# The Evaluation of Technology Implementation to Support Product Development Agility in FMCG Industry in Indonesia

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## Abstract

Pandemic covid-19 and the shifting of the digital market and the conventional market in recent years have affected FMCG companies to run their business, not only on supply chain and marketing but also on product development. To be competitive, FMCG companies must be able to be more agile in developing products. Technology adoption has been frequently proven to have a positive impact on agility in the FMCG supply chain. However, limited sources evaluate the role of technology adoption on product development agility. By using PLS-SEM (Partial Least Square Structural Equation Modelling) which the data were collected through semi-structured interviews and questionnaires, this research evaluates the breadth and the depth of implementation of six technology groups (pilot plant and prototyping, knowledge management, project management, cloud and information sharing, big data analytic, artificial intelligent), and the effect of supporting technology implementation factors to company's agile capability in product development. The results produce a model to understand the correlation between technology implementation factors and product development agility.

## Keywords
Agility, Agile Capabilities, Technology Implementation, Product Development, FMCG.

## 1. Introduction
The global business environment which is characterized by highly dynamic and cost-driven global competition demands operational excellence and business competitiveness. For a competitive business environment, innovation needs to be implanted/driven in all dimensions – product, process, and organization (Udokpro et al. 2020). Providing new products that fulfill changes in customer needs is required to get competitive advantages. Although new products promise increased profits, the process from start to finish is expensive, time-consuming, and full of uncertainty (Ofek 2008). By having more than 270 million people in Indonesia, the FMCG industry in Indonesia has many challenges and opportunities. Figure 1 shows the number or new registered consumer goods product in Indonesia, indicating business environment keep being more competitive. Thus, the company needs to be able to compete in developing more agile products to survive and grow in a changing environment.

Moreover, the challenge does not only triggered by competitor action but also the predictive and unpredictive changes in consumer demand like the development of the digital market and pandemic covid-19. The development of the digital market and the limited growth of the conventional market in recent years have affected the business orientation of FMCG. Mckinsey (2016) reports that digital growth in Indonesia is beginning to reshape the way people make decisions, improve customer experience, and create new business models to optimize value chains for unprecedented levels of efficiency. In today's dynamic market, companies are under intense pressure to introduce new products to compete with their competitors. In addition, new products become obsolete in a very short time.

The COVID-19 pandemic that has hit the world since 2020 has caused disruption in almost all sectors of life. The FMCG's industry is one of the industries that has been affected and has adapted and taken many opportunities amid


Figure 1. New registered product in Indonesia (BPOM, 2021)

limited conditions (Figure 1). Several companies carry out product development to meet the shifting needs of consumers during pandemics quickly while others do not. For example, Molto, a brand that focuses on fabric softener, issued a sanitary spray for clothes. Wipol, a brand that previously focused on floor cleaning solutions, took the opportunity to develop disinfectant wet wipes. Nutrisari, a fruit beverage brand, launched a multivitamin product.

The changes are always happening, not just in special conditions like pandemics. FMCG industry has a long history of delivering reliable growth through the mass product. However, the models that drive industry success are now facing enormous pressure as consumer behavior changes and the channel landscape changes (Mckinsey 2018). The shift in consumer behavior, especially in Indonesia, has been evident in recent years. Deloitte (2020) describes the process of shifting the market from physical stores, eCommerce, multichannel to omnichannel. Meanwhile, the role of millennials and gen Z, the covid-19 pandemic, and technology infrastructure have affected the exponential growth of the e-commerce market. Unlike supermarkets or hypermarkets, Minimarkets have a limited display capacity compared to supermarkets or hypermarkets, so only high-volume products are worth selling there. However, not all companies have the resources to compete in such a saturated market. Moreover, there are many segmented consumer groups whose needs can be met. The growth of e-commerce has facilitated to bridge of the gap. Manufacturers can offer their products to more target consumers. And consumers find it easier to find products that suit their needs. This condition causes mass customization. These changes affect FMCG companies in running their business, not only in the supply chain but also in product development. Deloitte (2019) published a report that 20% of respondents were willing to pay more for more personalized products. For example, in the trend of healthier, organic, and plant-based choices in packaged food products.

The shift in consumption patterns due to technological growth and the COVID-19 pandemic creates opportunities for producers to produce more variety in the market. To support this shift, companies must reconsider the entire value chain to take advantage of three pillars: speed of time to market, variety, and economies of scale (Tseng et al. 2017). In the FMCG industry, which is known to have dynamic environmental characteristics, companies must be able to develop products faster than before to take a competitive advantage. On the other hand, companies must maintain product quality safely and resources efficiently. The FMCG industry is one of the highly regulated sectors, which requires a series of validation steps to ensure product safety. This condition requires organizational agility. Companies need to be more agile in detecting changes and responding to them during the product development process

Technology is one of the competitive advantages that companies can adopt to increase their agility and competitiveness. Technology adoption has often been shown to have a positive impact on agility in FMCG manufacturing and logistics. There are many studies evaluating the effect of technology adoption on the agility of organizations (Desouza 2007), Kaliserry2007), Lui and Picolli 2007)). Most of the studies focus on operational and supply chain aspects. But sources are limited in evaluating the role of technology adoption on product development. This paper aims to fill this research gap by evaluating the role of technology in product development agility. The problem formulation of the problem in this study includes: How does the role of each technology affect product development agility? And what are the success factors for technology adoption to support agility in product development?

### 1.1 Objectives

Following are the objectives of this research:

- Identify the breadth and depth of technology implementation in product development in consumer goods companies in Indonesia
- Evaluating the impact of implementation level of each technology in product development agility of consumer goods companies in Indonesia

## 2. Literature Review

### 2.1 Agility in product development

Business agility has many definitions but there is one similarity that emphasizes adaptation capability to changes to survive and be competitive. Melarkode et al. (2004) defined it as "the capacity to anticipate changing market dynamics, adapt to those dynamics and accelerate enterprise change faster than the rate of change in the market, to create economic value. Sambamurthy et al. (2003) define it as the ability to detect and seize market opportunities with speed and surprise. Oosterhout (2007) defines it as the ability to sense highly uncertain external and internal changes and respond to them reactively or proactively, based on the innovation of the internal operational processes, involving the customer in exploration and exploitation activities, while leveraging the capabilities of partners in the business network. However, the terms may overlap between agility and flexibility. Oosterhout (2007) described flexibility as a predetermined response to a predictable change, while agility entails an innovative response to an unpredictable change. Flexibility is focused on single systems for low to medium rates of change, while agility is focused on groups of systems to deal with high rates of change.

The complexity of product development may be aggravated by the changes in internal or external companies. General change that may be faced by the company includes changes in customer requirement, network change, general economy, regulation, technology, market competition, social factor (Sharifi and Zhang 1999, Smith 2007, Yauch 2010, Tseng and Lin 2011). Before creating new products or improvements, companies should be able to sense those changes to be competitive. The capability of business agility could be classified into sensing capability and responding capability. The capability to sense the change in environment was stated as signaling environment (Desouza 2007) or detecting changes (Dove 2001).

However, after sensing the changes, there is a long series activity that involves many stakeholders from select product development types to concept realization. This requires response capability which was reflected by mobilizing resources to take advantage of future opportunities, continuously earn and improve the operations of the organization (Desouza 2007), and process changes adequately (Desouza 2007 and Dove 2011). Thus, the company needs to be agile in the overall series. The series of activities could be classified into three stages based on Serdar et al. (2011): discovery, development, and commercialization. Horvata (2019) and Fettermann and Echeveste (2014) have a similar approach. The discovery is a stage to find insight and idea, or in Fettermann and Echeveste (2014) stated as opportunity identification. In the development stages, a stage to turn an idea into a real product could be listed as planning, system-level design, detail design, testing in refinement (Fettermann and Echeveste 2014), or product design, product testing (Horvata 2019). Finally, the commercialization, a stage to turn the product into commercially available, is named production ramp-up (Horvata 2019). or product launch stage (Fettermann and Echeveste 2014).

The agile method which focuses on fast iteration requires synergy among product development stages. Agile promises to address many of the challenges facing the traditional FMCG synergy-focused model. Building an agile operating model requires abandoning the traditional command-and-control structure, where direction cascades from leadership to middle management to the front line, in favor of viewing the organization as an organism. This organism consists of a network of teams, all advancing in a single direction, but each given the autonomy to meet their goals in the ways that they consider best. The agile organization moves fast. Decision and learning cycles are rapid. Work proceeds in short iterations rather than in the traditional, long stage-gate process. Teams use testing and learning to minimize risk and generate constant product enhancements. The agile organization employs next-generation technology to enable collaboration and rapid iteration while reducing cost (Mckinsey 2018). Moreover, the output of an agile organization could be evaluated by responsiveness, competency, flexibility, quickness (Tseng and Lin 2011).

### 2.2 The opportunity of technology implementation in product development

There are many components in the agile system, one of them is technology. Lui and Piccoli (2007) illustrate the socio-technical system in figure 2. It illustrates both social consisting of structure and people, and a social system consisting of technology and process in the agile organization in figure 1. However, it requires not only the presence of all four components but also interaction with one another in a productive manner. This is because the four components, while distinct, are interdependent and constantly interacting, such that changes in one component create ripple effects on the others.

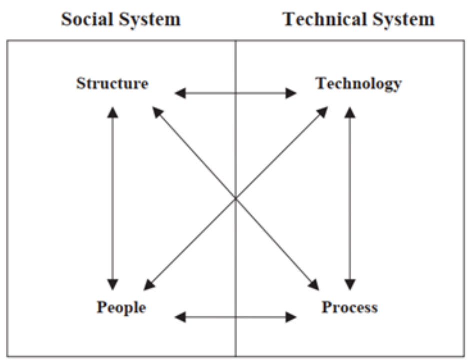


Figure 2. The socio-technical system

Some research evaluates the role of technology, however limited study that evaluate wide range of technology in supporting product development agility. Most study focus on information technology (IT) due to its characteristic. IT is pervasive in today's organizations to enable business electronically and to connect with customers, suppliers, and other strategic partners (Kallisery.2007). Another technology which applicable in product development process are pilot plant, knowledge management, project management, big data analytic, artificial intelligence (Serdar 2011, Deloitte 2020, Serdar 2021) but no study evaluates and compare all technology in product development stages. However, Ozer (2020) mention role of technology in supporting agility in terms of speed and productivity; collaboration, communication, and coordination; versatility; knowledge; decision quality; product service quality.

Moreover, the success implementation of technology does not rely on technology itself, but it is affected by many supporting success factors. List of proven success factors are common culture, employee evaluation and feedback management, identification, management communication, user training (Ozer 2000, Serdar 2021, HBR analytic 2021)

## 3. Methods

This exploratory research evaluates the correlation among implementation of technology type, technology supporting quality, agile capability, and product development agility which step is illustrated in figure 3.

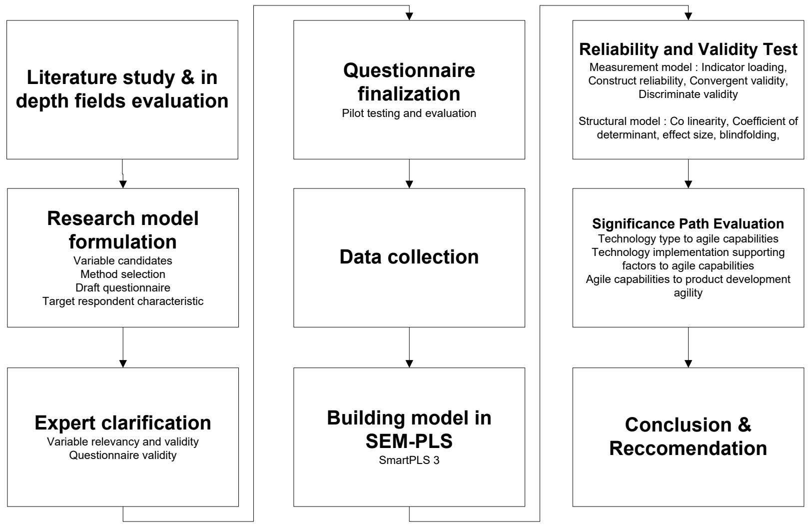


Figure 3. Research methodology scheme

PLS-SEM is a very useful technique for analyzing complex structural models increasingly encountered by researchers in this era. It is selected in this research because of its ability to explain the relationships among multiple variables simultaneously and its ability to measure unobserved or latent variables. PLS-SEM consists of two models, the measurement model (representing how measured variables represent the constructs) and the structural model (showing how constructs are associated with each other). The primary statistical objective of PLS-SEM is a prediction that maximizes the explained variance in the dependent variables is suitable for exploratory research (Hair et al. 2019). Based on a literature study, field review, followed by 7 experts of R&D in FMCG in Indonesia, the latent and indicator variables were selected. Table 1 shows experts' position and years of experience while table 2 shows final latent and indicator variables.

Table 1. List of R&D FMCG Experts

| Position | Years of experience |
|---|---|
| Head of Research and Development | 15 |
| Head of Research and Development | 15 |
| Head of Research and Development | 15 |
| Research and Development Manager | 13 |
| Research and Development Manager | 11 |
| Research and Development Manager | 8 |
| Brand and Market Research Manager | 10 |

Table 2. Latent and indicator variables

| Latent variable | Indicator variable |
|---|---|
| Level implementation of pilot plant technology | breadth implementation |
| | depth implementation |
| Level implementation of knowledge management technology | breadth implementation |
| | depth implementation |
| Level implementation of project management technology | breadth implementation |
| | depth implementation |
| Level implementation of cloud & information sharing technology | breadth implementation |
| | depth implementation |
| Level implementation of big data analytic technology | breadth implementation |
| | depth implementation |
| Level implementation of artificial intelligence technology | breadth implementation |
| | depth implementation |
| Technlogy implementation support | openness to technology culture |
| | congruity of evaluation and feedback system |
| | congruity of needs identification |
| | clarity of goal communication |
| | adequacy of user training |
| Sensing capability | ability to sense change in consumer needs |
| | ability to sense change in competitor action |
| | ability to sense change in partner (supplier, etc) |
| | ability to sense change in regulation |
| | ability to sense change in technology |
| Responding capability | ability to respond change without significant cost increase |
| | ability to respond change without significant additional time |
| | ability to learning from change |
| | ability to move resource (human, cost, etc) flexibly |
| Product development agility | time to market |
| | financial growth by new product |
| | covid 19 consumer fulfilment |
| | digital market consumer fulfilment |

Each indicator variable was translated as a reflective measurement model in the questionnaire. The measurement of breadth implementation of technology is based on the sum of implementation areas: ideation, development, commercialization. While the measurement of depth implementation is based on strategic level function: not implemented (1), basic operational (2), operational-tactical (3), tactical-strategic (4), very strategic (5). On the other, the indicator parameter of technology implementation support, sensing capability, responding capability, and product development agility were measured in Likert 5 scale (strongly disagree to strongly agree).

All the primary data are evaluated and modeled in SmartPLS 3. Since it uses reflective measurement, the evaluation Mode A SEM PLS is selected. Mode A uses the bivariate correlation between each indicator and the construct to determine the outer weights/loadings, typically associated with reflectively measured constructs (Hair et al. 2019). The measurement model reliability and validity are evaluated using indicator loading, construct reliability, convergent validity, discriminate validity. While the structural model is evaluated using co-linearity, coefficient of determinant, effect size, blindfolding. Finally, the significance of each path, direct and indirect, is evaluated.

## 4. Data Collection

The questionnaire was distributed to target respondents who have two characteristics: have been working in the FMCG industry in Indonesia and are intensely involved in product development projects. Networks of researchers and LinkedIn were used to select eligible respondents. The data were collected from 170 respondents from various FMCG companies in Indonesia, including personal care, home, packed food, and beverage companies, ranging from local to a multinational company. Job level distribution of respondents is 9.4% directors, 29.4% mid-senior managers, 29.4% junior managers, 20.6% supervisors, and 11.2% specialists with working experience in 8.9 years. Due to confidential issues, both respondent and company names are not shown in this report.

## 5. Results and Discussion

### 5.1 Measurement Model Test Result

The evaluation begins by evaluating indicator loading in figure 3. All of indicator loading in figure 4 is higher than 0.7 The loadings above 0.7 indicate the construct explains more than 50 percent of the indicator's variance. This confirms the indicator exhibits acceptable item reliability (Heir et al. 2019).

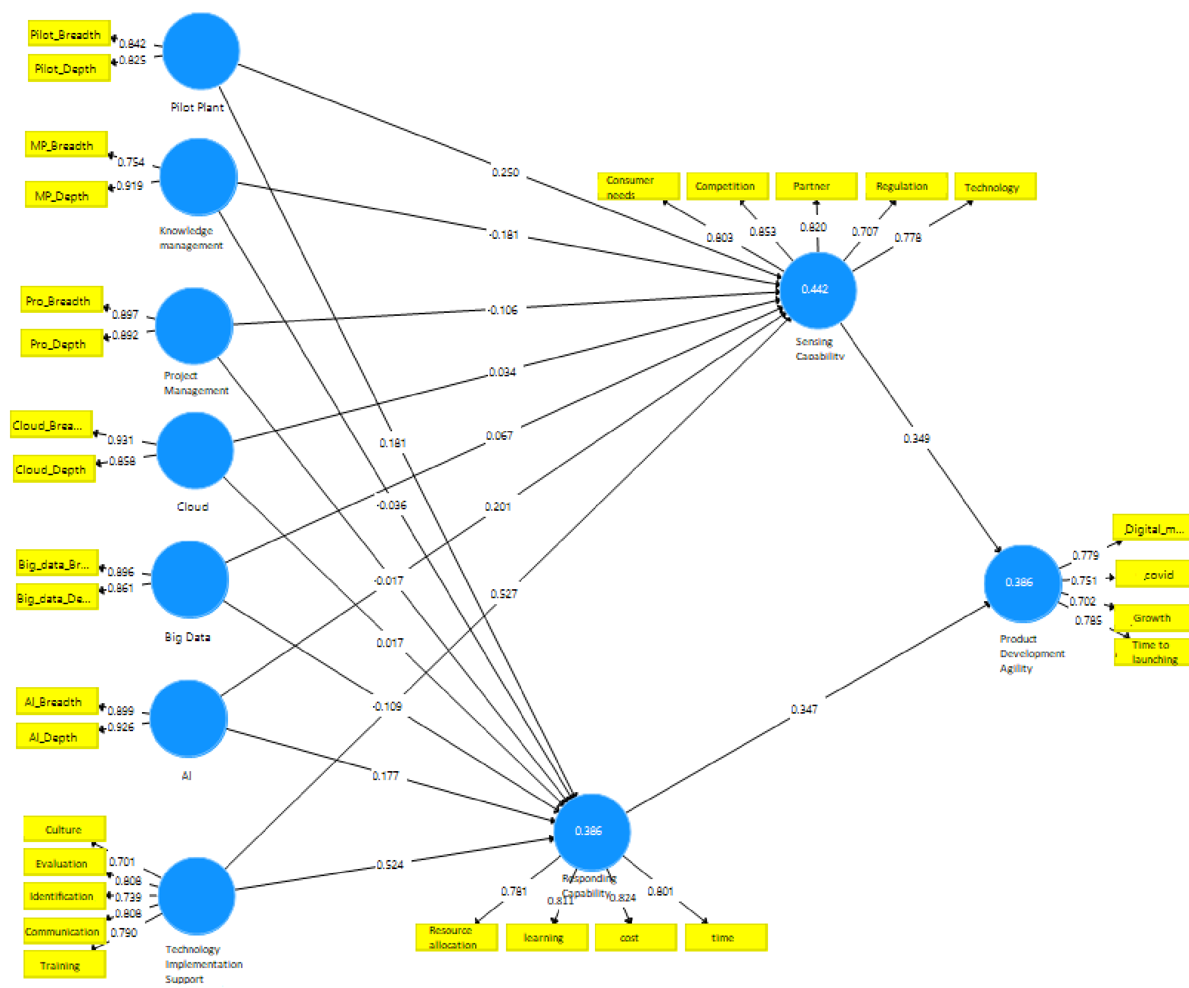

Figure 4. Result of SEM -PLS Models

The construct reliability in this research uses the composite reliability parameter. While Cronbach's alpha is a widely used method of assessing reliability, it does not weigh the individual indicators in the calculations. Composite reliability overcomes this limitation since it weights the individual indicators based. on their loadings and is therefore the preferred reliability approach (Hair et al. 2019). The composite reliability test in table 3, indicate that all measurement is reliable since the lower value is 0.82. Higher values indicate higher levels of reliability when interpreting internal consistency reliability results. Values between 0.60 and 0.70 are "acceptable in exploratory research," whereas results between 0.70 and 0.95 represent "satisfactory to good" reliability levels (Hair et al. 2019).

To evaluate the convergent validity, an overall metric of a reflective measurement model that measures the extent to which the indicators of a construct converge, the AVE (average variance extracted) are conducted The AVE is the average (mean) of the squared loadings of all indicators associated with a particular construct. The rule of thumb for an acceptable AVE is 0.50 or higher (Hair et al. 2019). The AVE test results in table 3 indicate that all AVE is higher than 0.50 indicates that the measurement model is valid.

Table 3. Composite reliability and AVE results

| | Composite reliability | Average Variance Extracted (AVE) |
|---|---|---|
| Level implementation of artificial intelligence technology | 0.909 | 0.833 |
| Level implementation of big data analytic technology | 0.871 | 0.772 |
| Level implementation of cloud & information sharing technology | 0.89 | 0.802 |
| Level implementation of knowledge management technology | 0.827 | 0.707 |
| Level implementation of pilot plant technology | 0.82 | 0.695 |
| Level implementation of project management technology | 0.889 | 0.801 |
| Technlogy implementation support | 0.879 | 0.594 |
| Responding capability | 0.88 | 0.647 |
| Sensing capability | 0.895 | 0.630 |
| Product development agility | 0.841 | 0.57 |

Discriminant validity is evaluated using heterotrait-monotrait ratio (HTMT) of correlations. The HTMT criterion is defined as the mean value of the indicator correlations across constructs relative to the geometric mean of the average correlations of indicators measuring the same construct. The result is shown in table 4. All the ratios are good, except responding capability to product development agility, 0.92, an HTMT value above 0.90 suggests a lack of discriminant validity (Heir et al. 2019). This indicates there is a very strong correlation between the two constructs. This makes sense because the better higher the response capability, the better product development agility. However, in this research, it is still maintained to be used because of researcher wants to know the effect or another capability, sensing capability to product development agility.

Table 4. Heterotrait-monotrait ratio results

| | Artificial intelligence technology | Product development agility | Big data analytic technology | Cloud & information sharing technology | Technlogy implementation support | Sensing capability | Responding capability | Knowledge management technology | Project management technology | Pilot plant technology |
|---|---|---|---|---|---|---|---|---|---|---|
| Artificial intelligence technology | | | | | | | | | | |
| Product development agility | 0.434 | | | | | | | | | |
| Big data analytic technology | 0.518 | 0.224 | | | | | | | | |
| Cloud & information sharing technology | 0.389 | 0.117 | 0.602 | | | | | | | |
| Technlogy implementation support | 0.217 | 0.502 | 0.196 | 0.169 | | | | | | |
| Sensing capability | 0.378 | 0.64 | 0.232 | 0.154 | 0.664 | | | | | |
| Responding capability | 0.33 | 0.66 | 0.093 | 0.168 | 0.68 | 0.695 | | | | |
| Knowledge management technology | 0.452 | 0.229 | 0.595 | 0.622 | 0.315 | 0.146 | 0.206 | | | |
| Project management technology | 0.203 | 0.162 | 0.269 | 0.507 | 0.137 | 0.074 | 0.148 | 0.471 | | |
| Pilot plant technology | 0.383 | 0.369 | 0.241 | 0.305 | 0.27 | 0.444 | 0.433 | 0.575 | 0.6 | |

## 5.2 Structural Model Test Result

The structural model is evaluated using Inner VIF, R2, and cross-validated redundancy. Table 5. Show VIF value of the structural model. The greater the VIV, the greater level of collinearity, and VIF above 5 are a definite indication of collinearity among the predictor constructs (Heir et al. 2019). The maximum VIF value of this model is 1.466, indicating the model is no collinearity among the predictor construct and could be evaluated for further validation.

Table 5. Collinearity statistic (VIF)

| | Sensing capability | Responding capability | *Product Development Agility* |
|---|---|---|---|
| Artificiall inteligence | 1.285 | 1.285 | |
| Knowledge management | 1.466 | 1.466 | |
| Project management | 1.364 | 1.364 | |
| Pilot plant dan prototyping | 1.309 | 1.309 | |
| Big data analytic | 1.409 | 1.409 | |
| Cloud and information sharing | 1.464 | 1.464 | |
| Technology implementation support | 1.08 | 1.08 | |
| Sensing capability | | | 1.551 |
| Responding capability | | | 1.551 |

Table 6. show the coefficient of determination of this model which measures in-sample predictive power. All parameters have $R^2$ less than 0.5. Based on Heir et al (2019), $R^2$ less than 0.50 is considered weak. Moreover, table 6 shows third criteria to examine is $Q^2$ which assesses the model's predictive power or predictive relevance. $Q^2$ larger than zero for a particular endogenous construct indicates the path model's predictive accuracy is acceptable for that construct while a value less than zero indicates a lack of predictive relevance (Hair et al. 2021). As shown in table 6, all three endogenous variables have a value more than zero. This indicates that although the model relationship is weak, the structural model has acceptable accuracy predictive relevance.

Table 6. Coefficient of determinant and model's predictive relevance

| | $R^2$ | $Q^2$ |
|---|---|---|
| Product development agility | 0.386 | 0.197 |
| Sensing capability | 0.442 | 0.254 |
| Responding capability | 0.386 | 0.229 |

## 5.2 Significance Test Result

The result of the significant structural model is summarized in table 7. A P-value is significant at the 0.05 level if zero does not fall within the 95 percent (bias-corrected and accelerated) confidence interval. (Hair et al. 2019). Among 16 paths in the model, we could indicate that only 7 bolded paths are significant. Among the six technology groups, only the level implementation of artificial intelligence is proven to affect sensing capability significantly by path coefficient 0.201. Moreover, only two technologies are proven to affect responding capability significantly. The level of implementation of artificial intelligence technology and pilot plant technology affect responding capability by path coefficient 0.177 and 0.181 respectively. The pilot plant, a small size production facility enables the company to respond to change by providing tools to minimize trial risk or trial cost during product development. Because of its characteristic that only requires small quantities, the company can evaluate faster, improve decision quality, and lower the risk. On the other hand, artificial intelligence enables the company to mimic human logic to evaluate and learn something from data faster than previously.

Table 7. Summary of Significance of Path Coefficient

| Jalur | P value | CI 2.5% | CI 97.5% | Path Cofficient | Status |
|---|---|---|---|---|---|
| Pilot Plant -> Sensing capability | 0.0030 | -0.067 | 0.394 | 0.25 | insignificant |
| Knowledge Management -> Sensing capability | 0.0460 | -0.38 | -0.029 | -0.181 | insignificant |
| Project Management -> Sensing capability | 0.1320 | -0.242 | 0.033 | -0.106 | insignificant |
| Cloud -> Sensing capability | 0.6320 | -0.116 | 0.16 | 0.034 | insignificant |
| Big Data -> Sensing capability | 0.3500 | -0.084 | 0.196 | 0.067 | insignificant |
| **AI -> Sensing capability** | **0.0010** | **0.073** | **0.32** | **0.201** | **significant** |
| **Technology implementation support -> Sensing capability** | **0.0000** | **0.382** | **0.64** | **0.527** | **significant** |
| **Pilot Plant -> Responding capability** | **0.0140** | **0.042** | **0.313** | **0.181** | **significant** |
| Knowledge Management -> Responding capability | 0.6130 | -0.181 | 0.105 | -0.036 | insignificant |
| Project Management -> Responding capability | 0.8200 | -0.209 | 0.104 | -0.017 | insignificant |
| Cloud -> Responding capability | 0.8060 | -0.139 | 0.14 | 0.017 | insignificant |
| Big Data -> Responding capability | 0.1730 | -0.265 | 0.038 | -0.109 | insignificant |
| **AI -> Responding capability** | **0.0160** | **0.036** | **0.326** | **0.177** | **significant** |
| **Technology implementation support -> Responding capability** | **0.0000** | **0.408** | **0.63** | **0.524** | **significant** |
| **Sensing capability -> Product development agility** | **0.0000** | **0.151** | **0.515** | **0.349** | **significant** |
| **Responding capability -> Product development agility** | **0.0000** | **0.153** | **0.507** | **0.347** | **significant** |

Moreover, technology implementation support affects both responding capability and sensing capability by bigger path coefficient 0.524 and 0.527 respectively. It means no matter what techniques are used, the good technology implementation support enables the technology to give better impact to both responding and sensing capability. To achieve the best benefit of technology implementation company should build an organizational culture that is open to technology, have a congruent evaluation, and feedback system, congruent needs identification, adequate user training, and last communicate the goal of implementation technology clearly. Last, the correlation between agile capabilities and product development agility of FMCG company in Indonesia is clearly seen significant. Both sensing capability and respond capability affect product development agility equally with similar path coefficient 0.349 and 0.347 respectively. It means company need to improve both abilities to get company more agile in developing new product.

## 6. Conclusion

The use of technology is indirectly affected the product development agility of the FMCG industry in Indonesia through improving agility capability. It works by catalyzing the product development agility by increasing the company's ability to respond to the changes. However, among the six technology groups, only artificial intelligence is proven to affect sensing capability significantly by path coefficient 0.201. Moreover, only artificial intelligence technology and pilot plant technology affect responding capability significantly by path coefficient 0.177 and 0.181 respectively. By this, it is highly recommended for FMCG company in Indonesia to invest in pilot plant or artificial intelligence technology and to balance both sensing and responding capability. For those who have implemented it, they may improve it by increasing the breadth and depth of application of both technologies. Moreover, to achieve the best benefit of technology implementation company should build an organizational culture that is open to technology, have a congruent evaluation, and feedback system, congruent needs identification, adequate user training, and last communicate the goal of implementation technology clearly. There are several gaps in our knowledge around technology implementation in research that follow from our findings and would benefit from further research, including an in-depth exploration of how combinations of technology support each other's to improve product development agility. It would also be helpful to develop a framework on technology implementation support comprehensively which may be used not limited in the FMCG industry.

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