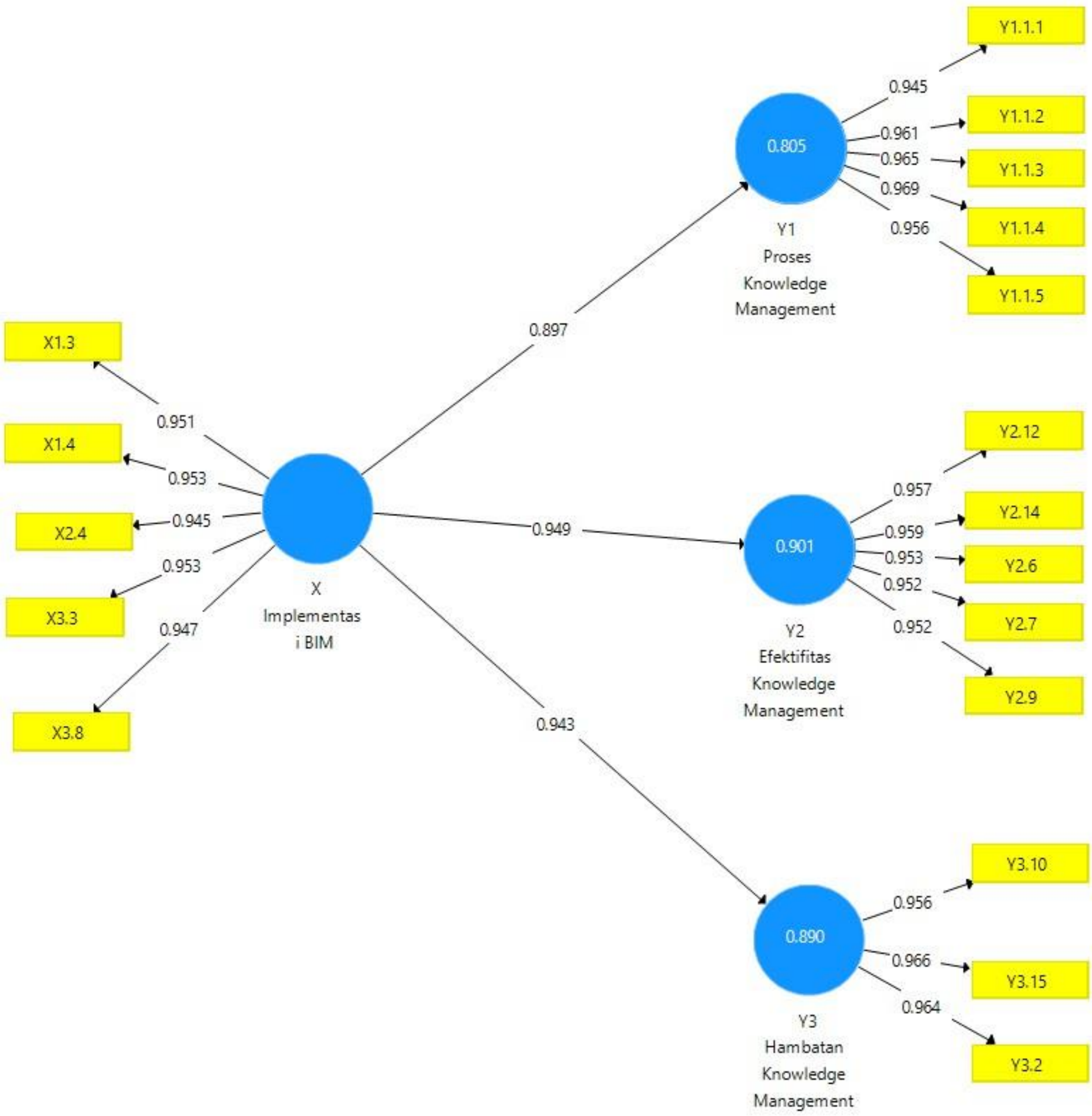

Figure 2. SmartPLS output after elimination running

Source explanation: The figure presented in Figure 2 is based on the results of SmartPLS with Discriminant Validity (Fornell-Larker Criterion) to obtain a construct AVE root value more significant than the correlation value between constructs after indicator elimination and recalculation.

Table 5. Results of discriminant validity test with Fornell larcker criterion after elimination

	X	Y1	Y2	Y3
X	**0.950**			
Y1	0.897	**0.959**		
Y2	0.949	0.899	**0.954**	
Y3	0.943	0.928	0.952	**0.962**

Source: results of the author's analysis, 2022.

Table 5 and Figure 2 show that the construct's AVE root value is greater than the correlation value between constructs after assessment or elimination of the indicator and has a small outer loading value. Thus, it is considered that the turbidity of exogenous and endogenous latent variables has met good discriminant validity.

3.3 Inner model test with R-Square

R-Square is a value that shows how much the exogenous variable affects the endogenous variable. The results of the inner model test with r-square can be seen in Table 6

Table 6. Test the inner model with R-Square

Variable	*R-Square*	Information
Y1 _Knowledge Management Process	0.805	Strong
Y2 _Effectiveness of Knowledge Management	0.901	Strong
Y3_Knowledge Management Barriers	0.89	Strong

Source: results of the author's analysis, 2022.

According to the above table, the variable Implementation of Building Information Modeling (BIM) (X) influences the strength of the endogenous variable by 80.5 percent Knowledge Management Process (Y1), 90.1 percent Knowledge Management Effectiveness (Y2), and 89 percent Barriers to Knowledge Management (Y3). The remaining influences may come from exogenous variables not part of the research model.

3.4 Hypothesis testing

Table 7. Hypothesis test from Path Coefficient

Hypothesis	Original Sample (O)	T Statistics	P Values	Information
X-> Y1	0.897	35.694	0.000	Accepted
X-> Y2	0.949	73.815	0.000	Accepted
X-> Y3	0.943	70.821	0.000	Accepted

Source: results of the author's analysis, 2022.

The results of statistical analysis utilizing the sample's bootstrapping approach are shown in Table 7. This study's crucial T value is 1.96. The threshold or standard at which the importance of the coefficient is established is known as the essential T value. The null hypothesis is rejected if the empirical T value exceeds the critical T value. For the significance levels of 1%, 5%, and 10%, respectively, typical essential values of t are 2.57, 1.96, and 1.65 (two-tailed test). The following are the outcomes of testing using bootstrapping from the PLS analysis:

- **H1: Implementation Building Information Modeling significantly affects the process of Knowledge Management.**

  The table above shows the significant relationship between Implementing Building Information Modeling and the Knowledge Management process, with a T-statistic of 35,694 > 1.96. then H0 is rejected H1 is accepted, meaning that the Implementation of Building Information Modeling substantially affects the Knowledge Management process. Original sample values included coefficients path. The positive one is 0.897, which shows a positive relationship that the greater the implementation of building information modeling will improve the process knowledge management.

- **H2: Implementation Building Information Modeling significant effect on effectiveness Knowledge Management.**
  The table above shows that the relationship between Implementation Building Information Modeling on effectiveness Knowledge Management is significant with a T- statistic of 73,815 > 1.96. then H0 is rejected H1 is accepted, meaning that the Implementation of Building Information Modeling significantly affects the effectiveness of Knowledge Management. Original sample values included coefficients path. The positive one is 0.949, which shows a positive relationship that the greater the implementation of building information modeling will increase the effectiveness of knowledge management.
- **H3: Implementation Building Information Modeling significantly affects overcoming obstacles in Knowledge Management.**
  The table above shows that the relationship between Implementation Building Information Modeling on effectiveness Knowledge Management is significant with a T- statistic of 70,821 > 1.96. then H0 is rejected H1 is accepted, meaning that the Implementation of Building Information Modeling significantly affects overcoming obstacles in Knowledge Management. Original sample values included coefficients path. The positive one is 0.943, which shows a positive relationship that the greater the implementation of building information modeling will help overcome obstacles to knowledge management better. Researchers have proven that the performance of building information modeling on knowledge capture, knowledge storage, and knowledge sharing has a positive effect on the process of knowledge management, the effectiveness of knowledge management, overcome obstacles in knowledge management which are also supported statistically. From the results above, overcoming obstacles in knowledge management is the most influential factor in implementing building information modeling.

4. CONCLUSION

According to the results and findings of knowledge management processes that can be improved using BIM, knowledge creation, Knowledge Sharing and Collaboration, knowledge capture, and Decision Support. As evidenced by the results of the analysis of process variables with the following indicators: Data saved in BIM can assist project teams in developing knowledge that can be used proactively to avoid mistakes (Y1.1.4), BIM data storage helps organizations to acquire and build understanding that might lessen disagreement in decision-making (Y1.1.3), The knowledge that can be created and reused by businesses thanks to information saved in BIM might help them avoid making the same mistakes over. (Y1.1.2), BIM enables firms to efficiently support decision-making by utilizing crucial information and expertise (Y1.1.5). Building knowledge that may proactively ensure the satisfaction of client needs can be done using the information in BIM. (Y1.1.1).

Based on a literature review and survey results analysis, this study offers factual proof that BIM may be utilized to enhance knowledge management processes in building projects. It has been determined that some BIM features, like BIM decision-making databases and BIM platforms that proactively interact with knowledge management, have the potential to enhance knowledge management in building projects.

Although this study benefits BIM-based KM, particularly in Indonesia, this study examines the possible use of BIM to support KM in construction projects, including capturing, storing, and disseminating BIM-based knowledge. It is based on quantitative survey research methodologies and uses the SEM-PLS analytic approach. BIM's potential to support other KM can be further investigated.

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