# Benefits and Importance of Digital Technologies as Digital Maturity Drivers: A Case Study of Finland

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**Abstract:** This research explores the factors driving digitalization in Finnish SMEs and contributes to the discussion on Digital Maturity Models (DMMs). It examines how perceived benefits and the importance of digital technologies influence SMEs' digital capabilities. By identifying key motivators and barriers, the study aims to provide practical insights for both academics and practitioners, bridging the gap between theoretical models and real-world applications. A stratified sample of 1002 Finnish SMEs is used. K-means clustering categorizes these companies into three distinct clusters based on their digital maturity levels. Logistic regression models predict the likelihood of a company belonging to each cluster, using perceived benefits and the importance of digital technologies as predictor variables. This approach systematically analyzes the relationship between these factors and digital maturity, offering a robust framework for understanding digitalization in SMEs. Additional analyses explore interaction effects between predictor variables, providing deeper insights into the dynamics of digital transformation. The study yields six logistic regression models with 19 statistically significant coefficients ($p<0.05$). Results indicate that perceived benefits and the importance of digitalization vary across clusters, highlighting different motivators for digital initiatives based on digital maturity levels. SMEs with higher digital maturity perceive greater benefits and place higher importance on different digital technologies compared to those with lower maturity. These findings emphasize the need for tailored strategies to support digitalization efforts and reveal significant variations in the adoption of specific technologies at different stages of digital maturity. The findings guide practitioners and academics in focusing on relevant technologies and their outcomes concerning SMEs' digital maturity. Targeted interventions and support mechanisms should address the specific needs of SMEs at various stages of digital maturity. The study contributes to the evolution of DMMs by providing empirical evidence on the factors driving digitalization in SMEs and underscores the importance of a phased approach to digital transformation. Future research should include cross-country comparisons and longitudinal studies to enhance the reliability and validity of the results and understand the temporal aspects of digital transformation.

**Keywords:** Digital Maturity Models, SME, Digital Transformation

## 1. Introduction

The digital revolution has been affecting companies in all shapes and sizes, starting from converting analog material into digital form (Xie and Matusiak 2016, p. 59) continued by implementing plans for user access and information reuse (Brown 2013, p. 20–21) in a business setting. This process – dubbed “digitalization” – is a prerequisite for a company’s digital transformation. Transitioning from isolated digital processes, digital transformation can be understood as an overarching influence on the entire organizational process. Lucas et al (2013) describe "digital transformation" as a phenomenon that drives multifaceted individual, firm, and even societal changes. Fitzgerald et al (2014) and Verhoef et al (2021) further highlight the strategic nature of digital transformation, asserting that it should facilitate significant business advancements. Additionally, Urbinati et al (2020) note that digital transformation and its associated technologies significantly impact the capture and dissemination of knowledge, enhancing not only operational efficiency but also innovation and value co-creation processes (see e.g. Klingenberg et al 2022; Balta et al 2021; Lähteenmäki, Nätti and Saraniemi 2022; Barykin et al 2022). By adopting digital technologies, even “traditional” non-digital industries can optimize their processes, automate tasks, and reduce manual errors, leading to increased productivity and cost savings (Chowdhury, Adafin and Wilkinson 2019). Consequently, digital transformation should be perceived not merely as a collection of new technologies but through a comprehensive, holistic lens.

Digitalization poses numerous challenges for Small and Medium-Sized Enterprises (SMEs), impacting their ability to innovate and grow economically. One significant challenge is the financial burden associated with adopting digital technologies. High investment costs and limited financial resources often hinder SMEs from fully embracing digitalization (Restrepo-Morales et al 2024; Hassan et al 2023). In addition to individual upfront costs for digitalization, the economic and governmental circumstances can affect the SME digitalization initiative, favoring regions where general governmental support systems for R&D investments are higher (Brodny and Tutak 2022). Moreover, the digital transformation of a company is a strategic-level decision encompassing all aspects of a business (Henderson and Venkatraman 1993; Verhoef 2021) making the case for having a well-qualified staff in transforming IT into a profit-generating mechanism on a business level as opposed to only a functional level (Drnevitch and Cronson 2013). On that note, SMEs frequently struggle to find and retain

employees with the necessary digital skills, which can impede the effective implementation of digital technologies (Rivza et al 2019; Rupeika-Apoga and Petrovska 2022). This skills gap is further exacerbated by resistance from workers who may be reluctant to adapt to new digital processes (Restrepo-Morales et al 2024). The nature of these skills gaps can be examined by using the absorptive capacity of SMEs, or their ability to recognize, assimilate, and apply new knowledge, as it plays a crucial role in their digital transformation (Cohen and Levinthal 1990; Zahra and George 2002; Todorova and Durisin 2007 and Coccia 2007). SMEs with higher absorptive capacity are better positioned to leverage digital technologies for innovation. However, many SMEs lack this capacity, which can stifle their innovation performance and overall competitiveness (Hassan et al 2023).

In the wake of the digital revolution, SMEs are increasingly tempted to utilize data-driven technologies and automation to increase their competitiveness. The Internet of Things (IoT) technologies and data-driven solutions enable companies to use e.g., context-based adaptive systems, robust scheduling, and a fusion of real-world and virtual design and manufacturing systems as well as customer touchpoints for a more immersive customer experience (Monostori et at 2016). Understandably, the successful interplay between such technologies is a complex scenario, requiring competence and self-assessment on multiple levels (Atzori et al 2010; Schuch et al 2014 and Li, Xu and Zhao 2015).

To ease companies into their digital transformation processes, a number of various Digital Maturity Models (DMMs) have been developed to help companies self-evaluate their digital potential. These DMMs are structured frameworks designed to assess an organization's readiness and capability to adopt digital technologies and practices, providing a systematic approach to evaluate the current state of digitalization within an organization and identifying strengths, weaknesses, and areas for improvement. By offering a clear pathway for digital transformation, the models assist organizations in navigating the complexities of integrating digital technologies into their operations and strategies, as well as integrating digital transformation methodologies into their culture (Ganzrain and Errasti 2016). There are numerous DMMs available, and the majority of them are tailored toward certain industries or offering various focus points regarding the drivers, dimensions, or types of digitalization (see eg. Zamora Iribarren et al 2024; Sassanelli et al 2022; Cognet et al 2020). Brodny and Tutak (2022) have conducted a comprehensive analysis of the most common DMMs, including the following models:

- A maturity model for Industry 4.0 Readiness
- The Degree of readiness for the implementation of Industry 4.0
- The multi-attribute mode
- An Overview of a Smart Manufacturing System Readiness Assessment
- The Connected Enterprise Maturity Model
- IMPULS—Industry 4.0 readiness
- Digital readiness for Industry 4.0
- SIMMI 4.0
- Towards a Smart Manufacturing Maturity Model for SMEs
- The Logistics 4.0 Maturity Model
- A Smartness Assessment Framework for Smart Factories Using Analytic Network Process
- Croatian Model of Innovative Smart Enterprise (HR-ISE model)
- Maturity and Readiness Model for Industry 4.0
- AMM (Adoption Maturity Model)
- Three Stage Maturity Model in SMEs

Additionally, Schumacher et al (2016) have extended the research on DMMs to include not only functional but also organizational metrics, such as “strategy”, or “leadership” further emphasizing the need for a holistic approach.

This research aims to gain insight into the drivers of digitalization capabilities in Finnish SMEs, contributing to the broader discourse on DMMs. By focusing on the perceived benefits of digitalization and the importance of various technologies, this study seeks to identify the key motivators and barriers influencing the digital transformation journey of SMEs. Understanding these factors is crucial for developing tailored strategies that support SMEs at different stages of digital maturity.

## 2. Theoretical Background

When assessing the digital maturity of a company in the Finnish context, the choice of measure variables was made to ensure that the results would be comparable with previous Finnish research. To align the existing literature with the DMM context, a cross-reference between the components of the most popular DMMs and a study by Kääriäinen et al. (2019) from the VTT Technical Research Centre of Finland was conducted. The maturity variables from Kääriäinen et al (2019) include:

- The use of corporate website solutions
- The use of social media solutions
- The use of digital calendar solutions
- The use of web conferencing solutions
- The use of digital accounting solutions
- The use of e-commerce solutions
- The use of cloud service solutions
- The use of e-purchase solutions
- The use of artificial intelligence (AI) solutions
- The use of Big Data solutions
- The use of IoT solutions
- The use of customer relationship management (CRM) solutions

By cross-referencing these maturity variables with the IMPULS (Lichtblau et al 2015), PwC (Geissbauer et al 2015), and Deloitte (Deloitte 2018, Kiron et al 2016) model components, we can see that most of the proposed maturity variables exist within the models (Table 1).

**Table 1: Digitalization maturity variables used in the research and their appearance in IMPULS, PwC, and Deloitte DMMs**

| Digitalization Variable | IMPULS | PwC | Deloitte |
|---|---|---|---|
| Utilization of web-based applications or websites | X | X | X |
| Utilization of social media presence | X | X | X |
| Utilization of ecommerce solutions | X | X | X |
| Utilization of video conferencing solutions | | | |
| Utilization of cloud services | X | X | X |
| Utilization of electronic scheduling solutions | | | |
| Utilization of electronic purchase solutions | X | X | X |
| Utilization of Artificial Intelligence | X | X | X |
| Utilization of Big data | X | X | X |
| Utilization of Internet of Things | X | X | X |
| Utilization of electronic accounting solutions | X | | X |
| Utilization of CRM solutions | X | X | X |

Even though video conferencing or electronic scheduling solutions were explicitly absent from the examined models, their relationship with these models can be inferred by examining model components such as “Ecosystem management,” “Applications,” and “Workforce enablement” (Deloitte model), “Information sharing” (IMPULS model).

When adopting new technologies, companies must have a primary motivation to do so. The most widespread and cited technology adoption model is likely the Technology Acceptance Model (TAM) by Davis (1989), extended by Venkatesh and Davis (2000) and Venkatesh et al (2003). Across all these major models, the user's perception of the benefits derived from using digital technology is a central and critical driver of their intention to adopt and use it. The belief that the technology will provide tangible advantages (like improved performance, efficiency, and effectiveness) is consistently shown to be a powerful predictor of acceptance. Moreover, putting the utilitarian, performance-based motivations aside, there might also be a suite of “necessary” activities the SMEs need to perform in order to improve their digital transformation. These activities can be related to e.g. compliance, security, strategic alignment, or social necessity, and are linked to the Performance expectancy,

Social Influence, and Voluntariness of Use components in the United Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al 2003). These two dimensions provide the framework for the final input variables in this research. In line with Kääriainen et al (2019), both the Importance and Benefit dimensions have been further expanded to include the following elements (Table 2):

**Table 2: The measured Importance and Benefit dimensions used in the research**

| Importance | Benefit |
|---|---|
| Digital marketing | Time-saving |
| Customer experience | Travel costs |
| Cybersecurity | Customer needs |
| Digitized material | Operational efficiency |
| Data, AI | New business models |
| Cloud services | New partnerships |
| Digital sales | |
| Internal processes | |

As this research aims to gain insight into the digitalization drivers by using the introduced Importance and Benefit components of digital activities, the first task will be categorizing SMEs based on their digital capabilities by using the digitalization maturity variables. We will utilize a three-tiered approach suggested by Kiron et al (2016), where SMEs will be classified as "Early", "Developing", and "Maturing" based on their digital activities. This topic has previously been explored by the author (Väisänen 2023) and thus, the level of digitalization will serve as the target variable for this research. Once the three clusters of SMEs have been established, the effect of each component in the Importance and Benefit dimensions placing the respondent company into a specific cluster will be analyzed.

## 3. Empiric Part

The data for this research was collected by a Finnish research agency for the LAB University of Applied Sciences' Digital Innovation Hub project in winter 2021, and targeted the southeastern region of South Karelia in Finland. The Finnish enterprise landscape, like the EU, is dominated by micro-organizations (Statista 2022; Statistics Finland 2022). Observations from all SME sizes were needed to get a comprehensive view of digitalization, as larger SMEs likely have different digitalization needs due to more resources. Stratified sampling was used to avoid oversampling smaller companies and gain insights from a smaller subset of larger SMEs (Iarossi 2006, p. 99). A phone survey targeting 1,000 respondents in southeastern Finland was chosen for higher reliability. Interviewers called companies from a stratified list proportional to personnel categories, moving to the next stratum once enough responses were received. The final sample size was 1,002 respondents. The digitalization maturity variables, determining to which cluster an SME belongs, was measured in the following three-point scale: 1=respondent does not use this technology and doesn't intend to do so in the future, 2=respondent does not use this technology but is looking to do so in the future, 3=already uses this technology.

K-means cluster analysis was chosen to analyze the digital profile of the companies without pre-existing assumptions. This method groups homogeneous data points together, ensuring heterogeneity between groups (Larose and Larose, 2014, pp. 211–212). The algorithm automatically classifies findings, requiring no prior knowledge of the population. The number of clusters was determined to be three to follow the approach by Kiron et al (2016), but also so that low-, mid- and high-tier SMEs could be identified and mitigate the risk of fragmenting the data into unnecessarily small clusters.

The clustering process yielded three clearly different clusters of SMEs based on their digital technology usage (Figure 1). Of the three clusters, one (n=386) was clearly under-utilizing digital technologies all across the board compared to the other two clusters. The next group (n=506) performed better but remained in a comparatively similar level regarding AI, data, and IoT usage. The final group (n=110) was the smallest of all but excelled in AI, data, and IoT usage. These results provide further validation to the connection with the existing DMMs, as they proportionally reflect the "Early", "Developing", and "Maturing" groups from the Deloitte DMM (Kiron et al 2016).

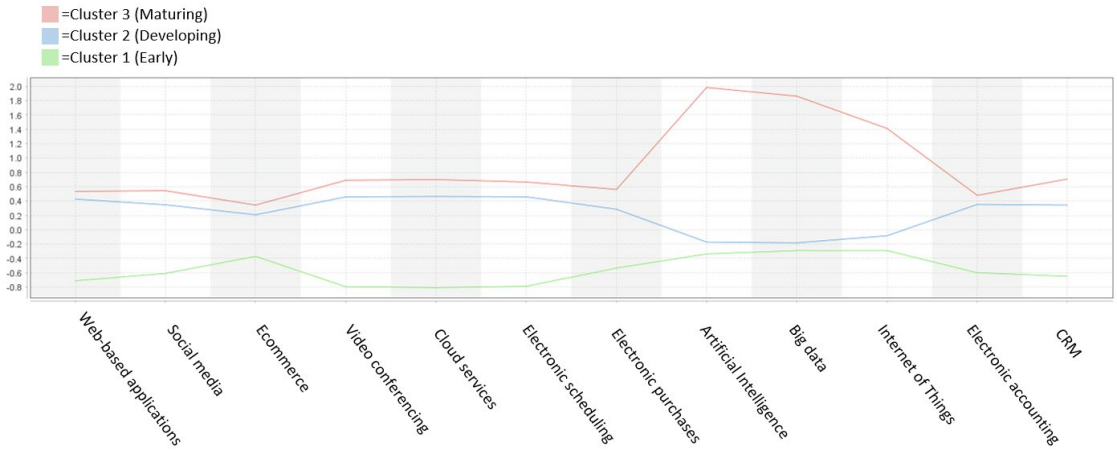


**Figure 1: Distribution of digital maturity variables by cluster. Higher values represent higher usage.**

Once the three clusters were identified, the next step was to understand the role of each component in the Importance and Benefit dimensions when predicting a company's association with each cluster. The dataset measured each of these components in a five-point Likert scale. The following six logistic regression models were created as binary classification tools for predicting if a company belongs to a specified cluster by using the components from the Importance and Benefit dimensions:

- Model 1.1 Effects of Importance dimensions when the company belongs to cluster 1 (Early)
- Model 1.2 Effects of Benefit dimensions when the company belongs to cluster 1 (Early)
- Model 2.1 Effects of Importance dimensions when the company belongs to cluster 2 (Developing)
- Model 2.2 Effects of Benefit dimensions when the company belongs to cluster 2 (Developing)
- Model 3.1 Effects of Importance dimensions when the company belongs to cluster 3 (Maturing)
- Model 3.2 Effects of Benefit dimensions when the company belongs to cluster 3 (Maturing)

Logistic regression offers a valid understanding of the mechanics behind classification and is commonly used in SME research. It can also perform comparatively against more complex methods, such as artificial neural networks (Abdin et al. 2020). To improve the validity and accuracy estimation of the results, a 10-fold cross-validation technique was used when constructing the models. By examining the results from the logistic regression models, we get the following six models with statistically significant ($p < 0.05$) dimensions highlighted (Tables 3-8):

**Table 3: Model 1.1. Effects of Importance dimensions for Early companies.**

| Importance Dimension | Standardized Coefficient | p-value |
|---|---|---|
| **Digital marketing** | **0.528** | **0.000** |
| **Customer experience** | **0.257** | **0.049** |
| Cybersecurity | 0.063 | 0.578 |
| Digitized material | -0.135 | 0.218 |
| Data, AI | -0.134 | 0.309 |
| **Cloud services** | **0.7187** | **0.000** |
| Digital sales | -0.056 | 0.670 |
| **Internal processes** | **0.652** | **0.000** |

**Table 4: Model 1.2. Effects of Benefit dimensions for Early companies**

| Benefit Dimension | Standardized Coefficient | p-value |
|---|---|---|
| **Time-saving** | **0.552** | **0.000** |
| Travel costs | 0.009 | 0.926 |
| Customer needs | 0.202 | 0.075 |

| Benefit Dimension | Standardized Coefficient | p-value |
|---|---|---|
| **Operational efficiency** | **0.472** | **0.000** |
| New business models | 0.078 | 0.532 |
| **New partnerships** | **0.310** | **0.009** |

**Table 5: Model 2.1. Effects of Importance dimensions for Developing companies**

| Importance Dimension | Standardized Coefficient | p-value |
|---|---|---|
| **Digital marketing** | **0.380** | **0.001** |
| Customer experience | 0.203 | 0.091 |
| Cybersecurity | 0.166 | 0.102 |
| Digitized material | 0.008 | 0.928 |
| **Data, AI** | **-0.819** | **0.000** |
| **Cloud services** | **0.412** | **0.000** |
| Digital sales | 0.099 | 0.383 |
| **Internal processes** | **0.581** | **0.000** |

**Table 6: Model 2.2. Effects of Benefit dimensions for Developing companies**

| Benefit Dimension | Standardized Coefficient | p-value |
|---|---|---|
| **Time-saving** | **0.391** | **0.000** |
| Travel costs | 0.003 | 0.974 |
| Customer needs | -0.036 | 0.734 |
| **Operational efficiency** | **0.244** | **0.014** |
| New business models | 0.012 | 0.918 |
| **New partnerships** | **0.311** | **0.004** |

**Table 7: Model 3.1. Effects of Importance dimensions for Maturing companies**

| Importance Dimension | Standardized Coefficient | p-value |
|---|---|---|
| Digital marketing | 0.185 | 0.397 |
| Customer experience | 0.229 | 0.325 |
| Cybersecurity | -0.189 | 0.372 |
| Digitized material | -0.295 | 0.053 |
| **Data, AI** | **1.207** | **0.000** |
| **Cloud services** | **0.788** | **0.000** |
| Digital sales | -0.294 | 0.096 |
| Internal processes | 0.062 | 0.751 |

**Table 8: Model 3.2. Effects of Benefit dimensions for Maturing Companies**

| Benefit Dimension | Standardized Coefficient | p-value |
|---|---|---|
| **Time-saving** | **0.465** | **0.019** |
| Travel costs | 0.076 | 0.547 |
| **Customer needs** | **0.790** | **0.000** |
| **Operational efficiency** | **0.422** | **0.019** |
| New business models | 0.021 | 0.911 |
| New partnerships | -0.076 | 0.662 |

Logistic regression models were employed to determine which factors (Importance and Benefit dimensions) significantly predicted membership in each cluster. For Early SMEs (Cluster 1) higher perceived importance of digital marketing, cloud services, and internal processes significantly increased the likelihood of belonging to this cluster. Importance of customer experience also showed significance. Higher perceived benefits in time saving, operational efficiency, and new partnerships were significant predictors. For Developing SMEs (Cluster 2) higher perceived importance of digital marketing, cloud services, and internal processes were significant predictors. Notably, a lower perceived importance of data and AI strongly predicted membership in this cluster. Higher perceived benefits in time saving, operational efficiency, and new partnerships were significant predictors. For Maturing SMEs (Cluster 3) a significantly higher perceived importance of data and AI and cloud services were the strongest predictors for this cluster. Higher perceived benefits in time saving, understanding customer needs, and operational efficiency were also significant predictors.

## 4. Conclusion

This research aimed to provide insight into the drivers influencing the digital capabilities and maturity of Finnish SMEs, contributing to the understanding of Digital Maturity Models (DMMs) in this context. By analyzing the perceived importance of various digital activities and the anticipated benefits of digitalization, the study successfully categorized SMEs into three distinct maturity clusters – Early, Developing, and Maturing – mirroring stages found in established DMM frameworks. Logistic regression analysis further illuminated the specific factors that differentiate these clusters. To address the validity of the results, the accuracy of each model was calculated. The accuracy scores of the models ranged from 63% (predicting classification into Developing SMEs using benefit dimensions as predictors) to 84% (predicting classification into Maturing SMEs using importance dimensions as predictors).

### 4.1 Theoretical Implications

The emergence of three distinct clusters based on technology usage empirically supports the tiered structure common in many DMMs, suggesting these models are applicable in the Finnish SME context. Additionally, the findings extend technology acceptance theories like TAM and UTAUT. While perceived benefits (like time savings and operational efficiency) are important across clusters, aligning with 'perceived usefulness' or 'performance expectancy' components of the models, the specific drivers vary significantly from cluster to cluster. For instance, the importance of 'data and AI' starkly differentiates Maturing SMEs from Developing ones, indicating that drivers evolve as maturity increases. The consistent importance of 'cloud services' and 'internal processes' for Early and Developing clusters might relate to foundational 'effort expectancy' or enabling conditions in UTAUT. While not directly measured, the results implicitly connect to absorptive capacity, as Maturing SMEs' focus on advanced technologies like AI and data suggests a higher capacity to recognize, assimilate, and apply complex digital knowledge compared to less mature SMEs.

### 4.2 Practical Implications

Understanding the distinct drivers for each cluster allows policymakers and support organizations in Finland to design more targeted interventions. For Early and Developing-stage SMEs the impact of cloud services as a necessity driver coupled with the need to improve internal processes suggests that improved uptake on utilizing cloud services would benefit them in organizing their activities in a more efficient manner, while Maturing-level SMEs most likely would benefit from supporting their data and analytics architecture through cloud services. Interestingly, only in the Maturing-level cluster was the use of AI deemed as a statistically positive indicator, making a case of demystifying AI or finding practical applications and use cases for it, a lucrative approach for accelerating Developing companies' digital transformation. Equally interestingly, the only negative statistically significant predictor was the perceived importance of AI and data when predicting the classification into a Developing SME. These findings would suggest that there might be a gap between the perception of the suitability of AI solutions between Developing and Maturing SMEs. To overcome this gap, the organizational DMM components from Schumacher et al. (2016) are more likely to be addressed than just technology uptake.

## Ethics Statement

Ethical clearance was not required in this research. All necessary permissions for research were obtained at the time of interviews, and the data used in the analysis was anonymized.

## AI Declaration

Generative Artificial Intelligence tools were used in the generation of this paper the following way: 1) Proofreading and grammatical errors (Grammarly), 2) Refining the overall tone of the text and checking for inconsistencies (Gemini 2.5).

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