# Digital Transformation Analysis in the Manufacturing Module in Aluminium Companies Using the TAM Method

Arif Saifunnasrullah [1,*], Kholiq Budiman [1]

[1] Department of Computer Science, Faculty of Mathematics and Natural Sciences, Universitas Negeri Semarang, Indonesia
*Corresponding author: pupunn@students.unnes.ac.id

ARTICLE INFO

**Article history**
Received 23 March 2023
Revised 31 March 2023
Accepted 1 April 2023

**Keywords**
Digital Transformation
Technology Acceptance Model (TAM)
Manufacturing Module
ERP System

ABSTRACT

This research was conducted to identify the factors affecting the success of digital transformation using the manufacturing module in aluminium companies. The Technology Acceptance Model (TAM) method was used to measure technology acceptance using the manufacturing module with variables of perceived usefulness (PU), perceived ease of use (PEOU), and perceived risk (PR) that affect the behavioural intention of use (BIU) at PT Allure Allumunio and the success of digital transformation are measured through descriptive analysis. The sample was taken using the entire population with a total of 50 manufacturing module users. The collected data was analyzed using Partial Least Square – Structural Equation Modelling (PLS-SEM) with SmartPLS 4.0.8 software. A total of 48 respondents with valid data were obtained, and validity and reliability tests were performed, resulting in valid and reliable instruments. The R-square, Q-square, and t-test were used to analyze the proposed hypothesis. The results showed that three hypotheses were accepted: PU > BIU, PEOU > BIU, and PEOU > PU, and one hypothesis was rejected: PR > BIU, because risk did not have a significant impact on the behaviour intention of technology acceptance. Additionally, the analysis of digital transformation success showed an increase in company productivity and a decrease in risk, marked by an increase in units received on time after digital transformation and a 78% level of adaptation satisfaction. The conclusion is that technology acceptance was achieved through perceived usefulness and perceived ease of use, as well as increased productivity, level of adaptation satisfaction, and decreased risk, which are factors contributing to the success of the digital transformation.



## 1 Introduction

The arrival of digital transformation has changed how people perform their jobs and make their lives easier due to technological progress. This change affects individuals and companies looking to excel in a competitive environment (Sudjiman & Sudjiman, 2018). By changing their management and using more modern technology, companies can increase their operational efficiency and employee performance, thereby boosting the company's value (Rivandi, 2018). This increased value, supported by digital transformation, can drive business growth and competitiveness. Business development must align with current technology advancements and digital transformation. Companies must adopt and integrate the latest technology into their business to stay competitive. According to (Dityawarman et al., 2016), adopting advanced technology and digital transformation is crucial for companies to adapt to the changing and competitive business environment.

According to (Cheng, 2018), companies commonly use ERP to support all organizational activities. It helps manage resources, share information across departments, and integrate complex business processes to increase business efficiency and effectiveness (Nandi & Kumar, 2016). ERP benefits companies by simplifying business processes, improving data management and productivity, and supporting competitiveness in the rapidly advancing technology era (Das & Dayal, 2016). However, the cost of adoption should be considered carefully before implementing ERP.

PT Allure Allumunio, an aluminium company in Indonesia, recently adopted ERP to improve productivity. The manufacturing module was migrated to Kedaireka cloud ERP for faster data recording. The transition from manual to digital processes caused new challenges, such as user adaptation and a complicated user interface which may slow down production and lower user satisfaction. According to (Alraja & Aref, 2015), risks such as data misuse, failure to achieve transformation benefits, and functional inefficiencies also exist with ERP migration. However, ERP in the manufacturing module can provide long-term benefits if these risks are minimized through risk analysis.

The research analyses the impact of using the manufacturing module in ERP systems on the success of digital transformation through productivity, user adoption, and risk levels. The results show the effectiveness of using the manufacturing module in ERP systems, leading to better work systems, increased productivity, and efficient work completion with low risk and ease of use. The study uses cost-benefit analysis (CBA) and Technology Acceptance Model (TAM) to measure the performance before and after digitalization, user satisfaction, and risk levels. Productivity, user adoption, and risk levels are indicators of the success of the digital transformation.

TAM is a suitable model for predicting individuals' interests and desires toward technology (Alfadda & Mahdi, 2021). Using a cost-benefit analysis, two main factors are adopted from the benefit perspective: perceived usefulness and perceived ease of use. Perceived ease of use refers to an individual's belief that using the system will increase their intention to use the manufacturing module. In contrast, perceived usefulness refers to the belief that the system is easy to use. Perceived risk, which is the perception of problems that could hinder the ERP information system production process, is taken as a cost. The risk is seen as a factor that can negatively affect the use of the manufacturing module and cause losses in time, productivity, and costs. Studies by (Chang & Hsu, 2019; Ha, 2020; Kamal et al., 2020) have applied cost-benefit analysis to TAM, with benefits measured through perceived usefulness and perceived ease of use and cost from perceived risk.

## 2 The Proposed Method

### 2.1 Digital Transformation

According to (Danuri, 2019), digital transformation is a process of change in performing tasks with the help of information technology to make work more effective and efficient. Digital transformation is vital for all companies in various industries that rely heavily on information systems, industrial strategies, and human resources. Digital transformation focuses on creating value from business processes and delivering it to users using data and analytics in the process to create new and innovative experiences.

Tangi et al. (2021) state that digital transformation has transformed the public sector by influencing how information systems work through processes, culture, organizational structure, and the roles and responsibilities of public employees. Digital transformation is also a change (or adjustment) in the business model resulting from rapid technological advances and innovation that leads to consumer and social behaviour changes. Therefore, Rogers (2016) in Linggadjaya et al. (2022) convey that productivity, adaptability, and risk can influence behavioural change before and after applying the digital transformation.

### 2.2 Enterprise Resource Planning (ERP)

ERP is a computer application that integrates information systems to handle important processes in a company, such as finance, production, marketing, and human resource management. The use of ERP was expected to have a positive effect on employee performance and increase productivity (Agustina, 2018). (Hanum et al., 2020) identify several factors used to evaluate ERP user performance, including work quality, work quantity, job knowledge, creativeness, dependability, initiative, and personal qualities. The research discussed in this paragraph focuses on the manufacturing module of the ERP system, as it is the main business process in the company.

### 2.3 Manufacturing Process

The term "manufacturing" comes from the latin words *manus* (hand) and *factus* (made), which means "made by hand" (Groover, 2020). Manufacturing involves converting a design into a finished product through various processes according to the agreed-upon design, selection of materials, manufacturing, quality assurance, management, and marketing of manufactured industrial products. The process of converting raw materials into a product consists of product design, material selection, and manufacturing process steps (Supriyanto, 2020). Today, manufacturing has transformed into a process that requires the production of goods from raw materials using various procedures, machines, and operations that are well-organized for each action (Supriyanto, 2020). This process produces objects that can support and assist in other manufacturing processes, such as machines for producing various items such as cars, painted objects, clothing, etc.

### 2.4 Technology Acceptance Model (TAM)

TAM is a significant theory in technology adoption that explains how individuals accept and use technology. It was introduced by Fred D. Davis in 1989 as an adaptation of the Technology of Reasoned Action (TRA). According to Davis (1989) on Alfadda & Mahdi (2021), the main purpose of TAM is to describe the most important factors that affect user acceptance of technology. It considers belief, attitude, intention, and user behaviour as key elements in explaining user acceptance. TAM aims to help users determine how external factors influence their beliefs, attitudes, and intentions toward technology (Ambodo et al., 2018).

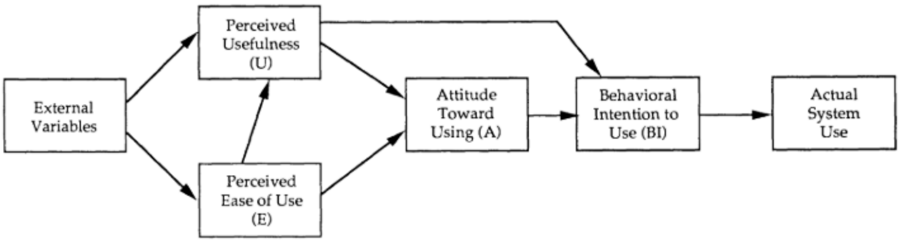


**Figure 1.** Technology acceptance model framework (Davis, 1989)

The TAM framework, as shown in Figure 1, includes five essential elements that help explain why people embrace new technology systems: perceived usefulness (PU), perceived ease of use (PEOU), attitude toward using (ATU), the behavioural intention of use (BIU), and actual system usage (AU). According to Alfadda & Mahdi (2021), perceived usefulness refers to the extent to which an individual believes using technology will enhance job performance, influenced by perceived ease of use (PEOU). PEOU refers to how easily people think they can use technology and has a significant contribution to determining PU but not to other elements. Attitude toward using technology (ATU) can influence intention and is influenced by the ease of use and the potential use of technology. BIU represents the tendency to continue using technology, and actual system usage (AU) is the real use of technology, which can be measured in various ways, including actual usage, frequency of usage, and user satisfaction (Fadlan & Dewantara, 2018).

### 2.5 Perceived Risk (PR)

PR is a user behaviour that causes risk because the system's consequences cannot be predicted with certainty, and some of these consequences tend to be harmful. According to (Bauer, 1960) and (Peter & Ryan, 1976), PR is defined as the risk perceived as a combination of uncertainty with the use of the results of the system. PR can affect user choices and can be interpreted as an estimate of the losses associated with system use and can limit the behaviour of system use. PR has two components, which are the probability of loss and the consequences of that loss. Users may consciously or unconsciously perceive risks when using a system, which can cause anxiety and discomfort (Rajak & Shaw, 2021). The complexity of using the system also adds to the problem of implementing and accepting the system (Yan et al., 2021). Factors influencing PR include information misuse, failure to gain product benefit, and functionality inefficiency risk (Alraja & Aref, 2015). This study adds PR as an external variable in measuring technology acceptance in the manufacturing module analysis.

### 2.6 Productivity of a Company

A company's productivity is defined as the ratio of output produced by the company to the number of resources used to produce it. According to (Sumanth, 1979) in (Tsarouhas, 2019), productivity means comparing the output produced and the input used. Factors that affect work productivity measurement include clear goals, employee performance comparison with standard time, quality of work produced, control of results obtained, and facilities provided to employees (Narpati et al., 2021). In digital transformation, productivity improvement can be measured by comparing results achieved before and after implementing a digital system (Budiman et al., 2022). Therefore, in this study, productivity will be measured by comparing production results before and after using the manufacturing module in the ERP system.

### 2.7 Adaptation Level

The adaptation level refers to how well a person or organization can adjust to new changes or situations. In the context of ERP, adaptation level refers to how well a company can adapt to a new system and be satisfied with its implementation. A high adaptation level is indicated by user satisfaction with the use of the manufacturing module (Prasetyowati & Kushartanti, 2018). The end User Computing Satisfaction (EUCS) model can be used to measure user satisfaction, which is an important indicator of the success of the digital transformation. The EUCS model evaluates the overall satisfaction of system users based on their experiences with the system. According to (Doll & Torkzadeh, 1988), EUCS comprises five main elements: content, accuracy, format, ease, and timeliness. A good quality information system that satisfies its users is a reliable indicator of the level of adaptation to the system used in the organization.

### 2.8 Risk Level

Risk is the potential loss or failure that can occur in a situation or project. (Widjaya & Sugiarti, 2013) found that risks can negatively impact company performance, which is inversely related to productivity. In this research, the measurement of the level of risk is the same as the measurement of a company's productivity. If the production results decrease, then the risk level is high, and vice versa. Therefore, risks must be considered and anticipated during the transformation process so that the company can take the necessary steps to reduce risks and maximize the benefits of using the manufacturing module.

### 2.9 Modified TAM

The Modified TAM is a variation of the TAM 1 model developed to accommodate factors not considered in the model. It can include adding variables or changes to the existing model structure. This study uses PU, PEOU from TAM 1 model, and PR from external variables as independent variables, while BIU is the dependent variable. The study's technology acceptance measurement is adapted to these variables. The research model aligns with studies by (Chang & Hsu, 2019) and (Regmi et al., 2019). Figure 1 of the TAM 1 model is adapted to Figure 2 for this research model.

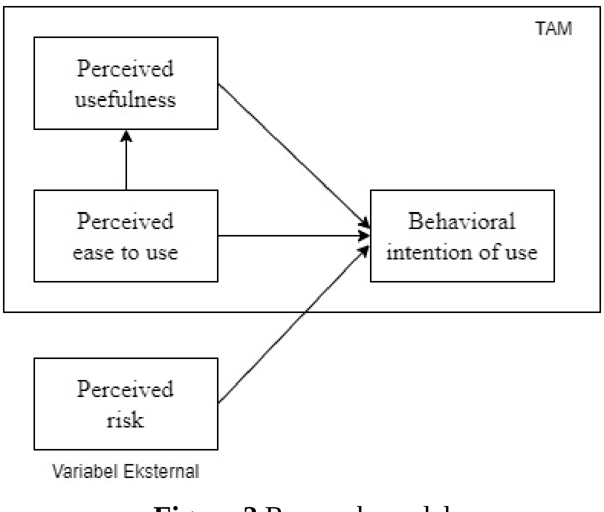


**Figure 2** Research model

## 3 Method

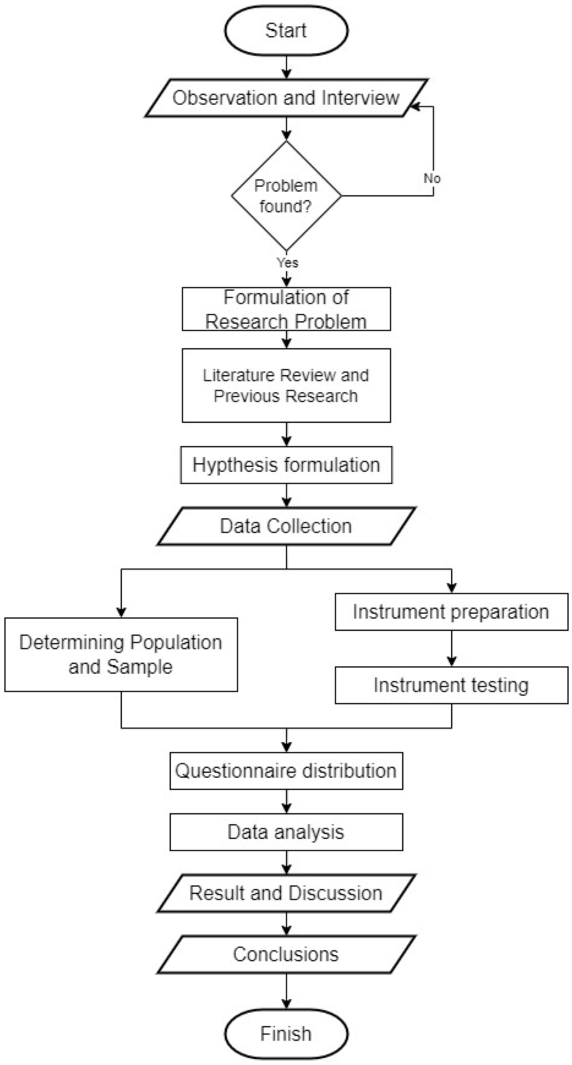


**Figure 3** Research flowchart

The research approach used in this study is quantitative, which analyzes the information using numerical data. This study is categorized as an ex-post facto research design because it does not alter the characteristics of the respondents (Matondang et al., 2020). The quantitative approach will be used to distribute questionnaires related to analyzing technology acceptance and measuring adaptation levels in supporting digital transformation success.

According to (Alfadda & Mahdi, 2021), The TAM is the research design that can explain the individual acceptance of information technology systems. The TAM hypothesis explains the company's technology acceptance and digital transformation success. This study uses the TAM theory, including external components, particularly PR. Data analysis is performed using the Partial Least Square - Structural Equation Model (PLS-SEM) method with the support of SmartPLS 4.0.8 software.

The measurement of digital transformation success is based on company productivity, adaptation level, and risk level. Productivity can be measured through document studies of internal company data such as documents and records to examine the company's products before and after using manufacturing modules. The adaptation level is measured using the EUCS model, and the risk level is inversely related to productivity.

# 4 Results and Discussion

## 4.1 Data Collection

The research was conducted by distributing a Google Form questionnaire to users of the manufacturing module at PT Allure Allumunio in the manufacturing process department. Fifty employees were selected as respondents, and the questionnaire was distributed through one of the PPIC managers who assisted in distribution. The author collected the questionnaire back with the help of the PPIC manager according to the availability of respondents to fill out the questionnaire.

A total of 50 questionnaires were given, and 48 questionnaires were usable for this research. According to (Latan et al., 2017), the minimum recommended sample size for research using the PLS approach is 30 to 100 cases or respondents. Therefore, 48 respondents can still be used as samples for research and meet the recommendation. The next stage in the research process is data cleaning, which includes checking for duplicate data, empty data, and outliers to determine the validity of the data used in the data processing.

The results of the data cleaning process, there are not found data from duplicate data, empty data, and outliers. After the data cleaning process, the collected data were grouped according to criteria such as gender, age range, education level, and length of service. Table 1 displays the data for the respondents based on the defined criteria.

**Table 1.** Respondent profile

| | Amount | Percentage (%) |
|---|---|---|
| **Gender** | | |
| Male | 43 | 89.58 |
| Female | 5 | 10.42 |
| **Age** | | |
| 16-25y | 20 | 41.67 |
| 26-35y | 20 | 41.67 |
| 36-45y | 5 | 10.4 |
| 46-55y | 3 | 6.25 |
| **Education** | | |
| Middle High School | 1 | 2.08 |
| High School | 30 | 62.5 |
| Bachelor | 16 | 33.33 |
| Magister | 1 | 2.08 |
| **Years of employment** | | |
| < 1 year | 8 | 16.67 |
| 1 – 3 years | 10 | 20.83 |
| 3 – 5 years | 21 | 43.75 |
| > 5 years | 9 | 18.75 |

### 4.2 Data Validity Test

Data quality is important since it represents the studied variables and proves hypotheses. The instrument must be valid and reliable. This study has convergent and discriminant measurement validity. The loading factor parameter and Average Variance Extracted (AVE) value assess convergent validity. The measurement is convergent if the loading factor and AVE values exceed 0.7 and 0.5. Each variable's cross-loading determines discriminant validity. The measurement discriminates if the cross-loading value is higher on the corresponding variable than on other variables.

This study examined convergent validity by correlating indicator scores and constructs. AVE > 0.5 and outer loading > 0.7 indicate high convergent validity in the PLS-SEM model. Table 2 shows the indication of outer loading values. Each indicator has an outer loading value above 0.7, indicating strong convergent validity.

**Table 2.** Outer loading

| | PU | PEOU | PR | BIU |
|---|---|---|---|---|
| **PU1** | 0.842 | | | |
| **PU2** | 0.809 | | | |
| **PU3** | 0.857 | | | |
| **PU4** | 0.805 | | | |
| **PU5** | 0.763 | | | |
| **PU6** | 0.808 | | | |
| **PEOU1** | | 0.799 | | |
| **PEOU2** | | 0.774 | | |
| **PEOU3** | | 0.863 | | |
| **PEOU4** | | 0.761 | | |
| **PEOU5** | | 0.790 | | |
| **PEOU6** | | 0.810 | | |
| **PR1** | | | 0.835 | |
| **PR2** | | | 0.803 | |
| **PR3** | | | 0.844 | |
| **BIU1** | | | | 0.811 |
| **BIU2** | | | | 0.846 |
| **BIU3** | | | | 0.831 |

In Table 3, the AVE value determines validity. In this study, if the AVE value is > 0.5, it can show that the four indicators can explain the four research variables.

**Table 3.** Average variance extracted (AVE)

| | AVE |
|---|---|
| **PU** | 0.664 |

| | |
|---|---|
| **PEOU** | 0.640 |
| **PR** | 0.685 |
| **BIU** | 0.688 |

To evaluate discriminant validity, the cross-loading value for each indicator must be higher for the relevant variable than for the other variables. Table 4 lists TAM measurement variable cross-loading values. The cross-loading value for each indication is higher than that of other indicators within each block, showing good discriminant validity.

**Table 4.** Cross loading

| | PU | PEOU | PR | BIU |
|---|---|---|---|---|
| **PU1** | **0.842** | 0.781 | -0.748 | 0.718 |
| **PU2** | **0.809** | 0.678 | -0.698 | 0.754 |
| **PU3** | **0.857** | 0.822 | -0.761 | 0.750 |
| **PU4** | **0.805** | 0.673 | -0.835 | 0.627 |
| **PU5** | **0.763** | 0.704 | -0.803 | 0.642 |
| **PU6** | **0.808** | 0.771 | -0.844 | 0.724 |
| **PEOU1** | 0.710 | **0.799** | -0.667 | 0.655 |
| **PEOU2** | 0.679 | **0.774** | -0.665 | 0.625 |
| **PEOU3** | 0.840 | **0.863** | -0.822 | 0.765 |
| **PEOU4** | 0.678 | **0.761** | -0.632 | 0.596 |
| **PEOU5** | 0.700 | **0.790** | -0.654 | 0.684 |
| **PEOU6** | 0.742 | **0.810** | -0.708 | 0.741 |
| **PR1** | -0.805 | -0.673 | **0.835** | -0.627 |
| **PR2** | -0.763 | -0.704 | **0.803** | -0.642 |
| **PR3** | -0.808 | -0.771 | **0.844** | -0.724 |
| **BIU1** | 0.681 | 0.663 | -0.656 | **0.811** |
| **BIU2** | 0.745 | 0.708 | -0.691 | **0.846** |
| **BIU3** | 0.723 | 0.743 | -0.657 | **0.831** |

Composite reliability tests variable indicator reliability. Composite dependency will be fulfilled if the variable is greater than 0.7. Table 5 illustrate this study's variable composite reliability values. Each variable has a composite reliability score above 0.7, suggesting strong dependability.

**Table 5.** Composite reliability

| | AVE |
|---|---|
| **PU** | 0.901 |
| **PEOU** | 0.892 |

| | |
|---|---|
| **PR** | 0.775 |
| **BIU** | 0.775 |

Table 6 demonstrate Cronbach's alpha reliability testing. Each variable's Cronbach's alpha value exceeds 0.7, indicating strong dependability.

**Table 6.** Cronbach's Alpha

| | Cronbach's Alpha |
|---|---|
| **PU** | 0.898 |
| **PEOU** | 0.887 |
| **PR** | 0.770 |
| **BIU** | 0.773 |

### 4.3 Data Analysis Test

Data analysis was performed using the PLS-SEM model with R-square, Q-square, and T-tests.

#### 4.3.1 ***R-Square Test***

The R-square test was used to evaluate the model's goodness of fit and explain the variance of the dependent variable being tested.

**Table 7.** R-square

| | R Square |
|---|---|
| **PU** | 0.827 |
| **BIU** | 0.777 |

The results showed in Table 7 that the influence of PEOU explained 82.7% of the variance of the PU variable, while the remaining 17.3% was affected by other factors. Additionally, 77.7% of the variance of the BIU variable was explained by the influence of PU, PEOU, and PR, while other factors influenced the remaining 22.3%.

#### 4.3.2 ***Q-Square Test***

In addition to the R-square test, the goodness of fit was also measured using the Q-square test to determine how well the model can explain the variation in the data. The higher the Q-square value, the better the model is at explaining the variation in the data. The calculated Q-square value for this study was 0.961, indicating that the structural model used in this study is highly suitable for the data and meets the goodness of fit criteria. So, the TAM measurement model developed can explain 96.1% of the data's variance.

### 4.4 Hipotesis Test

After confirming the data matches measurement standards, SmartPLS 4.0.8 software is used to apply the bootstrapping method to evaluate the structural model. The bootstrapping method reduces data analysis mistakes by continually sampling new data from the original data and executing the analysis on each new sample.

The t-statistic test evaluates the overall effect of independent variable X on the dependent variable Y concurrently. Comparing the resulting t-statistic value to the t-table value performs the t-test. If the t-statistic value is less than the t-table value, the null hypothesis is accepted, and the alternative hypothesis is rejected. However, suppose the t-statistic value is larger than or equal to the t-table value. In that case, the alternative hypothesis is accepted, and the independent variable substantially affects the dependent variable.

**Table 8.** Results of t-statistical analysis

| Hypothesis | Relationship | t-statistic | p-value | Conclusion |
|---|---|---|---|---|
| **H1** | PU has a positive effect on BIU | 3.412 | 0.000 | Accepted |
| **H2** | PEOU has a positive effect on BIU | 1.986 | 0.024 | Accepted |
| **H3** | PEOU has a positive effect on PU | 42.718 | 0.000 | Accepted |
| **H4** | PR has a negative effect on BIU | 1.174 | 0.120 | Rejected |

The structural model testing results can show if independent and dependent variables have a positive or negative effect. Table 8 shows three research hypotheses have been accepted since their t-statistic values are bigger than the t-table values. One hypothesis has been rejected because its value is smaller. H1, H2, and H3 significantly affect the dependent variable through the alternative hypothesis. H4 does not affect the dependent variable since the null hypothesis is accepted.

### 4.5 Discussion

After conducting a structural model analysis, referring to the problem statement, the analysis of the manufacturing module has been carried out through the PU, PEOU, and PR variables in the TAM method. The results of the structural model testing show that the formulated hypotheses will interpret the model used in this study. The following is an explanation of the hypotheses, and structural model analysis applied.

In summary, the results of a structural model analysis presented in Table 8 indicate that H1 is accepted. The variable of perceived usefulness (PU) significantly and positively influences a person's behavioural intention to use (BIU) a manufacturing module. This result is supported by previous studies (Althunibat et al., 2019; Fahmi et al., 2021) highlighting the importance of perceived benefits in technology used to determine behavioural intentions and improve technology acceptance. PU indicators which include the ability to speed up work, increase performance, productivity and effectiveness, as well as simplify work and provide benefits, can influence one's intention to use manufacturing modules. Thus, it is recommended to consider the benefits that users can obtain when implementing a manufacturing module, as it can create an intention to use it to facilitate data recording and achieve the company targets.

Table 8 reveals that H2 is accepted, demonstrating that perceived ease of use (PEOU) positively and significantly affects BIU manufacturing module use. The t-statistic is 2.260, and the p-value is 0.012. This supports (Kamal et al., 2020), and (Rafique et al., 2020) findings that perceived ease of use is a key factor in technology adoption behaviour. PEOU indicators include ease of learning, clear instructions, adaptability, and ease of use positively affect an individual propensity to continue using the manufacturing module. Hence, the manufacturing module's behavioural intention to use (BIU) is directly affected by PEOU. Technology acceptability depends on the manufacturing module's ease of use. Hence, it is advised to prioritize manufacturing module usability. This comprises easy-to-understand directions, device adaptability, and familiarization. These enhancements will make the manufacturing module easier to use and encourage users to keep using it to simplify inventory control and boost performance.

H3 is acceptable based on Table 8 analysis. This suggests that the manufacturing module's perceived simplicity of use positively impacts its perceived advantages. The t-statistic of 58.644 and p-value of 0.000 corroborate this. Perceived simplicity of use increases perceived usefulness, according to (Alfadda & Mahdi, 2021) and (Rafique et al., 2020). The perceived ease of use (PEOU) variable measures the manufacturing module's ease of use, which affects its perceived benefits. PEOU indicators, including simplicity of learning, control, and following clear directions, as well as flexibility and convenience, enhance the manufacturing module's benefits. The manufacturing module's benefits and technology adoption depends on the ease of use. These hypothesis results suggest that ease of use should be prioritized when installing the manufacturing module to improve its perceived benefits.

The research rejects hypothesis H4, indicating that perceived risk does not affect users' intention to use the manufacturing module. This is corroborated by the t-statistic of 0.739 and p-value of 0.230, which are greater than 0.05. Previous studies by (AlHadid et al., 2022) and (Rahmatika & Fajar,

2019) indicated that perceived risk does not significantly alter technology acceptance intention. The perceived risk (PR) variable of using the manufacturing module does not significantly affect the consumer's intention to use it, according to the study (BIU). Users' intention to utilize the manufacturing module was unaffected by PR signs such as vulnerability to information misuse, failure to acquire benefits, and inefficiency. The manufacturing module's risk does not affect technology acceptance intention. The hypothesis results suggest considering the cost of hazards associated with deploying the manufacturing module, such as data abuse, user benefits, and labour efficiency. This prevents users from abandoning the production module.

### 4.6 Measurement of Digital Transformation Success

The success of the digital transformation is measured through three indicators: company productivity, adaptation level, and risk level. Here are the measurements for each of these indicators.

#### 4.6.1 *Company Productivity*

Performance improvement based on effort measures company productivity. PT Allure Allumunio productivity checks monthly manufacturing process data recording per unit to evaluate if it can meet the target. Before using the manufacturing module, the company had fast production but slow data recording. The manufacturing module is intended to boost productivity and production data recording. Table 9 compares the company's production performance before and after deploying the manufacturing module with the percentage productivity gain over seven months.

**Table 9.** Production results per unit (%productivity)

| Month | Production Target (Unit) | On-Time Delivery | Late Delivery | % |
|---|---|---|---|---|
| Before Digital Transformation | | | | |
| **June** | 989 | 771 | 218 | 78 |
| **July** | 721 | 598 | 123 | 83 |
| **August** | 615 | 492 | 123 | 80 |
| **September** | 875 | 665 | 210 | 76 |
| **October** | 989 | 781 | 208 | 79 |
| After Digital Transformation | | | | |
| **November** | 823 | 716 | 107 | 87 |
| **December** | 795 | 739 | 56 | 93 |

Table 9 illustrates that the manufacturing module supported the company's production process and increased productivity by 10% to 15%.

#### 4.6.2 *Adoption Level*

The level of user adaptation to the use of the manufacturing module has been measured using the EUCS model. The results of the level of adaptation measurement are presented in Table 10, which shows the index score results for user satisfaction with the manufacturing module for each adaptation aspect, ranging from 75% to 81%.

**Table 10.** EUCS score measurement results

| Code | Satisfaction Indicator | Score | Category |
|---|---|---|---|
| **C1** | Accuracy of information | 77.1 | Satisfied |
| **C2** | Relevance of information | 78.3 | Satisfied |
| **C3** | Reports according to need | 78.8 | Satisfied |
| **C4** | Sufficiency of relevant information | 75.4 | Satisfied |
| | **Content Satisfaction** | **77.4** | **Satisfied** |
| **A1** | System accuracy | 79.6 | Satisfied |
| **A2** | Accuracy of information | 77.1 | Satisfied |
| | **Accuracy Satisfaction** | **78.3** | **Satisfied** |
| **F1** | Useful format | 80.8 | Very Satisfied |
| **F2** | Clarity of information | 75 | Satisfied |
| | **Format Satisfaction** | **77.9** | **Satisfied** |
| **E1** | User-friendly system | 78.3 | Satisfied |
| **E2** | Easy-of-use system | 80 | Very Satisfied |
| | **Ease of Use Satisfaction** | **79.1** | **Satisfied** |
| **T1** | Timely information | 77.5 | Satisfied |
| **T2** | Updated information | 77.1 | Satisfied |
| | **Timeliness Satisfaction** | **77.3** | **Satisfied** |

The overall satisfaction of users with the manufacturing module in the ERP system is 78% (satisfied). The lowest index scores are for C4 (sufficient information) and F2 (clarity of information). The average index score for user satisfaction with the manufacturing module is the lowest in terms of content and timeliness. Based on the results, user satisfaction with the manufacturing module is achieved with a score of 78%, indicating a good level of adaptation in improving the success of the digital transformation.

#### 4.6.3 ***Risk Level***

A drop in production-related performance measures company risk. PT Allure Allumunio records production process data per unit every month to identify units sent late. The company has a fast production process but slow data recording before deploying the manufacturing module. The manufacturing module should improve efficiency and the company's production outcome recording process. Table 25 displays the company's production process outcomes over seven months before and after deploying the manufacturing module and the risk reduction %.

**Table 11.** Production results per unit (%risk)

| Month | Production Target (Unit) | On-Time Delivery | Late Delivery | % |
|---|---|---|---|---|
| | | Before Digital Transformation | | |
| **June** | 989 | 771 | 218 | 22 |
| **July** | 721 | 598 | 123 | 17 |
| **August** | 615 | 492 | 123 | 20 |
| **September** | 875 | 665 | 210 | 24 |
| **October** | 989 | 781 | 208 | 21 |
| | | After Digital Transformation | | |
| **November** | 823 | 716 | 107 | 13 |
| **December** | 795 | 739 | 56 | 7 |

Table 11, which records production results per unit, demonstrates that the manufacturing module reduced risk by 10% to 15%. After the digital transition, the risk dropped from 24% to 17% to 7% to 13%. After installing the manufacturing module, the company's production process risk decreased. The measurement of digital transformation success shows that it increases firm productivity, satisfaction from adaption, and risk reduction.

## 5 Conclusion

This research yielded the following conclusions. This study used PLS-SEM to measure perceived utility, simplicity of use, and danger. All five variables passed model measurement testing, including outer loading, AVE value, and cross loading, to evaluate data validity and the composite reliability value over 0.7 in the reliability test. This study data is valid and dependable. In the structural model study, PU R-square was 0.827, and BIU was 0.777. Q-square yielded 0.961, suggesting good goodness of fit. PU>BIU, PEOU>BIU, and PEOU>PU were accepted in the hypothesis test, however, PR>BIU was denied since the t-statistic value was below the t-table value. This suggests that the manufacturing module's ease of use and benefits impact its adoption.

Each indication was tested for digital transformation success. Because firm productivity and risk are inversely related, production results were compared before and after the digital transition. After digital transformation, the company's production grew, as shown by the timeliness of dispatched units, and risk dropped because productivity increased. After adaptation level testing, users are satisfied with the production module, with a satisfaction index score of 78%. These good results suggest that digital transformation success depends on firm efficiency, adaptability level satisfaction, and risk reduction.

This study was conducted using the appropriate PLS-SEM testing guidelines, and the results met the established criteria and were supported by theory and previous research. However, some limitations in its implementation could result in bias and inaccuracies in the research findings. These limitations include: 1) The difficulty in accompanying respondents when completing questionnaires due to production processes, 2) The need for expansion of indicators to measure technology acceptance or use of different methods, 3) The limited number of respondents due to the scope of module users, and 4) The need for more specific productivity and risk measurements based on minutes. Further research is needed to apply more comprehensive methods or evaluate other aspects that may affect the research findings.

## 6 References

Agustina, N. (2018). Evaluasi penggunaan sistem informasi erp dengan metode pieces framework. Jurnal Informatika, 5(2), 278-286.

Alfadda, H. A., & Mahdi, H. S. (2021). Measuring students' use of zoom application in language course based on the technology acceptance model (TAM). Journal of Psycholinguistic Research, 50(4), 883–900.

AlHadid, I., Abu-Taieh, E., Alkhawaldeh, R. S., Khwaldeh, S., Masa'deh, R., Kaabneh, K., & Alrowwad, A. (2022). Predictors for e-government adoption of SANAD app services integrating UTAUT, TPB, TAM, trust, and perceived risk. International Journal of Environmental Research and Public Health, 19(14), 8281.

Alraja, M. N., & Aref, M. (2015). Customer acceptance of e-commerce: Integrating perceived risk with TAM. International Journal of Applied Business and Economic Research, 13(2), 913–921.

Althunibat, A., Zahrawi, A. A., Tamimi, A. A., & Altarawneh, F. H. (2019). Measuring the acceptance of using enterprise resource planning (ERP) system in private Jordanian Universities using TAM model. International Journal of Information and Education Technology, 9(7), 502-505.

Ambodo, B. S., Suryanto, R., & Sofyani, H. (2018). Testing of technology acceptance model on core banking system: A perspective on mandatory use. Jurnal Dinamika Akuntansi, 9(1), 11–22. https://doi.org/10.15294/jda.v9i1.12006

Bauer, R. A. (1960). Consumer behavior as risk taking. Boston: Harvard Univ.

Budiman, K., Adi, M. H., Munawar, A., & Purwinarko, A. (2022). The Telegram notification system for improving library services Universitas Negeri Semarang. Jurnal Kajian Informasi & Perpustakaan, 10(1), 75–88.

Chang, Y.W., & Hsu, P. Y. (2019). An empirical investigation of organizations' switching intention to cloud enterprise resource planning: A cost-benefit perspective. Information Development, 35(2), 290–302.

Cheng, Y.M. (2018). What drives cloud ERP continuance? An integrated view. Journal of Enterprise Information Management, 31(5), 724-750.

Danuri, M. (2019). Development and transformation of digital technology. Informasi Komputer Akuntansi dan Manajemen, 15 (2), 116–123.

Das, S., & Dayal, M. (2016). Exploring determinants of cloud-based enterprise resource planning (ERP) selection and adoption: A qualitative study in the Indian education sector. Journal of Information Technology Case and Application Research, 18(1), 11–36.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13, 319–340.

Dityawarman, F., Kertahadi., & Riyadi, R. (2016). Pengaruh task-erp fit dan pemanfaatan erp terhadap kinerja karyawan (Studi pada karyawan PT. PLN (Persero) distribusi Jawa Timur area Malang). *Jurnal Administrasi Bisnis, 35*(4), 104-113.

Doll, W. J., & Torkzadeh, G. (1988). The measurement of end-user computing satisfaction. MIS Quarterly, 12(2), 259–274.

Fadlan, A., & Dewantara, R. Y. (2018). Pengaruh persepsi kemudahan dan persepsi kegunaan terhadap penggunaan mobile banking. Jurnal Administrasi Bisnis, 62(1), 82-89.

Fahmi, M. A., Ciptomulyono, U., & Rahardjo, J. (2021). Analysis of ERP implementation in Perum BULOG with extended TAM 3 approach. *2nd International Conference on Global Development, 10*(2), 36–38.

Groover, M. P. (2020). *Fundamentals of modern manufacturing: materials, processes, and systems.* Hoboken, New Jersey: John Wiley & Sons.

Ha, N. (2020). The impact of perceived risk on consumers' online shopping intention: An integration of TAM and TPB. *Management Science Letters, 10*(9), 2029–2036.

Hanum, B., Haekal, J., & Adi Prasetio, D. E. (2020). The analysis of implementation of enterprise resource planning in the warehouse division of trading and service companies, Indonesia. *International Journal of Engineering Research and Advanced Technology, 6*(7), 37–50.

Kamal, S. A., Shafiq, M., & Kakria, P. (2020). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technology in Society, 60,* 1-10.

Latan, H., Noonan, R., & Matthews, L. (2017). *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications*. Cham, Switzerland: Springer International Publishing.

Linggadjaya, R. I. T., Sitio, B., & Situmorang, P. (2022). Transformasi digital PT Bank Jago Tbk dari bank konvensional menjadi bank digital. *International Journal of Digital Entrepreneurship*

*and Business, 3*(1), 9–22. https://doi.org/10.52238/ideb.v3i1.76
Matondang, P., Jalinus, N., & Ambiyar, A. (2020). Analisis pemetaan kemampuan numerik siswa smk model teori respon butir. *INVOTEK: Jurnal Inovasi Vokasional Dan Teknologi, 20*(3), 11–22.
Nandi, M. L., & Kumar, A. (2016). Centralization and the success of ERP implementation. *Journal of Enterprise Information Management, 29*(5), 728-750.
Narpati, B., Lubis, I., Meutia, K. I., & Ningrum, E. P. (2021). Produktivitas kerja pegawai yang dipengaruhi oleh Work from Home (WFH) dan lingkungan kerja selama masa pandemi. *Jurnal Ilmiah Manajemen Forkamma, 4*(2), 121-133.
Peter, J. P., & Ryan, M. J. (1976). An investigation of perceived risk at the brand level. *Journal of Marketing Research, 13*(2), 184–188.
Prasetyowati, A., & Kushartanti, R. (2018). User satisfaction analysis of primary care information systems in Semarang City with EUCS model. *Unnes Journal of Public Health, 7*(2), 120–125. https://doi.org/10.15294/ujph.v7i2.19305
Rafique, H., Almagrabi, A. O., Shamim, A., Anwar, F., & Bashir, A. K. (2020). Investigating the acceptance of mobile library applications with an extended technology acceptance model (TAM). *Computers & Education, 145*, 103732.
Rahmatika, U., & Fajar, M. A. (2019). Faktor-faktor yang mempengaruhi minat penggunaan electronic money: Integrasi model tam–tpb dengan perceived risk. *Nominal: Barometer Riset Akuntansi Dan Manajemen, 8*(2), 274–284.
Rajak, M., & Shaw, K. (2021). An extension of technology acceptance model for mHealth user adoption. *Technology in Society, 67*, 101800.
Regmi, R., Zhang, Z., Khanal, S., Zhang, H., & Kim, J. (2019). An empirical study on user acceptance of ERP system by international students in Chinese HEIs: A TAM approach. *International Journal of Higher Education Management, 6*(1), 67-82.
Rivandi, M. (2018). Pengaruh intellectual capital disclosure, kinerja keuangan, dan kepemilikan manajerial terhadap nilai perusahaan. *Jurnal Pundi, 2*(1), 41-54.
Rogers, D. L. (2016). *The Digital Transformation Playbook: Rethink Your Business for the Digital Age*. New York City, United States of America: Columbia Business School Publishing.
Sudjiman, P. E., & Sudjiman, L. S. (2018). Analisis sistem informasi manajemen berbasis komputer dalam proses pengambilan keputusan. *Teknologi Informasi dan Komunikasi, 8*(2), 55–66.
Sumanth, D. J. (1979). *Productivity measurement and evaluation models for manufacturing companies*. Chicago, United States of America: Illinois Institute of Technology.
Supriyanto, E. (2013). Manufaktur dalam dunia teknik industri. *Jurnal Industri Elektro dan Penerbangan, 3*(3), 1-4.
Tangi, L., Janssen, M., Benedetti, M., & Noci, G. (2021). Digital government transformation: A structural equation modelling analysis of driving and impeding factors. *International Journal of Information Management, 60*, 102356.
Tsarouhas, P. (2019). Improving operation of the croissant production line through overall equipment effectiveness (OEE) A case study. *International Journal of Productivity and Performance Management, 68*(1), 88–108.
Widjaya, P. E., & Sugiarti, Y. (2013). Penerapan risk management untuk meningkatkan non-financial firm performance di Perusahaan Murni Jaya. *Jurnal Ilmiah Mahasiswa Universitas Surabaya, 2*(1), 1–18.
Yan, M., Filieri, R., & Gorton, M. (2021). Continuance intention of online technologies: A systematic literature review. *International Journal of Information Management, 58*, 102315.