CLASSIFICATION MODEL FOR HOW LONG UNTIL EMPLOYEES ADOPT AGILE TRANSFORMATION: THE CASE OF A PRE-DIGITAL ORGANIZATION IN THAILAND

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ABSTRACT

[Purpose]: Pre-digital organizations have transformed their organizations for more agility. Agile transformation requires a significant investment of time and effort. The primary challenge encountered in agile transformation is employees' absence of an Agile mindset. If pre-digital organizations can identify employees who can adopt agile methodologies quickly, companies may expedite these employees' transition to an agile approach earlier. Thus, the research question is how pre-digital organizations can predict how long it will be until employees adopt agile. The primary research aimed to identify essential human factors affecting agile adoption.

[Design]: This research utilizes classification model development to classify employees who tend to embrace agile methodologies faster by relying on three algorithms, namely Decision Tree, Naïve Bayes, and k-Nearest Neighbors. The research mainly utilizes a quantitative approach, in which questionnaires collected data from 80 participants.

[Findings]: Research findings indicate that the classification model from the Naïve Bayes algorithm with evolutionary feature selection and range transformation normalization provides the highest accuracy at 53.75%. At the same time, k-NN and decision tree algorithms can provide accuracy at 47.50% and 42.50%, respectively. The finding also reveals that human factors, including collaboration, communication, trust, and administration, influence the duration of Agile adoption at a significant level. Moreover, researchers found a substantial correlation between Administration and Trust, Communication and Collaboration, and Administration and Communication.

[Originality]: This research fills the academic gap by demonstrating that organizations can develop the classification model to predict the duration of agile adoption for each employee using their human factors score.

Keywords: agile adoption; agile transformation; classification; human factors; machine learning

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I. INTRODUCTION

In the digital era, several pre-digital organizations have transformed their organizations for more agility, known as Agile Transformation. It has also happened in traditional industries such as insurance (Novarica Research Council, 2018). The Purpose of Agile Transformation is to enable the organization's ability to promptly respond to the change in customers' demands and the emergence of new digital advancements through the individuals' collaboration customers involvement within the teams (Abbas et al., 2008; Beck et al., 2001). Not only do technological capabilities improve, but traditional organizations also have to enhance the capabilities of their human resources, such as building new cultures, mindsets, or capabilities. Therefore, Digital Transformation often includes Agile Transformation since pre-digital organizations prefer to get the mutual reinforcement between these two elements (Chanias et al., 2019).

However, Agile Transformation requires significant time and effort since employees in traditional organizations often lack familiarity with agile methodologies. Therefore, human factors become the key challenge in the company's Agile Transformation (Tolfo, 2011). One of the primary challenges encountered in the Agile Transformation in large organizations is the absence of an Agile culture and mindset among their employees (Kolmodin, 2019). Thus, the average duration of Agile Transformation process required for completion in general organizations often takes 2 to 3 years (Ghani et al., 2016). This transformation process is widely considered a lengthy period with much-required effort for the Agile Transformation team and the organization.

From the pre-consideration, if pre-digital organizations can identify employees who are able to adopt and adapt agile ways of work quickly, they may expedite the transition of these employees to an agile way of working earlier. This will assist the organization to implement its Agile Transformation faster. Organizations are able to prioritize and recruit these people to work in Agile teams first so that the number of Agile teams or Agile employees in the organization can grow more rapidly. In addition to the academic research, there is a lack of literature addressing the use of machine learning knowledge in the Agile transformation realm. Thus, the research question is how pre-digital organizations can predict how long it will be until employees adopt Agile Transformation. This study aims to explore using a classification model in the data analytics field, with the relevant human factors to predict the adoption duration.

The paper is comprised of the following five parts. Start from section I, which is the introduction. This is followed by section II, which shows the information found in a literature review. Section III explains the research methodology in this study. Section IV presents the findings and discussion. Lastly, section V contains the conclusions, limitations, and future study.

II. LITERATURE REVIEW

The literature review section contains three sub-sections of the knowledge utilized in this paper. They consist of Agile Transformation and Agile Adoption, Human factors, and Machine Learning.

Agile Transformation and Agile Adoption

Agile Transformation has various definitions but usually relates to the business agility in 'culture', 'reactive/responsiveness to change,' and 'continuous improvement' (Barroca et al., 2019). Pre-digital organizations can utilize Agile methodology to enhance their business agility. Agile methodology consists of four values in the agile manifesto (Beck et al., 2001), including Individuals and interactions over processes and tools, Working software over comprehensive documentation, Customer collaboration over contract negotiation, and Responding to change over following a plan. The agile concept has been used widely in software development (Larman, 2004; Beck et al., 2001) and project management (Aguanno, 2004; Chin, 2004). Agile practices such as Scrum (Schwaber, 1997) have been utilized more in business functions (Oprins, 2019). This practice aims to enhance collaboration for the benefit of the cross-functional team.

Since Agile Transformation requires significant effort and time (Ghani et al., 2016), the company also requires appropriate measurements to indicate the Agile Transformation level in the organization. Agile adoption is one of the key measurements that plays a key role in the Agile Transformation in the organization (Moreira, 2010). The increasing Agile adoption level in the pre-digital organization also requires a period of time (Ghani et al., 2016). The existing academic literature reveals the measurement of Agile adoption level in various approaches.

Moreira (2010) considers Agile adoption a roadmap and separates the adoption period into three phases: Readiness, Deployment, and Support. The organization has to provide the Coaching throughout these three periods in the roadmap. Jovanović et al. (2017) also classify agile in three phases: Preparation, Transformation (team level), and Agile organization. Qumer and Henderson-Sellers (2008) initiated their Agile adoption and improvement model (AAIML), which consisted of six adoption levels: Agile Infancy, Agile Initial, Agile Realization, Agile Value, Agile Smart, and Agile progress. Sidky and Arthur (2007) utilize the agile principle and define Agile adoption in five levels: Collaborative, Evolutionary, Effective, Adaptive, and Encompassing.

Based on the Agile adoption practices, this study draws upon the adoption model proposed by Sidky and Arthur (2007). This is due to the fact that their methodology may be used at the individual level of Agile Transformation, making it suitable for addressing the research question of this study. Besides, several types of factors have been found to influence the adoption and implementation of Agile Transformation, categorized in three main factors: Technical factors (Abdalhamid and Mishra, 2017; Senapathi and Srinivasan, 2012), Organizational factors (Altuwaijri and Ferrario, 2022; Dhir et al., 2019; Abdalhamid and Mishra, 2017), and Human factors (Tolfo, 2011; Abdalhamid and Mishra, 2017; Altuwaijri and Ferrario, 2022; Mahanti, 2006; Chagas et al, 2015; López-Martínez et al., 2016).

Human Factors

Human factors play a crucial role in adopting Agile (Tolfo, 2011). Various academic research papers stated that human factors influence Agile adoption. This paper studies the literature review from eight research articles on human factors and Agile adoption. The result of the referenced quantity in each human factor is in Table 1.

Table 1

Referenced Quantity of Each Human Factor

Human factors	**Referenced quantity**
Collaboration	5
Customer centricity	3
Communication	2
Trust (in Teams)	2
Resistance (to Change)	2
Administration	2
Hierarchy	1
Personality	1
Transparency	1
Control	1
Hinder	1

Abdalhamid and Mishra (2017) show that Communication, Administration, and Customer centricity are relevant to the adoption level of employees. This is consistent with the study by Altuwaijri and Ferrario (2022), which found that customer-centricity influences the adoption of Agile Transformation. Abidin and Ghani (2016) also found that Collaboration, Transparency, Hinder, and Communication are the keys to success in the Agile environment. In addition, Chagas et al. (2015) found that Collaboration, Communication, and Trust are the most often mentioned in their research. This finding aligns with Abidin et al. (2017), who performed the literature reviews with the case study and found that collaboration is the most often mentioned factor, followed by resistance to change and trust.

This research aims to study the utilization of the classification model to predict employee's agile adoption duration. To achieve the research objective, this paper utilizes six key human factors: Collaboration, Customer centricity, Communication, Trust (in Teams), Resistance (in Agile), and Administration. These human factors and some employee demographics will be classified as features for the classification model. Furthermore, these factors will also be examined using statistical analytic techniques to find the relationship with Agile adoption.

Machine Learning

This research relies on Machine Learning knowledge for the model development to explore the utilization of a classification model for addressing the research question. Machine Learning is defined as "a subset of artificial intelligence (AI) that is all about getting an AI to accomplish tasks without being given specific instructions." (IBM, 2023). Machine Learning is vital to human lives and digital transformation these days (Zaki, 2019). Machine Learning can be categorized into two main categories: Supervised and Unsupervised. The classification model is classified as the supervised learning model.

This research employs the classification model to predict the duration until employees adopt Agile Transformation in pre-digital organizations. Predictive modeling is the use of statistical techniques with historical data to predict future outcomes (Lawton et al., 2023). This study utilizes the historical data of the demographics and human factors, with the adoption duration of the employees working in an agile team. Furthermore, predictive modeling is mainly developed using the classification model (Bhardwaj and Pal, 2012). Several researchers have used various classification algorithms in their studies, particularly relevant to the human aspects, such as the Decision Tree (Al-Radaideh and Al-Nagi, E, 2012), Naive Bayes (Pratama and Sarno, 2015), and k-Nearest Neighbors (kNN) (Bhannarai and Doungsa-ard, 2016). The following part explains more detail about the research methodology and classification algorithms used in this research.

III. RESEARCH METHODOLOGY

This section explains in more details the use of research methodology to address the research question. The structure of this section consists of the research method, case study company selection, and data collection.

Research Method

This research mainly utilizes the quantitative approach, particularly in data collection and analysis. As mentioned in the first section, the primary objective of this research is to verify relevant human factors that influence the duration of employees who tend to adopt Agile Transformation. From the literature review in section II, the research incorporates six human factors, including Collaboration, Customer-centricity, Communication, Trust (in team), Resistance (to change), and Administration, together with some demographic information as data inputs. At the same time, the output is the duration until each employee adopts agile transformation in the company. Using the quantitative method helps the researchers understand the relationship between those human factors and the duration of Agile adoption for the employees.

A small qualitative method is also used for questionnaire development. The researchers use a focus group technique with five agile coaches in the organization to get insight for developing the appropriate questions. An unstructured interview is used in the focus group. This ensures that the questionnaire is reliable and reflects the studied organization's context. Additionally, this is to ensure the questions are understandable for the informants. Then, this paper leverages Machine Learning knowledge to develop classification models to classify employees more likely to embrace agile methodologies faster. The classification models used in this research are based on three classification algorithms: Decision Tree, Naïve Bayes, and k-nearest Neighbors (k-NN).

Case Study Selection

This research aims to study the Agile Transformation in the pre-digital organization, which was established before the emergence of digital technology. This kind of organization usually faces challenges in its digital and agile transformation (Chanias et al., 2019; Dikert et al., 2016). Therefore, this research selects one of the pre-digital organizations in Thailand as a participating company. The selection of the company is by purposive sampling. The researchers chose this pre-digital organization since it has been implementing the Agile Transformation for two years, from early 2021 to the present day. This organization also has a dedicated Agile Transformation team responsible for implementing Agile Transformation and increasing Agile adoption in the organization.

Data Collection and Analysis

According to the quantitative research approach, this research develops the questionnaires to collect data using an online survey platform called 'QuestionPro.' The questionnaires contain some demographic information, including Age, Tenure, Gender, Working type, Agile type, and Department. The questionnaires also have specific 5-score Likert scale questions for addressing six human factors-related questions. Each human factor contains three questions, and the research sums the Likert score to the length of 1-15 scores for each human factor. Thus, the questionnaires have twelve independent variables, including numerical and non-numerical data. Lastly, a question is asked about 'How long until you adopt agile in the company?' to get the Agile adoption duration as a dependent variable and as a label data for training the model for further prediction. This Agile adoption duration is classified into four categories: less than three months, 3 – 6 months, 6 – 12 months, and more than 12 months.

Researchers use primary data collected by questionnaires from 80 participants who have experienced agile methodologies with agile coaches in the participating company from 2021 to 2023. This is the period from the start of the Agile Transformation journey in the organization until the present day. This organization is still implementing Agile Transformation. In addition, this research used pilot surveys with 15 employees and Index of item–objective congruence (IOC) techniques to construct appropriate questionnaires, with input from the Agile Transformation team.

For the data analysis and model development, this research uses the machine learning platform 'RapidMiner Studio' for statistical analysis, including Correlation Analysis and ANOVA analysis, to find the relationship between the human factors and the period until employees adopt agile transformation. Then, this research develops the classification model to study how machine learning can be utilized in Agile Transformation to predict the duration of Agile adoption. The researchers have used numerous techniques to modify the models, including adding normalization and feature selection in the process to enhance the model's accuracy. In addition, this research utilizes the cross-validation test technique for testing the model's performance. A cross-validation test is a resampling approach that involves partitioning the dataset into two subsets: training set and test set (Lakshana, 2023). This testing technique is suitable for the small set of data and is also able to prevent the over-fitting issue. It makes the testing results more reliable.

IV. FINDINGS AND DISCUSSION

The findings of this research can be demonstrated in data exploration from the questionnaires, statistical analysis results, and the classification model development results.

Data Exploration

After collecting the data, the researchers perform data cleansing to ensure that there is no inappropriate data, such as missing data or incorrect format, in the data set. The researchers then explore the data set to see the overall characteristics of the data before further processing, as shown in Table 2 and Table 3. Moreover, the researchers also used the box plots for data explorations, as illustrated in Figure I. The box plots reveal the outliers for all human factors. However, when considering the context of these data, the outliers derived from the questionnaire answers by the participants with more Agile adoption duration. Therefore, researchers decided to keep such outliers in developing the classification model since they belong to the participants' information.

Table 2

Data Exploration Results from Numerical Data

	Min	Max	Average	Standard Deviation
Age (Years)	26	59	38.97	8.24
Tenure (Months)	4	381	90.06	94.03
Collaboration score	5	15	11	2.12
Customer centricity	3	15	10.54	2.75
Communication	5	15	11.03	2.24
Trust	5	15	11.67	2.30
Resistance	5	15	11.74	1.96
Administration	5	15	11.77	1.93

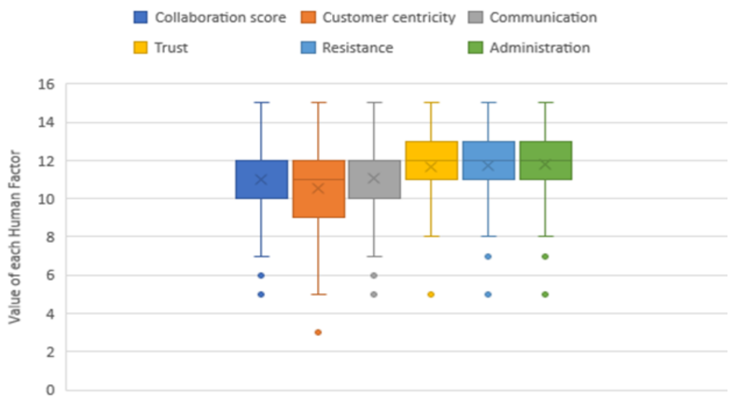
Table 3

Data Exploration Results from Non-Numerical Data

	Explored information (Amount)
Gender	Female (37); Male (43)
Work Type	Routine (35); Others (30); Project (15)
Agile Type	Self-team (40); Cross-function (40)
Department	Operation (42); Distribution (20); Marketing (12); Digital (6)
Adoption duration	Less than 3 months (15); 3-6 months (30); 6-12 months (25); more than 12 months (10)

Figure 1

Box Plots of Human Factors Survey Results



Statistical Analysis Results

This research utilizes a statistical method to identify the relationship between human factors and agile adoption duration. The researcher found the top three most significant correlations between administration and trust, communication and collaboration, and administration and communication, as illustrated in Table 4. Meanwhile, researchers utilize the ANOVA analysis to examine more insights from the categorical data. The finding reveals that human factors, including Collaboration, Communication, Trust, and Administration, influence the duration of Agile adoption with a significance level ($p\text{-value} < 0.05$), as shown in Table 5.

Table 4

Correlation Analysis Results

	Age (Y)	*Tenure (M)*	*Collaboration*	*Customer centricity*	*Communication*	*Trust*	*Resistance*	*Administration*
Age (Y)	1.00							
Tenure (M)	0.58	1.00						
Collaboration	-0.05	-0.09	1.00					
Customer centricity	0.11	-0.02	0.45	1.00				
Communication	-0.10	-0.20	0.60	0.48	1.00			
Trust	-0.09	-0.03	0.56	0.37	0.53	1.00		
Resistance	0.17	0.14	0.33	0.23	0.39	0.41	1.00	
Administration	0.20	0.14	0.53	0.33	0.57	0.66	0.38	1.00

Table 5

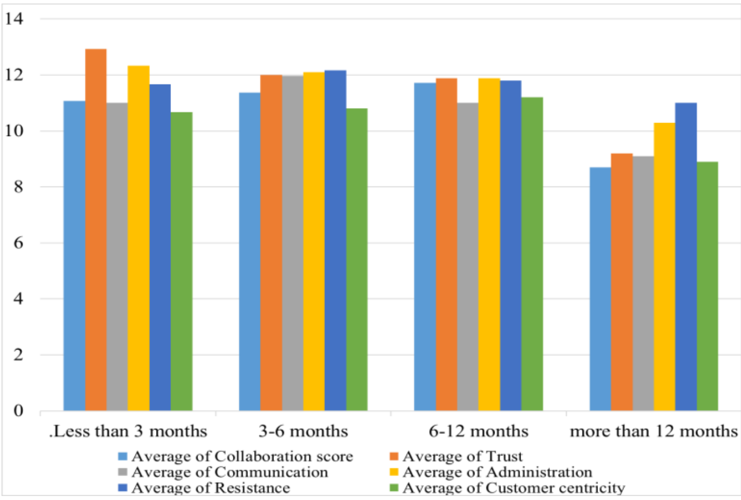
ANOVA Analysis Results

ANOVA Attribute	Result of the Adoption Period
Age (Y)	0.355
Tenure (M)	0.603
Collaboration	**>0.001***
Customer centricity	0.103
Communication	**0.001***
Trust	**>0.001***
Resistance	0.335
Administration	**0.029***

According to Figure 2, when considering the average score of six human factors, it is evident that these average numbers exhibit a high degree of similarity among 'less than three months,' '3 – 6 months', and '6 – 12 months' which are 11.61, 11.73, and 11.58 respectively. Meanwhile, the human factors average score of 'more than 12 months' reduces to 9.53. Thus, if the human factors average score is reduced to some particular points, the agile adoption of this employee will be at 'more than 12 months'. On the other hand, when considering the 'less than three months,' it is noticeable that trust has a higher average score compared to other factors, in either this duration or different duration. Therefore, trust can be considered a key factor influencing employees' adoption of Agile Transformation. These six human factors can be used as input data for AI or machine learning in order to generate further exciting insights, such as the Agile adoption duration.

Figure 2

Average Score of Six Human Factors



Classification Model Development Results

Table 6

Performance of Classification Models from Various Example Tunings Scenarios

Algorithms	Model Tuning Scenarios	Average Accuracy (%)	Remarks
Decision Tree	without tuning (confidence level 0.1)	32.50%	
	Z-normalization and forward selection	45.00%	Cannot predict 'less than 3 months' and 'more than 12 months'
	Z-normalization and backward selection	35.00%	Cannot predict 'less than 3 months
	Z-normalization and Evolutionary selection	38.75%	
	Z-normalization, Evolutionary selection, confidence level to 0.5	42.50%	
Naïve Bayes	without tuning	38.75%	
	Z-normalization and forward selection	47.50%	Cannot predict 'less than 3 months
	Z-normalization and backward selection	37.50%	
	Z-normalization and Evolutionary selection	47.50%	
	Range-normalization and Evolutionary selection	53.75%	
k-NN	without tuning (k=5)	26.25%	Cannot predict 'more than 12 months'
	Z-normalization and forward selection	45.00%	
	Z-normalization and backward selection	42.50%	
	Z-normalization and Evolutionary selection	48.75%	
	Evolutionary selection with k = 4 with weighted vote	47.50%	

According to Table 6, the model development results indicate that the classification model developed from the Naïve Bayes algorithm with evolutionary feature selection and range transformation normalization provides the highest accuracy at 53.75%. At the same time, the k-NN and decision tree algorithm with evolutionary feature selection and Z-transformation normalization provide accuracy at 47.50% and 42.50%, respectively. It is noticeable across all models that evolutionary feature selection enhances the efficacy in various models since it can select the potential features to be used more appropriately than the other selections. Although the forward selection provides better model accuracy in some scenarios, the model cannot predict all types of agile adoption duration. For instance, they use a decision tree algorithm with Z-normalization and forward selection.

In addition, the range transformation normalization is considered the most appropriate technique for the Naïve Bayes algorithm since it transforms the data to a range between 0 and 1 consistent with the probability logic inherent in Naïve Bayes classifiers. In addition, for the k-NN algorithm, the 'k' value equals 5, which provides the most accurate prediction to the model. This result indicates that the optimal quantity of data for this classification model is when the 'k' parameter is set at 5. A change from the value of 5 for the 'k' parameter consistently results in reduced accuracy. However, the key takeaway drawn from the classification model results is to demonstrate the practical use of machine learning or AI knowledge in Agile Transformation.

V. CONCLUSIONS, LIMITATIONS, AND FUTURE STUDY

In conclusion, this research combines knowledge from the fields of data analytics and Agile Transformation to explore the possible solution for the pre-digital organization to predict the duration of each employee's adoption of Agile Transformation. The findings of this research demonstrate that companies can develop the classification model and apply it to classify and predict the duration until employees adopt agile transformation by using their human factors score. It supplements the existing academic literature (Bhannarai and Doungsa-ard, 2016) that studies the use of human factors with machine learning to develop the predictive model for an agile topic. This finding also proves that the knowledge of machine learning, which is a subset of artificial intelligence (AI) (IBM, 2023), can be used in other fields of academic research, not only data analytics. There is an opportunity to utilize machine learning AI to predict interesting data to support Agile or Digital Transformation.

In addition, the research findings show consistent results with the prior research (Tolfo, 2011; Chagas et al., 2015) that described the human factors, including Collaboration, Communication, Trust, and Administration, that influence Agile adoption. It also sees some inconsistency with a small part of the existing literature (Altuwaijri and Ferrario, 2022; Mahanti, 2006) since Customer-centricity and Resistance lack a statistically significant degree of impact on the Agile adoption in this study. However, these results may vary from the different groups of study. The result of this research emerges from the study in this particular organization. Nevertheless, the pre-digital organizations can still utilize this proposed data analytics model within their Agile Transformation. It will assist the company in predicting and selecting potential employees to attend the agile team earlier. This will foster the company's ability to expand the Agile Transformation faster and more effectively.

There are a few limitations in this research. Firstly, since this research employs the case study approach within a single company, there is a limited generalization to apply the research findings to different sectors or other countries. Secondly, this research only collects the human factors data via questionnaires with self-assessment. There is a potential for participants to exhibit bias in their responses, lowering the absolute accuracy of the data.

Future studies that relate to the topic should collect a more significant number of data sets to create more effective model training. This can improve the reliability of the model as well. Additionally, the other researchers can apply 7-score Likert scale questions for addressing six human factors-related questions to have broader data values that may effectively classify the predicted results. Moreover, the researchers should deploy the study in various pre-digital organizations to enhance its generalization. These are examples of how researchers and practitioners can modify their models to improve the model's accuracy. Researchers and practitioners can utilize more AI to find the most appropriate modifications for the model's accuracy improvement. Moreover, academic researchers and practitioners can also study other AI knowledge apart from machine learning, such as Deep Learning or Generative AI, in the Agile or Digital transformation field.

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